and diverts automobile users in the outlying suburban areas to the new service. Because the new express bus routes have fewer stops en route, overall travel-time savings accruing to the commuters will induce some riders from other existing transit modes. Location of such service in the corridors where good transit service, e.g., commuter rail, already exists should therefore be avoided.

The preceding analyses indicate that 14 corridors connecting 25 park-and-ride locations throughout the DVRPC region show promise for instituting the service. If all the routes are made operational, they will attract approximately 4,300 additional daily riders from the existing automobile users. Some shifts in the ridership of other transit modes will also result, diverting about 4,900 trips to the new service (Table 3).

The next step in this project is to advance the park-and-ride and express bus service to the implementation stage. In view of the fact that the financial resources are becoming increasingly scarce, the transit operating agencies may not be able to implement all corridors at the same time. The work described in this paper will then be expanded to study selected corridors in more detail and refine the demand estimation and operational and physical characteristics of the parking lots and routes. Operational agreements, if any, should be investigated with two or three owners of the parking lots falling in the corridor as well as with the transit operating agency that will provide the express bus service.

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Role of Quantitative Analysis in Bus Maintenance Planning

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Transit maintenance costs increased dramatically between the late 1970s and early 1980s. At the same time, transit funding assistance has become less available. These circumstances require that managers operate their maintenance systems more efficiently and that they adopt new cost-cutting policies. It is proposed that maintenance managers use quantitative techniques in planning the operations and policies of maintenance systems. The suggested quantitative techniques, commonly used in other areas of business, industry, and government, may be employed to plan transit maintenance system policies and operations. A simplified simulation model of a hypothetical maintenance system is presented as an example of the use of analytical techniques in maintenance planning.

More stress has been placed on the performance and efficiency of transit maintenance in the past few years. Although greater emphasis on maintenance is often attributed to the financial pinch between escalating maintenance costs and decreases in the availability of federal and local operating assistance, the reasons for paying more attention to transit maintenance are not so simple. Granted, transit industry maintenance costs have grown in recent years at a rate of approximately $400 million per year while at the same time funding assistance has been reduced; however, financial problems are only the most noticeable symptom of the basic problems facing transit maintenance (1).

Faced with this situation, transit maintenance managers must deal with the following basic questions:

1. What are the causes of escalating transit maintenance costs?
2. How can transit maintenance systems be made more efficient?
3. What are the cost trade-offs for various levels of maintenance service and bus dependability and availability?
4. How do maintenance policies and service requirements affect fleet life-cycle costs?
5. At what level can the transit industry afford to fund maintenance systems?

In this paper, it is shown how analytical tools can be used to aid transit managers in answering the first four questions. More specifically, it is proposed that once sufficient maintenance information exists, analytical planning tools can be used to better understand the relationships among maintenance policies, costs, bus availability (spare levels), parts availability, life-cycle costs, and other factors that can be used for a better understanding of the complex problems that maintenance managers face. The need for analytical planning tools is defined, their capabilities and limitations are described, and, last, a simplified example is given of a rudimentary maintenance simulation model.

NEED FOR ANALYTICAL MODELS

The escalation of maintenance cost has been more rapid than that of inflation in the past few years (1). Increasing labor, parts, maintenance-facility, and equipment costs have added to cost escalation, but because the rate of increase has outstripped the average inflation rate of labor and materials, other factors must be contributing to transit maintenance's rapid rate of cost escalation. These factors are probably related to recent changes in vehicle designs, to regulation of vehicle procurement and maintenance practices, and to other, less tangible factors such as changes in the makeup of the bus maintenance labor force.

In the past (1950s, 1960s, and early 1970s), bus designs remained relatively standard and design modifications were gradual. Maintenance managers developed a working knowledge of performance and reliability and maintainability. With the advent of advanced-design buses in the late 1970s, vehicle designs became more complex, equipment available for vehicles became more varied, and maintenance managers lacked familiarity with the reliability of the new buses. Because of lack of experience with these vehicles and the associated uncertainties, and for other reasons, some transit systems are designing and using the automated maintenance information system (MIS). These systems automatically summarize and analyze the maintenance status of buses, material, and labor. For example, the MIS will usually keep track of the date and mileage of repairs and mileage between failures and will automatically produce fleet averages for experiences with the same component. A notable example of an MIS is the one being designed and tested by the five members of the Western Transit Maintenance Consortium (2).

The MIS permits the maintenance manager to access a computerized data base that contains information related to the most current as well as historical information related to maintenance operations. Other information-summarizing options are often built into the data base, such as the flagging of exceptions, preventive-maintenance scheduling, work-order processing, parts and consumables inventory controls, and others. Note that what the MIS has given the maintenance manager is the information necessary to inventory existing conditions. An MIS only provides information to aid in the management of the maintenance operation under existing conditions. This capability is certainly an improvement over conditions without the MIS; however, it leaves the maintenance manager with only judgment and experience when evaluating the impact of new policies or when forecasting future needs. For example, a current MIS could not tell the maintenance manager what the trade-offs are between increases in the maintenance work force and the percentage of the bus fleet that should be held as spares nor does the MIS provide the maintenance manager with an estimate of the number of buses that will experience a specific component failure in the future so that the maintenance system can be prepared for surges in the failure rates of specific components.

