TRANSIT COOPERATIVE RESEARCH PROGRAM

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TCRP Report 1

Artificial Intelligence for Transit Railcar Diagnostics

Transportation Research Board
National Research Council

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Report 1

Artificial Intelligence for Transit Railcar Diagnostics

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TRANSIT COOPERATIVE RESEARCH PROGRAM

The nation's growth and the need to meet mobility, environmental, and energy objectives place demands on public transit systems. Current systems, some of which are old and in need of upgrading, must expand service area, increase service frequency, and improve efficiency to serve these demands. Research is necessary to solve operating problems, to adapt appropriate new technologies from other industries, and to introduce innovations into the transit industry. The Transit Cooperative Research Program (TCRP) serves as one of the principal means by which the transit industry can develop innovative near-term solutions to meet demands placed on it.

The need for TCRP was originally identified in *TRB Special Report 213--Research for Public Transit: New Directions,* published in 1987 and based on a study sponsored by the Urban Mass Transportation Administration--now the Federal Transit Administration (FTA). A report by the American Public Transit Association (APTA), *Transportation 2000,* also recognized the need for local, problem-solving research. TCRP, modeled after the longstanding and successful National Cooperative Highway Research Program, undertakes research and other technical activities in response to the needs of transit service providers. The scope of TCRP includes a variety of transit research fields including planning, service configuration, equipment, facilities, operations, human resources, maintenance, policy, and administrative practices.

TCRP was established under FTA sponsorship in July 1992. Proposed by the U.S. Department of Transportation, TCRP was authorized as part of the Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA). On May 13, 1992, a memorandum agreement outlining TCRP operating procedures was executed by the three cooperating organizations: FTA, the National Academy of Sciences, acting through the Transportation Research Board (TRB), and the Transit Development Corporation, Inc. (TDC), a nonprofit educational and research organization established by APTA. TDC is responsible for forming the independent governing board, designated as the TCRP Oversight and Project Selection (TOPS) Committee.

Research problem statements for TCRP are solicited periodically but may be submitted to TRB by anyone at any time. It is the responsibility of the TOPS Committee to formulate the research program by identifying the highest priority projects. As part of the evaluation, the TOPS Committee defines funding levels and expected products.

Once selected, each project is assigned to an expert panel, appointed by the Transportation Research Board. The panels prepare project statements (requests for proposals), select contractors, and provide technical guidance and counsel throughout the life of the project. The process for developing research problem statements and selecting research agencies has been used by TRB in managing cooperative research programs since 1962. As in other TRB activities, TCRP project panels serve voluntarily without compensation.

Because research cannot have the desired impact if products fail to reach the intended audience, special emphasis is placed on disseminating TCRP results to the intended endusers of the research: transit agencies, service providers, and suppliers. TRB provides a series of research reports, syntheses of transit practice, and other supporting material developed by TCRP research. APTA will arrange for workshops, training aids, field visits, and other activities to ensure that results are implemented by urban and rural transit industry practitioners.

The TCRP provides a forum where transit agencies can cooperatively address common operational problems. The TCRP results support and complement other ongoing transit research and training programs.

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FOREWORD

By Staff
Transportation Research Board

This report will be of interest to transit railcar maintenance professionals concerned with improving railcar maintenance fault-diagnostic capabilities through the use of artificial intelligence (AI) technologies. For the purpose of this report, AI is defined as a computer program that uses human problem-solving techniques to assist and augment the diagnostic process. Seven AI technologies--expert systems, case-based reasoning, model-based reasoning, artificial neural networks, computer vision, fuzzy logic, and knowledge-based systems-are investigated to determine their potential for application to the diagnosis of transit railcar systems and subsystems. The report concludes that AI technology is sufficiently mature for cost-effective application in the transit railcar diagnostic process and provides recommendations for implementation of the technology.

Under TCRP Project E-2, research was undertaken by ANSTEC, Inc. to assess the potential application of AI techniques to diagnostic practices in the railcar maintenance environment and, where appropriate, to recommend steps to introduce such practices.

To achieve the project objectives, site surveys were conducted at transit railcar maintenance facilities and at railcar subsystem suppliers to gather information regarding current and future diagnostic and maintenance practices, possible barriers to implementing advanced AI technology, and maintenance cost data. In addition, an extensive review of the literature was performed to identify any AI techniques currently in use for railcar diagnostics and to identify and describe AI-based maintenance support systems developed and used in other industries that would have potential application for railcar maintenance. An economic analysis was performed to provide an estimate of the cost savings expected by reducing the diagnostic effort resulting from the application of AI techniques. Finally, strategic recommendations for the introduction of AI-based diagnostic practices in the railcar maintenance environment were developed. Thus, this report is a valuable resource for transit railcar maintenance professionals considering the use of AI techniques to improve railcar maintenance diagnostic capabilities.

