Table 6. Transit trip generation in northeast Edmonton.

Item	Year	Northeast Sector[a]	North of 127 Avenue[b]	Beverly-Highlands[c]
Transit passengers	1975	NA	10 313	6 360
	1976	25 499	11 313	6 014
	1977	28 292	13 688	7 028
	1978	31 942	17 415	6 923
Population	1975	139 985	66 003	27 905
	1976	143 135	74 037	27 147
	1977	150 218	81 042	27 202
	1978	151 529	84 791	26 525
Trips generated as percentage of population	1975		15.6	22.8
	1976	17.8	16.2	22.2
	1977	18.8	16.9	25.8
	1978	21.1	20.5	26.1

Note: All passenger counts are based on data from the transportation planning section of Edmonton Transit.
[a]East of 97 Street and north of the North Saskatchewan River.
[b]East of 97 Street and north of 127 Avenue.
[c]East of LRT, north of the river, south of the CN tracks.

tional constraints, and that there were favorable construction conditions. Any comparisons, therefore, should take these unique factors into account, since it may not be possible to duplicate these conditions again, not even in Edmonton.

The operating phase shows that the promised labor saving from LRT was not realized initially in Edmonton. The main reason for this lack of productivity is the type of fare collection adopted. With the adoption of the POP system, the operating ratio for LRT should improve in the coming years in comparison with the remainder of the transit system.

The real value of the LRT system will not show until the new areas in the northeast sector have been fully developed and the trains have been lengthened. Although costs are expected to increase because of the lengthening of the line, revenue should also increase. The prospect, therefore, is that the operating ratio will improve for LRT whereas that of an all-bus system cannot improve at the same fare levels.

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Abridgment

Management Decision Model for Light Rail Vehicle Service: Development and Application

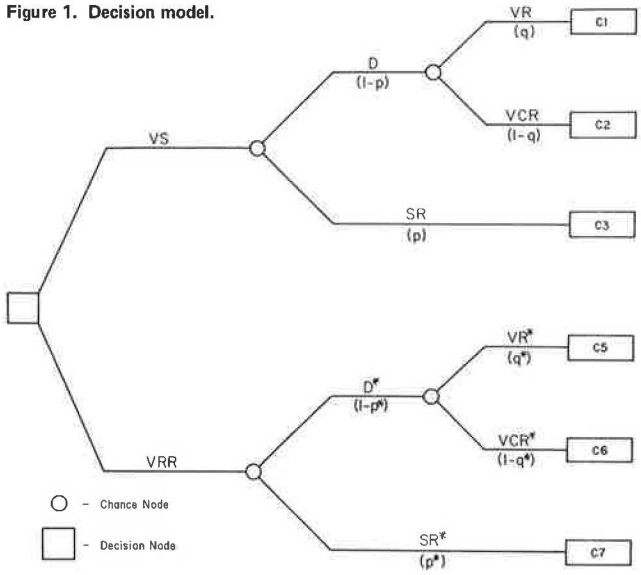
RICHARD J. SCRANTON, STEPHEN M. STARK, AND JOHN G. SCHOON

A vehicle reliability methodology to aid in the determination of an operating service policy or maintenance schedule for a light rail transit system is presented. A decision-theoretic approach is developed to balance the costs of troubleshooting and regular maintenance against the risks of breakdown, repair, and passenger delay. The reliability of a vehicle is compared with a critical vehicle reliability obtained from the decision-theoretic approach to determine the suitability of a vehicle for service or to determine the optimal scheduling of the next regular maintenance to minimize expected cost. This expected cost includes the cost of passenger delay in addition to operating and maintenance costs. To provide an example of how the methodology is used, reliability distributions were fitted to the miles between discrepancies for the propulsion, electrical, brake, and door subsystems based on data from the Massachusetts Bay Transportation Authority. Flexibility in applying the technique is illustrated in a sensitivity analysis. Changes in the decision process are shown with respect to changes in five key parameters.

Vehicle procurements throughout the past decade have brought about dramatic changes in the design and complexity of rail transit vehicles. Increased complexity, however, often causes total equipment reliability to decrease (1, p. 5).