The capability to estimate the impacts of policies and to make forecasts of failures, parts demand, maintenance labor required, and so forth, may be achieved through the use of planning models. Planning models extend rather than replace the MIS. In fact, planning models are calibrated and updated on the basis of information that is commonly produced by an MIS. The importance of adding planning capabilities to an MIS lies in the two general types of information that such a system would provide: (a) forecasts of the impacts resulting from changes in maintenance system policies or operation and (b) forecasts of future events while the maintenance system's policies and operation remain constant. The latter of the two types of information could be determined without planning modeling capabilities by simply waiting until events occur and using this experience in conjunction with the manager's judgment to project the occurrence of similar events into the future. Of course, one must assume that the maintenance manager will stay at the same position for an extended time, that bus designs will remain constant, and that the manager can keep track of the many events that occur simultaneously. On the other hand, a computer-based planning model can almost instantly forecast events (e.g., failure rates for several components) simultaneously, and the results will be completely consistent with whatever experience with the event is available. Such forecasts would be especially valuable in predicting surges in component failures so that the maintenance system and parts inventories could be prepared in anticipation of the surge; in the case of low failure rates of a particular type, resources could be devoted to other maintenance functions.

Computer-based planning models are particularly valuable in obtaining forecasts of the results of system changes (the first general type of information). Once a computer model is created to symbolize the system, the model can be used to experiment with the system. The user can ask what-if questions. For example, what impact will changing the number of mechanics have on the number of spare vehicles required to support the active fleet? Besides not disrupting the actual system with an experiment, a computer model has two important advantages. First, the results are obtained very quickly, perhaps within a few minutes, whereas the same experiment with an actual system might take years to produce results. Second, since all of the system variables in the model are controlled, the analyst knows that the results from the experiment were produced by the variable or variables manipulated. In other words, results obtained from an experiment with the real system may be affected by variables that cannot be controlled and that change during the course of the experiment, such as the weather or a union contract. These factors can be held constant in a computer model. Thus, a computer model can be less disruptive, faster, and more accurate than an actual experiment on the maintenance system.

Examples of the impacts on transit maintenance systems that could be estimated with the use of a computer model would include

1. Testing the impact of various alternatives for reducing the portion of the fleet used as spares (for example, one strategy that could be tested is to increase the number of mechanics devoted to various maintenance activities);
2. Determining the internal cost savings and reallocatable resources made available by sending buses to private repair shops for particular types of repairs (for example, testing the implications of sending buses to a maintenance contractor for brake repairs);
3. Testing the impact of varying preventive-maintenance policies (for example, a computer model

could determine the impact, in terms of in-service breakdowns and maintenance work load, of increasing or decreasing the interval between the preventive replacement of a particular part; the model could also test the impact of instigating a preventive replacement policy for a particular part); and

4. Analyzing the impacts on the maintenance system in shifting new purchases of buses to different models or to buses with different major components (for example, buses with smaller engines may experience less frequent transmission-related failures than buses with larger engines; however, buses with smaller engines may experience more frequent engine-related failures--the trade-offs between buses with different engines and failure rates can be tested).

The interests and concerns of individual maintenance managers may include those listed above or others. What is particularly important about the examples of tests listed above is that they illustrate the types of new policies and system changes that computer-based models can be used to analyze. As the maintenance manager seeks to improve the maintenance system's efficiency and productivity through various changes, changes can be tested before they are instituted by running a computer-based model that includes the proposed changes. If these changes do not cause the expected or desired result, the manager will know quickly. Then plans can be changed and the model run until the manager has the information required to choose the best of the available options and eliminate inferior changes in the maintenance system.

Given current conditions in the transit industry, the value of these types of planning models is great. Bus designs have changed substantially, and uncertainty about the reliability of components and maintenance requirements has grown dramatically. In addition, stricter regulations are being placed on vehicle-fleet spare levels and on bus-procurement practices. Thus, the decisions maintenance managers face have become more complex, the input to decisions has become more varied, and there is a greater degree of uncertainty about the results of decisions made. At the same time that uncertainty has increased, budgets have become tighter and thus less tolerant of error. Therefore, there is an increased need to develop computer-based planning models that can be used to summarize the outcomes of changes to the maintenance systems and aid the maintenance manager in instituting efficient system and policy changes.

COMPUTER-BASED PLANNING MODELS

Capabilities and Inabilities

Computer-based planning models are commonly used in many fields of private business and public service. Often these models take the form of simulations of systems. For example, in urban transportation planning, highway and mass transportation planners commonly use UMTA's UTPS simulation of urban travel to test the impact of transportation network changes. Traffic engineers have several traffic and highway operation simulation models (e.g., TRANSYT, NETSIM, FREQ, PASSER) to estimate the impact of changes in traffic control and in physical changes to highways. Simulation modeling has also gained in popularity in business as computing costs have dropped. Today, many general-purpose simulation packages are available for many types of computing systems.