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The research reported herein was performed under TCRP Project E-2 by ANSTEC, Inc., and LTK Engineering Services. ANSTEC was the contractor for this study. The work undertaken by LTK Engineering Services was under a subcontract with ANSTEC.

Ian P. Mulholland, Program Manager for ANSTEC's Advanced Technology Group, and Raymond A. Oren, Principal Engineer, LTK Engineering Services, were co-principal investigators.

ARTIFICIAL INTELLIGENCE FOR TRANSIT RAILCAR DIAGNOSTICS

SUMMARY

This report presents the results of an evaluation of seven Artificial Intelligence (AI) techniques, which may be applicable to the diagnosis of malfunctioning transit railcar systems and subsystems. The seven AI techniques included expert systems, case-based reasoning, model-based reasoning, artificial neural networks, computer vision, fuzzy logic, and knowledge-based systems. These techniques were chosen for evaluation because they have already shown potential for performing diagnosis in other industries and operations. With the exception of computer vision, all of the AI techniques were found to be appropriate for use in railcar systems diagnostics. A criterion based on maintenance operational requirements was developed to prioritize the AI techniques.

Surveys of transit railcar maintenance personnel and system manufacturers were conducted to determine the status of current and planned maintenance and diagnostic operations. These surveys revealed a need to improve diagnostic capability in their systems and showed an appreciation for the potential cost savings that could result from such an improvement. Although such issues as cost, system support, and personnel capability should be addressed in any AI diagnostic program implementation, the personnel surveyed believed that the program would be acceptable if it were user friendly and proved to be an effective tool in improving diagnosis. The maintenance personnel also indicated that the greatest impact in cost savings could come from improvement in diagnosis of the railcar propulsion system. They also believe that the initial AI program should be developed to perform as an assistant to the maintenance technician rather than perform the complete function by itself.

A cost model titled "Cost Savings Potential from Improvement in Railcar Reliability and Maintainability" was calibrated with data from a generic transit authority. The American Public Transit Association (APTA) Annual Financial Statistical Report of 1992 was used to calibrate the model for a generic authority of 600 vehicles. Exercising the model revealed that a modest improvement in diagnosis could have cost savings in maintenance, operations, and capital costs. For example, if the number of "No Defect Found" reports was reduced by 5 percent in each of the vehicle systems, a net annual cost reduction of $576,000 would be realized. Another run of the cost model showed that an AI diagnostic tool that initially cost $172,000 would only have to provide a 7.2 percent reduction in the propulsion system Mean Time to Repair (MTTR) to pay for itself from the cost savings in one year.

Recommendations

AI technology is mature enough to be used to develop a program that will support the diagnostic process in transit railcars. The development of an initial AI diagnostic program

consisting of a hybrid of model-based reasoning and expert system approaches is recommended. Such a program will provide the greatest flexibility and potential for this application. Commercially available AI software can be used as the basis for this program, requiring the human-computer interface to be established and the knowledge required to support the AI program to be developed in a knowledge base. The initial AI program should be developed as an assistant to the maintenance technician. It is also recommended that the railcar propulsion system should be the initial focus for the AI diagnostic program. Incremental increases in capability can be added in the future by including more railcar systems or additional AI techniques to the initial program.

Although the AI diagnostic program could be used in a stand alone mode, its capability will be increased if it is integrated into the existing maintenance support system. This would allow the AI program to interface with the maintenance historical data base, electronic technical manuals, engineering or schematic drawings, and test equipment.

Conclusions and Suggested Research

AI diagnostic programs offer the potential to be placed on board the railcar itself as an embedded diagnostic system. Such a system would perform complete systems' startup and shutdown diagnosis on command, and continuously monitor the systems while the railcar was in operation. The on-board AI program also can perform fault identification and some fault prediction. Research is suggested to achieve this capability.

Research into the initial AI program support system architecture will provide a starting point with which to evolve a more automated solution. At the same time, research should begin into the architecture for the on-board AI program. Research should be conducted into the optimal type and placement of on-board sensors required to support identification and prediction of system faults. Finally, the predictive capability of various AI techniques should be researched.