The American Public Transit Association (APTA) has been developing a program that identifies the scope and estimated acquisition and maintenance costs of information and data, including hardware components critical to system availability and dependability. Problems with maintenance scheduling and fleet availability have also resulted from equipment complexity. The application of reliability techniques has evolved to reduce the escalating costs of maintenance; to assist in this regard, the federal government has recently begun to collect and organize vehicle failure data through the Transit Reliability Information Program (TRIP) (2). Within specific systems, reliability assessment of the Bay Area Rapid Transit (BART) system includes "analyzing the slope of the failure rate trend, following preventative maintenance, to be used as a guide for

Figure 1. Decision model.



evaluating the proper period between planned maintenance actions" (3). The Research and Development Division of the Ontario Ministry of Transportation and Communications computes the mean miles between defects, miles between defects, and an appropriate probability density function of the miles between defects for various vehicle types (4, p. 1).

A decision framework is proposed in this paper to determine whether a light rail transit (LRT) vehicle is sufficiently reliable to place into revenue service. The model can also be used to determine the optimal period until the next regular maintenance should be scheduled.

Two key terms are defined in APTA's glossary of reliability terminology (5). A discrepancy is a nonconformance of equipment or nonequipment items to stated standards exclusive of the external environment. A service failure not only prevents the unit from performing its intended function but also disrupts or delays scheduled service.

METHODOLOGY

Decision Framework

Consider first the immediate decision to approve or not to approve a vehicle for revenue service. Figure 1 summarizes the alternative decisions and possible outcomes. It is assumed that an operating manager may choose to place the vehicle into service (VS) or remove that original vehicle and replace it by a backup vehicle (VRR). In either case, the vehicle in service either suffers a discrepancy (D or D*) or completes the run with no discrepancy (SR or SR*). If a discrepancy occurs, depending on its nature, either the operating vehicle is able to complete the run and is then repaired (VCR or VDR*) or it must be removed from service immediately. C1 through C7 represent the costs associated with the various combinations of events. It is important to note that some of the costs must include the cost of passenger delay. p and p* represent the reliabilities (i.e., probabilities that no discrepancy occurs) for the original and backup vehicles, respectively. q and q* represent the proportions of vehicles suffering discrepancies that must be removed from service (i.e., the conditional probabilities of a discrepancy being serious enough to require immediate removal of the vehicle from service).

The operating manager must choose VS or VRR and will encounter one of the costs C1 through C7 based on a combination of the probabilities p, p*, q, and q*. Assuming that all costs, including passenger delay, can be measured in dollars, it is reasonable to choose the option that results in the minimum expected cost. For the decisions VS and VRR, the expected costs, EC(VS) and EC(VRR), can be written as

$$EC(VS) = (1 - p)[(q)C1 + (1 - q)C2] + (p)C3 \tag{1}$$

$$EC(VRR) = (1 - p^*)[(q^*)C5 + (1 - q^*)C6] + p^*C7 \tag{2}$$

Thus, if EC(VS) is less than EC(VRR), the vehicle should be put into service. If EC(VS) is greater than EC(VRR), the original should receive maintenance and the backup vehicle should be put into service.

Alternatively, we could determine that value of the vehicle reliability p, at which EC(VS) = EC(VRR) or at which the manager is indifferent between placing the original vehicle into service or removing it. This critical value of p is denoted p_{cr}. Decisions will be made as follows. If the vehicle reliability p is greater than p_{cr}, the original vehicle should be placed into service. If p is less than p_{cr}, the original vehicle should receive service and the backup vehicle should be used.

Setting the two expected costs equal and solving for p,

$$P_{cr} = \{[(q)C1 + (1 - q)C2] - (1 - p^*)[(q^*)C5 + (1 - q^*)C6] + p^*C7\} \div \{[(q)C1 + (1 - q)C2] - (p)C3\} \tag{3}$$

This framework can also be used for scheduling regular maintenance if the vehicle reliability is a function of the vehicle mileage.

Vehicle Reliability

A vehicle can be modeled as a set of interacting subsystems. If it is assumed that discrepancies occur independently within subsystems, then the vehicle reliability p becomes the product of the subsystem reliabilities. If stochastic independence is not appropriate, then other models can be used, leading to more complicated functions.

By using available data on some indicator of vehicle use such as miles between discrepancies (MBD) and an appropriate failure-rate distribution, the reliability of each subsystem can be written as a function of, say, MBD.

When one knows the number of miles since the last discrepancy for each system, one can determine each subsystem reliability and therefore the vehicle reliability. Alternatively, knowing p_{cr} and using the inverse process, one can determine the number of miles that the vehicle has yet to travel until its reliability is reduced to p_{cr}. Regular maintenance can be scheduled for the time when this number of miles will be accumulated.