Although computer-based modeling is a tremendously powerful tool to be used in estimating the outcomes of complex experiments, all computer models have limitations. A computer model is only a symbolic representation of the relationships between system variables. The relationships of all system variables are simultaneously considered in the computer model to determine the response of system variables to changes in one or more variables. For example, a relationship between wear and the failure of vehicle components could be estimated by modeling the distribution of observed failures and the mileage accumulated on actual buses until a failure occurred. Other relationships could be the distribution of time taken to make a repair or the interchangeability of facilities used to conduct various repairs. These relationships are measured from past experiences and are simultaneously considered within the symbolic structure of the model.

Computer models make forecasts by considering the impact of the manipulated variable on all other variables through relationships based on historical information. Although the model provides a highly ordered structure to extend observed relationships, it does not permit the prediction of the outcomes of changes where the model has no observed information upon which to base forecasts.

Sample Maintenance-Planning Model

In the following section, an example of a simplified, illustrative computer-based simulation model is described. The technique used is described elsewhere (3), and the mathematics of the approach is not described in detail here.

The model uses probability distributions of component failures as a function of accumulated bus mileage. From these distributions, and by using an average factor for miles accumulated per week, the simulation estimates the number of vehicles that will experience a failure during each week over the forecasting period. During any given week a fixed number of vehicles are repaired. Repaired buses are returned to active service and begin to accumulate wear. Unrepaired buses waiting in a maintenance queue and those being repaired are specified as spare vehicles. Once a vehicle leaves the maintenance queue and is repaired, all components (including those not repaired) begin accumulating wear.

The data used in the simulation and the assumptions made are purely hypothetical. However, the results of the example illustrate the utility of the technique. If the model were to be applied to an actual system, it would have to be carefully structured so that the model would accurately characterize the maintenance system analyzed. In this example, to make the illustration as general as possible and to make the explanation of the approach as understandable as possible, the assumptions made and the characteristics of the system are oversimplified. However, given the characteristics and peculiarities of an actual system, the model could be structured to simulate almost any situation. For instance, in the sample runs of the simulation model, it is assumed that components are only replaced after they fail. Many bus components are commonly repaired before they fail in anticipation of their failure and to prevent in-service breakdowns. If the model were used to simulate such a system, it would have to be structured to account for preventive repairs.

The inputs and assumptions of the model, for this example, are as follows:

1. The model requires that the number of vehicles to be considered in the experiment and their ages be specified. In this example, it is assumed that there are 500 buses in the fleet and that all are purchased (and begin wear) at roughly the same time.

Table 1. Hypothetical model parameters.

Component	Mean Distance Between Failures (miles)	SD of Between-Failure Mileage	Repair Rate (buses per week)
AC alternator	39,000	7,650	6
Brake lining			
Front	34,235	2,560	5
Rear	36,750	3,450	5
Brake relay valve	125,000	3,540	2
Chassis retro comp	30,000	4,525	6
Cylinder head			
Left	280,000	25,750	1
Right	240,000	12,500	1
Engine blower	145,000	12,300	2
Engine injector	94,000	7,250	3
Engine starter	80,000	5,206	3
Fluid fan drive	115,000	12,875	2
Leveling valves	64,000	5,500	4.5
Steering box	168,000	15,435	2.25
Transmission	95,000	15,000	3
Water pump and heater	150,000	8,750	2
Air-conditioner compressor	200,000	25,750	1.5

2. The model requires that the length of the experiment (in weeks) be specified. In the example, the experiment spans 12 yr, which is considered to be the entire life of the bus.

3. The model requires that the average wear (in miles per week) while in active service be specified. In the example, it is assumed that all buses travel an average of 700 miles per week.

4. The model requires that a repair rate be specified for every component considered. In the example, repair rates are specified as a maximum number of repairs that can be made for each type of component per week. The initial repair rates are listed in Table 1 (4).

5. The model requires the distribution of the mileage between failures. In the example, hypothetical distributions (and even hypothetical components) are used.

The reasons for using hypothetical distributions as opposed to actual information are as follows: (a) there is little available information on the distribution of bus part failures and (b) those that are available from empirically observed data do not distinguish between repairs made in anticipation of failures and repairs made due to actual failures (4,5). Therefore, to simplify matters, hypothetical data are used.

The parameters of the hypothetical distributions of wear between failures are shown in Table 1. All of the wear between failures is assumed to be Weibull distributed with a skew of 2. Weibull-distributed wear between failures is assumed partly due to the simplicity of using a Weibull distribution and partly because the Weibull distribution has properties that make it a popular choice to model the distribution of periods between failures.