CHAPTER 1

INTRODUCTION AND RESEARCH APPROACH

INTRODUCTION

Problem Statement

Transit agencies spend a significant portion of their operating budgets on problem diagnostics and maintenance of equipment subsystems and systems. The diagnostic task associated with the maintenance activities is an area that has a substantial influence on the overall maintenance cost as well as on railcar reliability and availability. Although little analysis has been done to quantify the diagnostic portion of the total maintenance cost in transit agencies, it is believed to be significant. Misdiagnosis leading to inappropriate repairs or to "no defect found" (NDF) can be a substantial cost.

Improvements in transit railcar diagnostics and maintenance can have a major effect on both maintenance budgets and fleet availability. Information from the Bay Area Rapid Transit District (reported by Plummer *(1)*) indicates that there is an annual budget of $35 million for primary maintenance (where primary maintenance is defined as the "evaluation of a car that has indicated some operating problem, identifying the source of that problem, and either removing or replacing the problem component"). The report also states that approximately 90 percent ($31.5 million) of the total direct expense is for unscheduled maintenance. Additionally, the report shows that "vehicle-caused delays rank number one in importance both in terms of number of delays and minutes of delay time"; that is, 53.71 percent of train delays.

The purpose of this effort is to determine the potential for using such computer technologies as Artificial Intelligence (AI) techniques to improve transit railcar diagnosis, with the overall goal being to increase transit railcar availability and save costs by decreasing the maintenance labor-hours required to predict and diagnose failures.

Objective

The objective of this report is to provide transit authorities with the results of an investigation in the use of AI techniques to improve transit railcar systems and subsystems maintenance and diagnostic capabilities. Decreasing the time required in diagnosing equipment problems, by using advanced computer software technology, has the potential of substantial cost savings.

For this study, site surveys of transit properties and subsystem suppliers were performed in order to understand the current diagnostic practices and concerns, and to obtain data with which to perform a cost analysis. The assessment revealed the range of potential savings and which railcar subsystems could have the greatest potential impact on cost through improvements in the diagnostics process.

Information was gathered from other industries about AI techniques used in diagnosis of equipment and systems used in those industries and how those techniques might be applied to the transit railcar industry. Implementing advanced AI computer-based diagnostics may involve the overcoming of some operational and technical barriers. Those barriers were investigated and are discussed in this report. Finally, an analysis was performed of which AI techniques should be implemented and what function in the diagnostic process these techniques should perform.

Research Technology-Artificial Intelligence

For purposes of this report, AI can be narrowly defined as a computer program that assists and augments problem solving by techniques inspired by human problem-solving approaches. Although an AI program is designed and developed somewhat differently than a conventional computer program (e.g., data bases or accounting programs), its use is very similar. Al programs can provide personnel with answers to problems, suggest courses of action, or act automatically by being embedded within a system. The problems solved by AI techniques are those that were most often too difficult for conventional software programs and were, therefore, solved by human experts. The difficulty of these problems resulted from their having a large number of interacting variables or a structure that was poorly defined. For many AI techniques, the specific approach of the technique was inspired by how the human expert seemed to solve the problem.

There are many different AI techniques, just as there are many human problem-solving approaches. The AI techniques investigated in this effort are expert systems, Case-Based Reasoning (CBR), Model-Based Reasoning (MBR), Artificial Neural Network (ANN), Computer Vision (CV), fuzzy logic, and Knowledge-Based Systems (KBS). Although there are additional AI techniques, these appeared to have the highest potential for application to the diagnostic domain. A short discussion of these AI techniques will aid in understanding their potential use in the diagnostic process.

Experts who have been performing diagnosis for a long time have seen faults, symptoms, and causes for certain problems so often that they sometimes develop a set of generalized rules that cover many of the problems. The generalized rules are developed from seeing many examples of the same problem and can usually be characterized as, "If this symptom is seen, then this is the cause of the fault." This "if-then" rule is used by expert system computer programs to try to arrive at the same conclusion as the human expert. The expert system rule set is derived directly from the human expert and is called the *knowledge base.* The data input into an expert system is the same or similar to what the human expert would use: that is, primarily symptom information. The expert system has some controlling software, called an *inference engine,* which is used to run through the rules to find which ones are true and then arrive at the correct answer.

Occasionally, a fault occurs that does not happen very often. A human expert may have seen a similar fault only once or twice before, and, therefore, has not developed a generalized rule for it. The human expert can correctly diagnose the fault, anyway, by remembering the specific cases seen before and realizing that the current fault, which is unknown, is similar to those past cases. This is the technique used by CBR computer programs, which contain many specific cases of past events. Each case is stored with the information important to the case and with data related to the diagnostics. For example, a case may contain the system, subsystem, and component involved; the symptoms displayed; the circumstances (e.g., date, location, mileage); and results of various tests. When an unknown fault occurs, the symptoms, as many circumstances as possible, and any test results that are available are input into the CBR program. The CBR program attempts to find the stored case that matches the input data closest. If the match is close enough, then the program retrieves the case and presents it as the solution to diagnosing the fault.