FORMULATION OF SERVICE POLICY

Basic Assumptions

The methodology previously described is applied to an LRT line modeled on a section of the Massachusetts Bay Transportation Authority (MBTA) Riverside Line. A profile of the line's operating characteristics during a workday morning peak period included stations, distances, travel times, boardings, and alightings along the route.

Based on available data and average costs for maintenance of way, maintenance of equipment, power, the conducting of transportation and administration, and miscellaneous, a total cost of \$7.32/mile (in

1979 dollars) was estimated. Furthermore, passenger time was assumed to be worth \$4.00/h, the diagnosis of a discrepancy was estimated to be \$9.01, and an unscheduled maintenance action was \$77.25/action on the average. For this example, C1--assumed to include the cost of a run, expected passenger delay time, and an unscheduled maintenance action--was estimated at \$286.28. Expected passenger delay was calculated by using probabilities proportional to distance between stations. It was further assumed that delayed passengers would wait 7 min (the headway) until the next regularly scheduled vehicle arrived. C2, estimated to be \$143.03, was assumed to include the cost of a run and an unscheduled maintenance action. C5, C6, and C7 were assumed to be equal to C1, C2, and C3, respectively, plus the cost of diagnosis (\$9.01 for the original vehicle in each case).

The data also indicated that about 50 percent of all discrepancies required the vehicle to be removed from service. Hence, q was taken as 0.5. The reliability of the replacement vehicle, p*, was assumed to be 0.70.

Decision Rule

By using the data, the basic assumptions noted previously, and Equation 3, p_{cr} was calculated to be 0.22. Although this may seem to indicate a very unreliable vehicle, note that there is a 61 percent chance that no passengers will be delayed, since 50 percent of the vehicles that develop an equipment discrepancy can still complete the run.

Assessment of Vehicle Reliability

MBTA vehicle 3400 was chosen for this example. The vehicle was modeled as the independent interaction of four subsystems: propulsion, electrical, brakes, and doors. For each subsystem, the probability of a discrepancy was modeled as a function of the MBD by using a two-parameter Weibull distribution and fit by the method of moments (6, p. 40). A chi-square test was used to check acceptable goodness of fit. The Weibull distribution was chosen because of its common use in failure-rate analysis and its general flexibility of shape. In this form, each subsystem reliability was calculated as $\exp[-(\text{MBD}/\theta)^{\beta}]$.

Decision

Each subsystem reliability was estimated, and this resulted in a vehicle reliability of 0.84. The data for this estimate are as follows:

Subsystem	θ	β	Miles Since Last Discrepancy	Reliability
Doors	6756	0.83	200	0.95
Electrical	7740	0.89	150	0.96
Propulsion	7463	0.83	300	0.97
Brakes	9571	0.94	180	0.95

Since the reliability is greater than $p_{cr} = 0.22$, the vehicle should be approved for service.

Alternatively, by using the same models and data, it can be shown that the reliability of vehicle 3400 would be reduced to 0.22 after it has been in service for another 2300 miles. Thus, regular maintenance should be scheduled when the vehicle is expected to achieve this mileage.

Sensitivity of Parameters

The decision rule was formulated as a basis for illustrating the concepts used. Some key parameters assumed in this base problem are likely to be different in actual operations. A sensitivity analysis was performed in order to assess the effects of changes in five parameters (proportion of in-service discrepancies, reliability of replacement vehicle, value of passenger travel times, number of delayed passengers, and peak-period headways) on the critical value of p.

CONCLUSIONS

A framework has been presented for determining a service policy that combines several aspects of transit operation usually considered independently. A decision model is developed that is intended to minimize the long-run operating costs of an LRT system. Of key consideration to the process is the light rail vehicle and how well it can be expected to perform. Vehicles are put into revenue service, or regular maintenance is scheduled contingent on an expectation of realizing a minimum expected cost, which includes the cost of passenger delay.

To make this framework operational for any LRT system, the model must be structured carefully. Do other decision options exist for the operating manager? Are the estimated costs sufficiently accurate? Is the model consisting of independent subsystems realistic? Is the Weibull distribution appropriate, and what other distributions may be more suitable under specific circumstances? Is it realistic to assume that, in the event of a service failure, passengers will be delayed an amount of time equal to the headway? Are subsystem reliabilities functionally dependent on MBD only?

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