Figures 1 through 6 show the predicted failure rates in buses per week for 6 of the 16 components examined based on the distribution parameters and repair rates shown in Table 1. (The remaining 10 failure-rate curves are not shown for the sake of brevity.) It is assumed in the estimation of these failure rates that while a bus is waiting for a re-

Figure 1. Weekly failure rate, front brake lining.

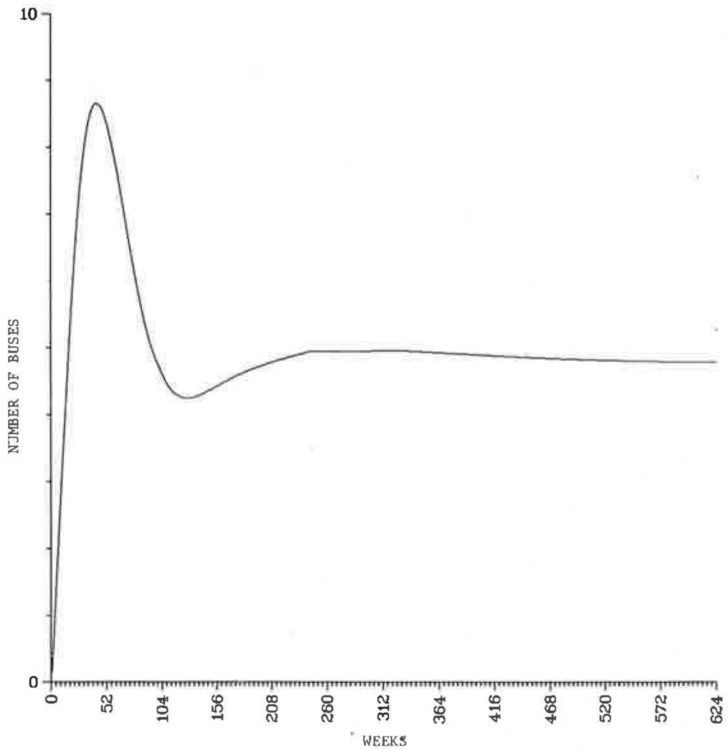


Figure 2. Weekly failure rate, rear brake lining.

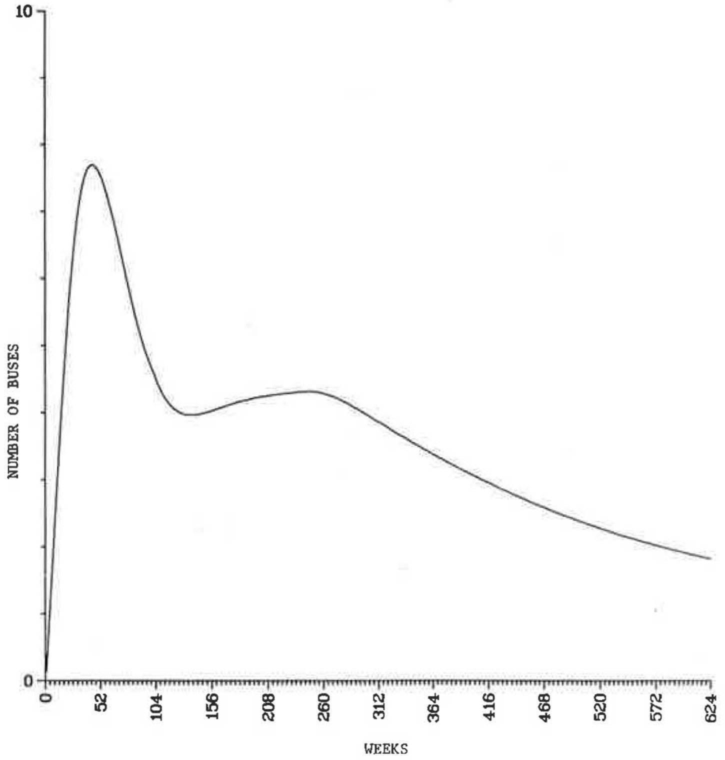


Figure 3. Weekly failure rate, chassis retro comp.