Human experts may be confronted with a diagnostic problem for which they have neither rules nor previous cases with which to solve it. In this situation, experts may have to use their knowledge of the workings of the system to systematically understand how the fault could occur and what the resulting symptoms would be. Human experts accomplish this by mentally building a model of the system and walking through the activities associated with the fault. This model could come from a schematic drawing or some other abstract model. The AI technique of MBR uses a very similar approach in which one or more models of the system are developed. Usually, the functional model appears as a diagram with a box for each functional component making up the system or subsystem. There are values for the inputs (data and model parameters) and output of each box. The functional model input and output values will closely match those of the railcar system modeled. This allows the model to be manipulated in such a way as to show what components could fail to produce the same results as the railcar system when it has a problem. Additionally, a casual model may be built that shows how one component (box) affects or is affected by another component. Using these models, MBR can evaluate what is expected to be normal and abnormal behavior in the system. Complex faults can be determined by exercising the models with different input values.

Human experts also have the capacity to receive complex data patterns and match them with memories of those patterns that are stored. Matching the patterns often requires no logical thought on the part of the expert. Once the pattern is matched, then information about that pattern is remembered and can be used in one of the logical processes described above (i.e., use of generalized rules, remembered cases, or understanding the system). The pattern-matching activity in humans is often associated with the senses. Sight, smell, and sound are examples of human pattern matching at work. An AI technique that also uses pattern matching is ANNs, a computer program that "learns" patterns of complex data and can associate the patterns with certain states. An example of such data is a waveform produced by a printed circuit board. The waveform is a complex set of data whose structure indicates the current state of the board. The data from many properly functioning boards are presented to the ANN along with the fact that the boards are good; conversely, data from many improperly (degraded) functioning boards are presented to the ANN along with the fact that the boards are bad (or degraded). When the waveform of a board of unknown state (good or degraded) is presented, the ANN can often determine if the board is good or degraded. This is true even if the ANN was not trained on a waveform identical to the new one presented. Of course, just like the human expert, the closer the unknown set is to the training set, the more likely the ANN will correctly classify the pattern. ANNs are especially useful in classifying complex patterns of data.

The type of pattern recognition most often used by human experts in diagnosis is visual. Understanding what a human sees often includes more than just pattern recognition. The complete understanding of a picture, for example, requires recognizing the patterns in the picture as well as the relationships between the patterns. The AI technique, CV, which is sometimes called *image understanding,* deals with processing and understanding electronic images such as those in a computer. An example is the digital image of a blackened, cracked, and misshapen piece of metal. The CV technique could potentially understand the state of the metal.

The AI technique of fuzzy logic has been found to help various diagnostic approaches. Human diagnostic experts have to blend specifications that have precise numbers with the knowledge that most systems do not fail at precise points. Most equipment manufacturers specify precise points that are to be used as threshold values. For example, an electrical component may be specified by the manufacturer as operating correctly if its resistance is between 9.2 and 10.3 ohms. This specification implies that a value of 9.1 or 10.4 ohms would indicate a 100 percent failed component. The human expert knows that in most cases this is not true; many components do not have a precise point of failure that is true for all the identical components. Many components (as well as systems) have varying degrees of failure. Setting the threshold specifications is often a trial-and-error affair for the manufacturer even with the help of maintenance experts. Time is often expended on newly received systems attempting to establish a threshold for fault logging, which is a compromise between the threshold specifications being set too low and creating many false alarms and its being set too high and allowing a failed system without the fault being logged.

Fuzzy logic allows the diagnostic system to use such imprecise terms as *high, normal,* and *low.* Additionally, fuzzy logic provides for varying degrees of degradation of components (nodes) instead of the traditional working/failed (on/off). Thus, fuzzy logic allows diagnostic systems to be much more flexible in evaluating realistic systems. This can often reduce the false alarm rate in diagnostic systems while giving indications of system degradation.

KBSs can include any computer program that has knowledge derived from a human expert as a major part of its problem-solving approach. One technique relevant to diagnostics is that associated with procedural activities such as troubleshooting. Diagnosis on established systems consists of procedures developed in large part by the diagnostic experts. If an organization has a large number of novice maintenance personnel, a program used to assist them in performing diagnosis could be very cost-effective. The program would be an "intelligent troubleshooter" and be derived from the diagnostic procedural knowledge of the expert.