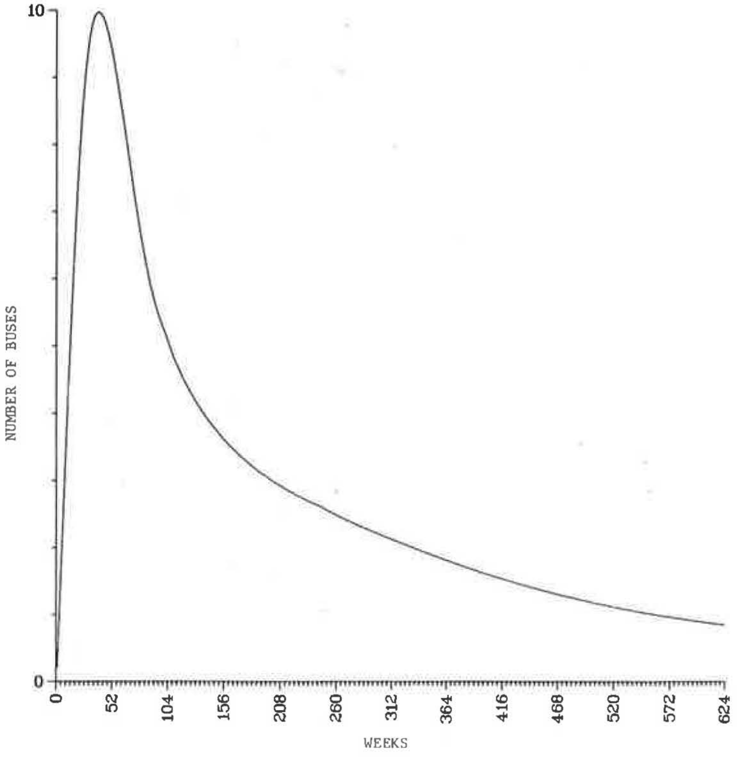


Figure 4. Weekly failure rate, left cylinder head.

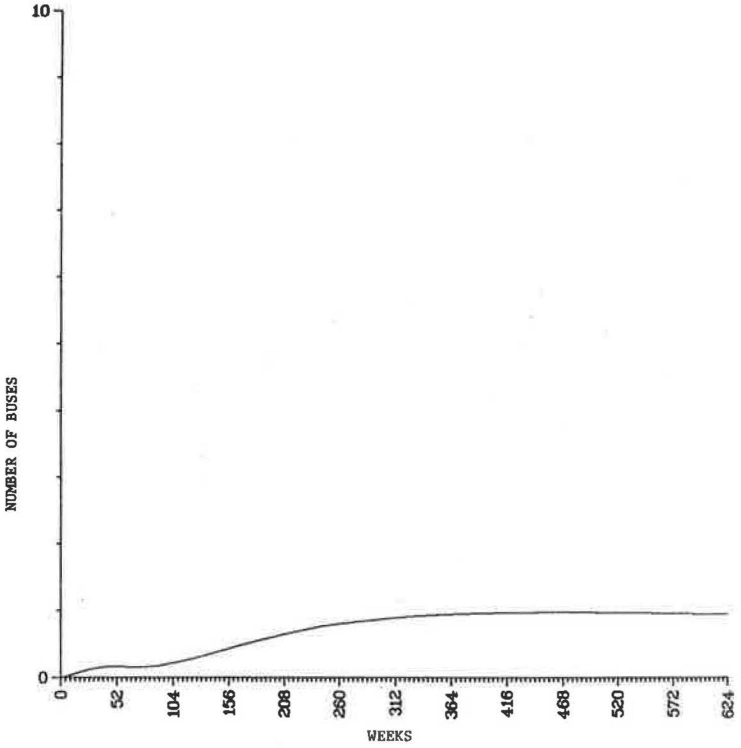


Figure 5. Weekly failure rate, leveling valve.

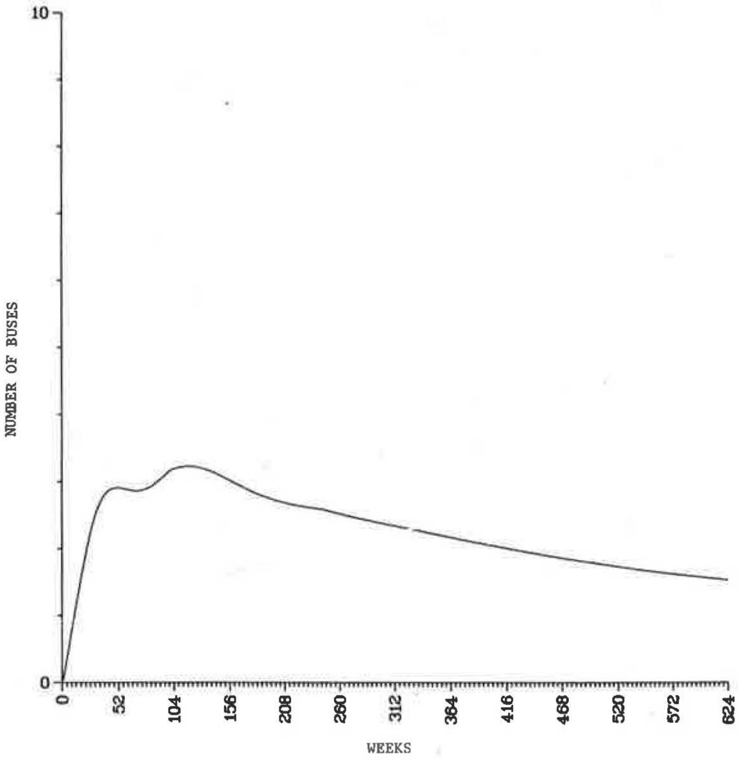


Figure 6. Weekly failure rate, steering box.

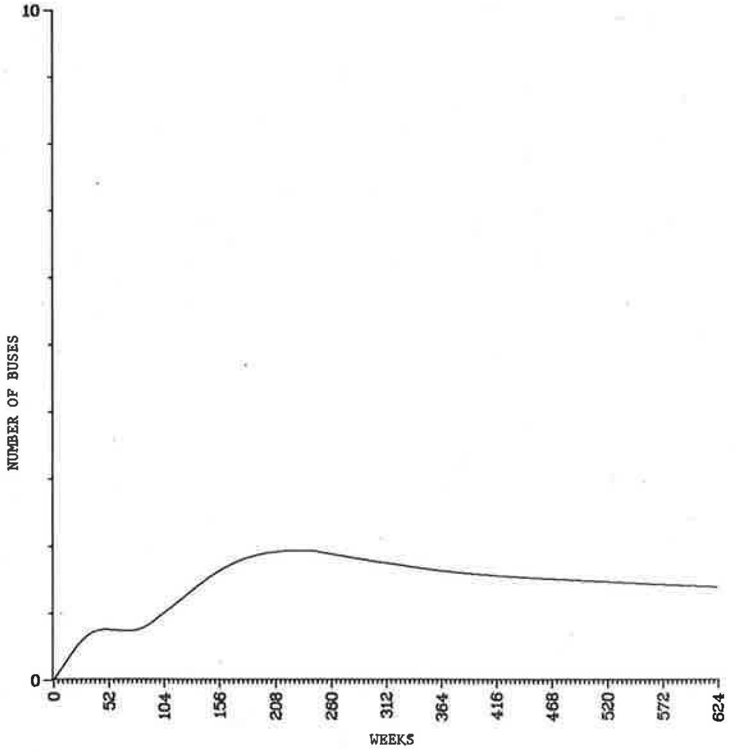
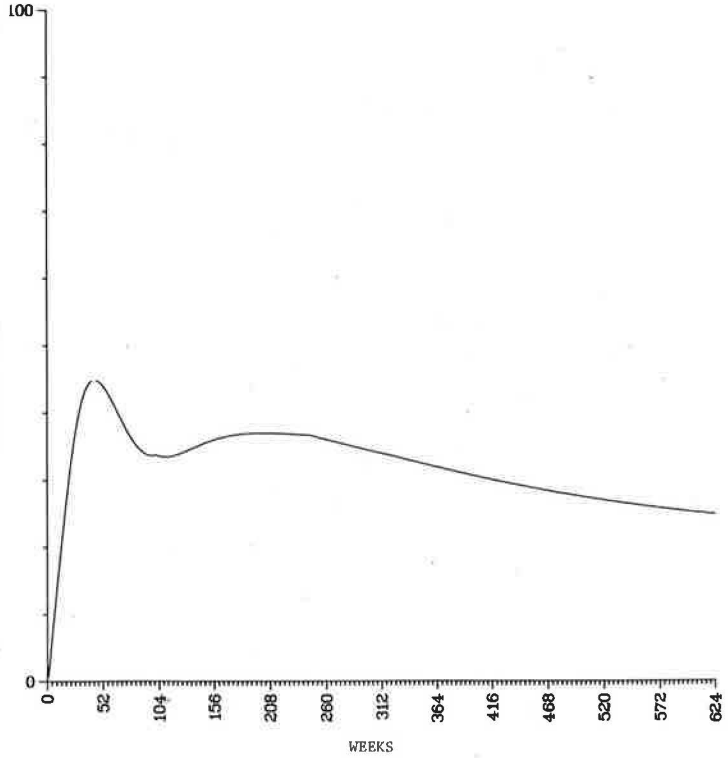


Figure 7. Total weekly failure rate.



pair, all other components do not accumulate wear and that wear on all parts begins once the bus is repaired and returned to active service. Note the relatively abrupt surge of brake-lining failures in Figures 1 and 2 around week 52 (remember that the assumed mean life is 34,235 miles and 36,750 miles for front and rear linings, respectively). Also note the abrupt surge of chassis retro comp failures in Figure 3. The reason for the surge around the 52nd week is that all have mean lives between 30,000 and 37,000 miles and all have relatively small standard deviations. A small standard deviation clusters a large amount of the distribution about the mean life. For example, front brake linings have a mean life of 34,235 miles and a standard deviation of 2,560 miles, which means that approximately 66 percent of all buses will experience their first front brake-lining failure after accumulating between 31,675 and 36,795 miles (34,235 ± 2,560). The surge in brake-lining failures may be contrasted with the relatively flat failure-rate curve of left cylinder-head failures shown in Figure 4, where left cylinder-head failures have a standard deviation of 25,750. The cumulative failure rate per week of all 16 components, as shown in Figure 7, tapers off after the mean ages of most components are reached and as the age of the components becomes more varied across the fleet.