Although a considerable amount of research and early prototype development of those AI techniques has been performed in many domains, their operational application to real-world problems has been limited. There are perhaps many reasons for this, but certainly the practical implementation issues (as with any emerging technology) have a major impact on AI's acceptance and utility. Promoters of AI techniques in diagnostics have been faced with such issues as which technique to use, how the technique should be incorporated into the diagnostic process, how to determine the extent of the diagnostic problem that will be solved by the technique, and what the costs and benefits are from using the techniques. Because most of the applications research has been through the proof-of-concept prototype stage only, these issues have not been considered in great depth. Additionally, since the application of each of the AI techniques is specific to a domain within a particular environment, these questions have to be reevaluated each time an AI technique is considered.

Most AI development programs require three major software components. The knowledge base contains the knowledge from the experts that is specific to the domain or problem to be solved. The software used to control and manipulate the knowledge is called the *inference engine.* There is also software to interface to the users of the system and to perform other necessary or desired functions (such as developing reports or accessing external data bases). Most of the AI techniques developed to the prototype or operational stage during the 1970s and 1980s were completely customized. This is a costly and time-consuming process. Although the knowledge base has to be domain specific, and therefore customized, the software for the inference engine and other functions does not. A more recent trend has been the development of more generalized "shells" that contain all the necessary software to support a specific AI technique. Essentially, all that is needed to be customized is the knowledge base. As the shells have been commercialized, the cost and time necessary to implement particular AI techniques to specific domains has dropped significantly.

RESEARCH APPROACH

The study described in this report was conducted in six tasks described in the following paragraphs.

Task 1. Railcar Subsystems and Current Diagnostic Practices

The goal of Task 1 was to compile a listing of rail transit vehicle subsystems describing their use and features relative to effects of failures, inherent diagnostic complexity, and current industry diagnostic practices. The approach to reaching this goal was to initially draw on the experience of the project team and supplement that with selected site surveys and telephone surveys with representative industry operators and suppliers. Data were also solicited for identifying potential sets of measurements for maintenance diagnostic activities, such as mean time to repair, and for identifying the operators' greatest diagnostic concerns. The railcar subsystems were categorized according to criteria relating relative importance of the subsystem.

Task 2. Al Techniques Used for Diagnosis

The goal of Task 2 was to identify AI-based techniques that have been used to improve the diagnostic process in various industries and that could be profitably used on transit railcars. The AI-based applications may improve diagnostics on current or future configurations of railcars and may be applicable to railcars from many different agencies. The AI techniques investigated included expert systems, KBS, MBR, CBR, ANN, fuzzy logic, and CV systems. An extensive literature search and information-gathering activity was launched. Sources of information included the Department of Defense through the specific armed services and through the Advanced Research Projects Agency, National Aeronautics and Space Administration, university technical data bases, the DIALOG on-line technical data base service (through which the Transportation Information Service and INSPEC data bases were queried), AI software vendors and AI development companies, and individual research projects.

Task 3. Al Techniques-Railcar Subsystem Correlation

Task 3 used information acquired during Tasks 1 and 2 to develop an understanding of how the different AI techniques could be used on the railcar subsystems. The goal of Task 3 was to rank the railcar subsystems and the AI diagnostic techniques in such a way that high-probability-of-success AI techniques were matched to railcar subsystems whose improved diagnosis would provide a major impact in cost reduction. Two sets of criteria were developed from the site surveys and AI technique information-gathering tasks. One set of criteria, based on the applicability of each AI technique to work against the railcar subsystems, was used to rank the subsystems with the AI techniques. The other set of criteria was based on the operational requirements for implementation in the maintenance environment and was used to rank the AI techniques.

Task 4. Economic Analysis

A mature cost model was used in this task to develop an understanding of potential cost saving through application of

AI techniques to railcar diagnostics. Data to drive the model were developed from transit authorities. The model was exercised through a range of potential improvements in diagnosis for all of the railcar subsystems. Additionally, a representative AI program was analyzed for implementation cost, and the cost model was used to determine the payback period for such a program.

Task 5. Barriers to Implementation

The goal of Task 5 was to identify potential barriers to the implementation of AI diagnostic techniques in the maintenance process at the transit authorities. Discussions with maintenance experts and managers were used to identify the operational, system, and cost barriers. Review of AI diagnostic information in other industries revealed potential technical barriers to implementing the different computer-based techniques.

Task 6. Recommendations

The goal of Task 6 was to develop recommendations for both application and research. The recommendation for nearterm implementation of an AI diagnostic program was developed from the understanding of the mature AI techniques and how they apply to railcar systems. The research recommendation was developed from the understanding of the eventual diagnostic goals which were expressed by transit authority maintenance personnel surveyed during the course of the investigation.