In Figure 8 the number of vehicles waiting to be repaired (spares) is shown. In the first year the number of vehicles waiting to be repaired increases to more than 300 buses. This surge is mainly due to the sudden surge in brake-lining failures and chassis retro comp failures. Later, the number of vehicles waiting to be repaired begins to build slowly as later-occurring failures become more frequent.

In the first run of the model, there are as many as 300 out of 500 buses waiting for repairs at the peak (see Figure 8). This appears to be an unsatisfactory result. Hence, changes must be made in the system to relieve the surge and reduce the number of buses waiting for repairs to an acceptable level. Because brake-lining failures seem to be the main factor contributing to the early surge in buses waiting for repairs, the simulation model is run again with increased repair rates. Suppose that mechanics are willing to work overtime during the few weeks around the surge in brake-lining failures and that the maximum repair rate for both front and rear brake relinings per week is increased from five to seven.

The simulation model is rerun by using both a front and rear relining repair maximum rate of seven per week. The resulting quantity of buses waiting for repairs per week is plotted in Figure 9. Note that there still is a relatively sharp surge in the buses waiting for repairs around week 52, when there are as many as 200 buses waiting for repairs. This represents a drop of 100 buses per week from the peak in the previous run, but it still appears to be an unsatisfactory portion of the fleet waiting for repairs. Therefore, increasing the rate of lining repairs to seven per week did not decrease the early surge to a satisfactory degree.

Next, suppose that each week all buses with brake-lining failures that exceed the number of bus brake linings that can be repaired within the transit system's maintenance facility are taken to a private repair shop. This, in effect, increases the system's capacity to repair brake-lining failures to the point where all brakes can be repaired within the same week.

By using a brake-lining repair rate greater than

Figure 8. Weekly maintenance queue: first model run.

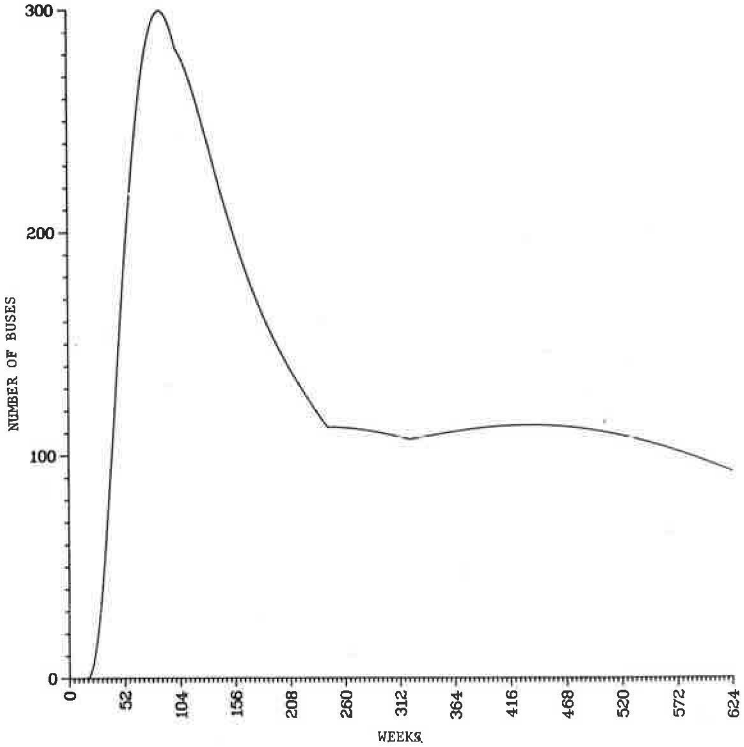


Figure 9. Weekly maintenance queue: second model run.