ORGANIZATION OF REPORT

Chapter 2 reports the findings of the site surveys of the transit railcar maintenance properties, the literature search in AI diagnostic techniques, the AI technique to railcar subsystem correlation, an economic analysis related to implementing AI techniques in the diagnostic process, and the barriers to implementing AI technology at the properties. Chapter 3 discusses details of how the AI technology can be applied in the near term and for potential follow-on applications. Chapter 4 discusses the conclusions of the report and where additional research could support the improvement of the diagnostic process.

Appendix A describes the transit railcar subsystems that were investigated in detail. Appendix B contrasts the differences between heavy, light, and commuter rail transit systems. Appendix C presents samples of maintenance data derived from various reports from four transit authorities. Appendix D provides a point of contact for interested individuals to obtain information on commercial AI software products. Appendix E contains the references and bibliography.

CHAPTER 2

FINDINGS

RAILCAR SUBSYSTEMS AND CURRENT DIAGNOSTIC PRACTICES

Site Surveys and Contacts

As part of the efforts of Task 1, a number of transit-operating authorities and suppliers were visited or contacted by telephone. The contacts made are shown in Table 1. The properties selected for site visits represented the breadth of equipment and diagnostic practices necessary to provide the needed information. The purpose of these surveys was to develop the vehicle system characterization and obtain data to rank the importance of the vehicle systems, learn the authorities' concerns with diagnostic needs, and uncover potential obstacles to implementing different techniques. Additionally, data were collected to conduct an economic analysis of the impact of reducing system diagnosis using AI. A formal site survey form was developed for use by the survey team; however, the visits were conducted on an informal basis in order to elicit more open responses to the team's inquiries.

The site visits and telephone contacts created a limited and directed survey. The response from the properties visited were strikingly similar; therefore, originally planned visits to Chicago Transit Authority (CTA) and the South Eastern Pennsylvania Transportation Authority (SEPTA) were not conducted. However, the scope and range of information obtained from the contacts that were established was as expected. There were no unexpected diagnostic concerns or topics that suggested the need for a more extensive survey. The site surveys and contacts served to substantiate the comprehensive knowledge of the research team.

Because this project was defined as related to maintenance activities, no time was allocated during the visits to explore operational problems with diagnosing and isolating failures during revenue service. The approaches to and complaints about diagnosing vehicle problems were universal.

TABLE 1. Project Visits and Contacts

PERSONAL VISITS
Washington Metropolitan Area Transit Authority (WMATA) Lemuel Proctor, General Superintendent
Port Authority Transit Corporation (PATCO) - Dick Burt, Superintendent of Equipment
Bay Area Rapid Transit District (BART) - Eugene Nishinaga, Research and Development Manager
WABCO - Rick Mazur, Principal Engineer
GE Transportation Division - Dave Phelps, Manager
Maryland Department of Transportation (MD-DOT) Raymond Carrol, Director Systems & Equipment Engineering
TELEPHONE CONTACTS
AEG Westinghouse - Tom Faber, Project Engineer
Kawasaki - Brad Craig, Project Engineer
New York City Transit Authority (NYCTA) - Charles Timmons, Manager, R 110A Project
Port Authority Trans-Hudson System (PATH) - William Fellini, Engineer

Source Ray Oren

Diagnostic Practices and Concerns

The diagnostic-related practices and concerns of rail transit authorities can be categorized in four major areas: cost, system support, personnel capabilities, and railcar diagnostic focus. A detailed discussion of these areas follows. Additionally, the diagnostic approach of subsystem manufacturers and how that approach may affect properties is discussed.

Cost Considerations. Properties are feeling the pressure to reduce costs. The maintenance area is a prime target because it is a large portion of the operating cost. The managers in charge of the maintenance activities feel that reducing the diagnostic effort is one of the major areas left where cost reductions can be made. Those surveyed feel that from the cost reduction aspect, the overall maintenance process has been "scrubbed" extensively and that costs have been reduced. However, more innovative ways of cutting costs must be found, and the diagnostic process is a prime target.

The emphasis on cost reduction will also carry into whatever approach is taken to improve the diagnostic process. The application of advanced technology, such as an AI program's, must come under the cost-effectiveness umbrella. The properties feel that any AI diagnostic program's cost and benefits must be highly visible. Specifically, emphasis must be placed on a "quick-payback" period without substantial capital outlay. Additionally, the properties feel that incremental implementation of an advanced AI approach to diagnosis with extensive interaction between the developer and maintenance personnel is necessary to reduce risk.

System Support. Properties use various system architectures to support their diagnostic and maintenance activities. The architectures include computers, electronic and paper data bases, electronic and paper technical publications, test equipment, and various software packages. Both current maintenance practices and application of new technology have to interface with the support system.

In many properties, maintenance personnel have available historical maintenance data that are usually stored in an electronic data base. The data's use and utility vary from property to property. It is felt by many maintenance personnel that the operations department failure reports are not sufficient nor consistent enough to permit shortcuts in the diagnostic procedure. Most often, the maintainer must begin with a complete system checkout; many believe that this method entails time "wasted" in checking parts of a system that are already functioning properly. The line maintenance supervisor has the responsibility for job assignments, but some supervisors intentionally do not provide the maintainer with a full fault description, thus forcing a full system checkout. On the other hand, some supervisors use their experience, vehicle and fleet history, and the initial report to direct the maintainer to specific portions of the failed system. All line supervisors know their best maintenance experts and reserve this resource for the tough problems.

Suppliers of new microprocessor-based control systems are providing what they refer to as "diagnostic aids" as a fallout from the use of the processors; in most cases, however, what is provided is a fault-logging capability. Most of the fault loggers use the control system algorithms and have been implemented by suppliers to satisfy the needs of system setup. As a consequence, the faults recorded may be too restrictive for normal operation: the fault logging may shut down the monitored system too frequently and needlessly. Predictive failure techniques and techniques for handling repetitive, intermittent faults are not currently part of these fault-logging systems. Where the fault loggers are available, they are being used by maintainers as an aid in the fault diagnosis process. In some of the newer vehicle procurements, with the latest technology, the fault logger identifies the failed Line Replaceable Unit (LRU), thus enhancing vehicle repair and turnaround. It is not known whether the criterion for failure identification is most efficient; the system might be just diverting the diagnostic difficulties to the back shop. It is most likely that the procedure for determining a failure relies on the use of very accurate alignment values. Larger tolerances might be acceptable for normal operations. How accurate a system component must be, or the combination of stacked inaccuracies, or the time until the next system alignment are not yet considered in the fault-logging procedures.

Another diagnostic improvement concept forwarded by the supervisors is to put system data, manuals, and schematics close to the worksite in a handy, easy-to-use manner. Authorities have been trying to implement this concept by specifying the format and content of maintenance manuals (including their having soil-resistant finishes) and placing the manuals at the work sites. The manuals, while generally useful, are still difficult and cumbersome to use. One authority is translating its maintenance manuals to electronic media, with the intent of possibly presenting the data in this form at the worksite. Most maintenance supervisors believe that this data, coupled with software that leads an inexperienced maintainer through a diagnostic process, would be a significant improvement.

One of the difficulties every property faces is using system support architectures that have been pieced together over time. The pieces seldom interface with each other. Maintenance personnel feel that the capability to have compatible hardware and software would greatly enhance the maintenance process, and that the addition of any new technology should help this situation.

Personnel Capabilities. Some authorities believe the diagnostic capability of their staffs is decreasing. One stated that the maintainer takes troubleshooting only to the first obvious fault-but this fault may not be the cause of the system failure. Another authority relies heavily on its experts: it believes that expert maintainers will spend time performing complete system checkouts and routine preventive maintenance tasks, such as cleaning and adjustment, as part of their normal diagnostic approach. This is believed to clear faults, even when an explicit fault is not found. The time spent is not all diagnostic time.

Most authorities agree that some standardization of maintenance practices based on expertise would be helpful. By developing a mechanism to help maintenance personnel perform a minimum set of diagnostic activities, the problem of quitting after finding the first obvious fault can be reduced.

The larger authorities have training programs in place, to which maintainers are assigned by the supervisors. However, the programs mostly cover system operation explanations and do not cover improvements in diagnostic skills.

Discussions with maintenance personnel indicated that there is a wide variation of computer literacy. Most managers believe that the growing use of computers in society is being reflected in more personnel feeling comfortable with computers. It is also believed that maintenance personnel can learn and will accept computer-based technology if it is easy to use and truly helps do the job. It was emphasized, however, that the introduction of computer-based technology would only be successful if the programs were very user friendly and produced results the personnel found helpful. It was also stated that the interface had to use terminology with which the personnel were comfortable. Finally, the credibility of the program had to be high. The ability of the program to explain its logic to the personnel was deemed very desirable.

Maintenance managers were asked where in the diagnostic process they believe a diagnostic program should be located. Although it was hoped that eventually such a program could reside on board the railcar to automatically monitor, detect, and diagnose faults, most managers believe that a program that assists the maintenance individual should be the first priority.