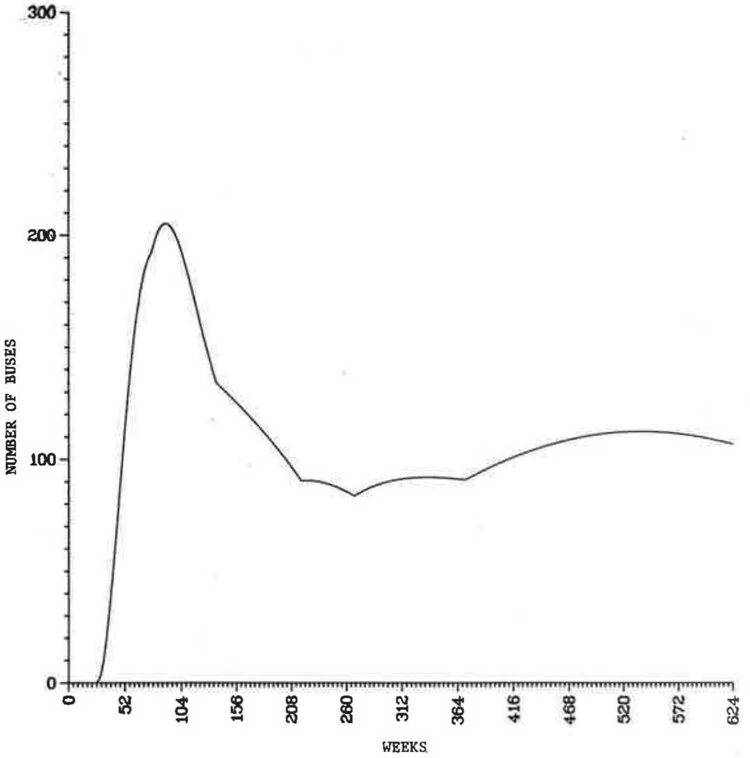
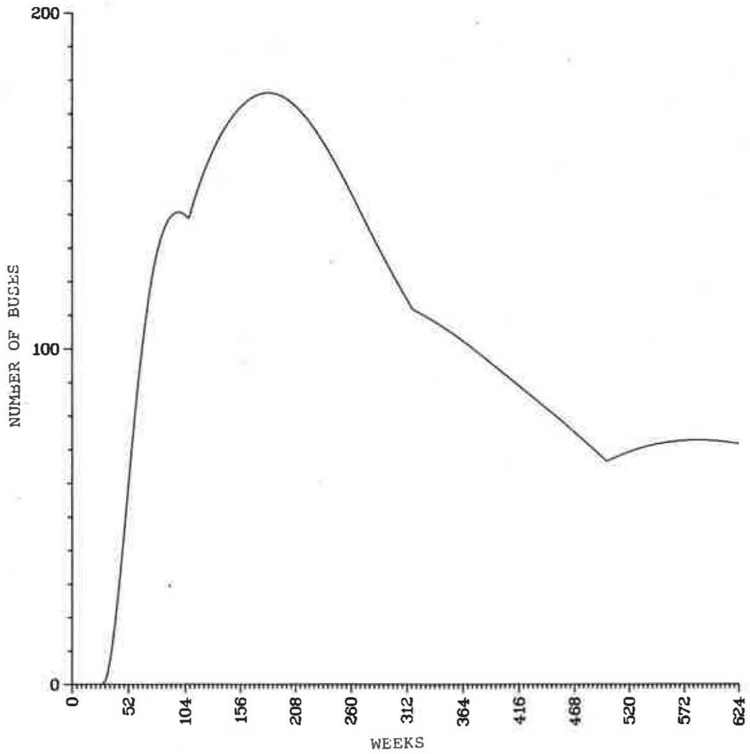


Figure 10. Weekly maintenance queue: third model run.



the maximum weekly failure rate, the simulation model is rerun; the resulting number of buses waiting for repairs during each week is shown in Figure 10. Note that the surge around week 52 has disappeared but is replaced by a nearly equal surge that takes place around week 180. At that time, the increase in buses waiting for repairs is brought on by the combined increase in the rate of failures of engine starters, transmissions, fluid fan drives, and brake relay valves. The surge around week 180 did not occur in previous experiments because in the first and second experiments, a large portion of the buses are waiting for brake-lining repairs. Because buses waiting in the maintenance queue do not accumulate wear, other components experienced a lower rate of failure. The model clearly illustrates that by relieving the problem of buses waiting for brake relinings, another problem is inadvertently caused in another portion of the maintenance system.

As can be seen from this simplified 16-component example of the use of a simulation model, changes in the maintenance system may have complex impacts on other parts of the system. As demonstrated by the third experiment, change in one portion of the system to relieve a specific problem may aggravate another portion of the system. Because of the complex and simultaneous relationships among vehicle wear, failure rates, repair rates, spare level, fleet size, and so on, all likely impacts of system changes are not obvious nor is it likely that they can be predicted by using intuition, hence the need to test for these impacts with a computer model. When one considers that the inputs to the examples are far fewer than those that would be considered in an actual application, the situation becomes more complex and the need for quantitative methods to predict the outcomes of system changes becomes even greater.

CONCLUSIONS AND RECOMMENDATIONS

Some of the contemporary issues in transit maintenance are described and reasons why transit maintenance managers should use quantitative tools to aid in addressing these issues are explained. Computer-based quantitative models are commonly used to aid in the planning of operations and policy in other fields of transportation and in other industries. In other areas, quantitative tools are often used to aid decision makers when the system of concern is too complex and varied to analyze by using intuition or hand calculations. As the problems faced by transit maintenance managers are made more complex by new and more varied bus designs, pressure for maintenance cost containment, increased demands on in-service vehicle reliability, pressure to decrease the number of spare vehicles carried to support the fleet, and so forth, it seems essential that maintenance managers use state-of-the-art quantitative techniques to aid in making decisions.

Quantitative planning models can be quite valuable in the decision-making process; however, a model is no better than the data used in calibration. Therefore, before maintenance-planning models can be tested and designed, there must exist data in sufficient quality and quantity to permit the estimation of true relationships between the relevant variables. The recent push toward the automated MIS is a step toward making useful and reliable maintenance data available. The next step is to use these data in the maintenance-planning process.

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