Diagnostic Focus. Almost all the maintenance supervisors indicated that a significant diagnostic problem was with intermittent faults, either in cabling or by other means. The problem with diagnosing these faults is the inability to duplicate the fault as reported. The intermittent fault and short duration might even be a reason for the obscure failure description. Because of reported failures that cannot be duplicated and multiple system configurations producing similar fault conditions, inordinate resources are frequently spent in diagnosing "unfound" faults.

All the authorities have experienced repeat failures, which are vehicles that return to the shop with similar failures over a short period of time. Repeat failures indicate that the real cause of the failure was not found or that the wrong repair was performed. This is attributable in part to intermittent or pending failures, and to inadequate diagnostic capability. Some authorities feel this last factor may be the primary reason.

Maintenance managers were asked to which railcar subsystem they believed advanced diagnostic capability should be applied. Most responded that improving diagnosis on the propulsion system would provide the greatest benefit: the difficulty in diagnosis, the expertise required, and the impact of a failed propulsion unit were cited as the reasons. Automatic Train Control (ATC) was also mentioned, primarily because of the impact of a failure.

Suppliers' Diagnostic Push. System suppliers were contacted about advances in diagnostics for their systems. Many systems are being developed with microprocessor controls, which lend themselves to data-logging and diagnostic capability, and most suppliers did state that they were developing the capability to log data. Often, system parameters are monitored and recorded: if the system parameters remain within set threshold values, no action is taken to save the recorded values. If, however, the system parameters are found to be out of specification, then, within a time window around that event, the recorded data were saved. The suppliers term this activity "fault logging." After further discussion, however, the suppliers admitted that it was really "event recording," because there is no guarantee that a fault has actually occurred. There is little done with the data logged beyond making them available to the maintenance expert, and the maintenance expert has to use that information to perform diagnostics. Some suppliers stated that they are investigating the development of advanced diagnostic capabilities in their systems; however, they said that the purchasing authorities have not shown enough interest in such capabilities to justify their development.

Discussion with the suppliers revealed that even in the case of event logging, the data recorded and the sensor locations were not designed for any particular diagnostic approach. Additionally, some of the system designs precluded the easy inclusion of sensors or monitoring devices for add-on diagnostic capability.

Vehicle System Characterization. Transit railcar systems include a wide spectrum of different system types. Traditionally, relay logic is used for providing control of systems related to safety, such as train control and door control. Relay logic, with multiple contact points and mechanical action, is subject to hard-to-locate, intermittent, and inaccurately described faults. Operating properties specify lamps or lights on some of these relay functions to indicate when the relay is in a particular state. However, for a particular vehicle, there usually is no history of correct or incorrect relay or relay system operation: diagnostics usually entail tracing the circuit using a schematic or wiring diagram and electrical meter. Difficulty is often encountered in establishing the equipment operating condition that reproduces the reported fault. Because of known and accepted failure modes, the application of relay-logic-based systems to safety circuits will persist in the transit railcar industry.

Analog electronic systems are used for most control systems on transit railcars. Data available for troubleshooting these systems depend on the specific equipment, who supplied it, and a property's resources when the equipment was specified. On the low end this is a system schematic with no signal data; on the high end, system-specific bench testers with output signal comparators are provided. As with relay logic systems, reproducing the equipment operating condition is often difficult.

Transit railcar control systems are being implemented with microprocessor logic. The switch from analog electronics is due to microprocessor speeds and the capability to provide a satisfactory simulation of continuous control functions. The switch from relay logic is also occurring because techniques are being provided to operate the microprocessor in a fail-to-a-safe mode. The microprocessor technology offers flexibility beyond relay logic, the major feature being event logging. Generally, this is a time-history logging in nonvolatile memory of specific parameters in the control system with a shutdown of the logging function at the occurrence of an identifiable fault. Properties are requesting and suppliers are providing this as a "first-cut" diagnostic aid.

Transit railcar systems also include power-switching circuits (contactors and interlocks) in the 1,000-Vdc, 1,000-A range for providing power to the traction and auxiliary systems. There are no data indicating a pending fault for these subsystems, so these systems fail thus resulting in a vehicle shutdown condition. In most cases, then, fault isolation only requires identifying a missing function, such as no interior lights, or visually identifying a destroyed component (an overly simplified statement). Solid-state power electronics are replacing power switching systems. At present, these subsystems are fault-monitored in a way similar to that of contactor systems. The systems go to a full-fault condition, while intermittent anomalies, if data are available, might indicate a pending failure.

At the vehicle level, the industry is only just beginning to specify car-level monitoring of on-board system operations. Most of this is an event recording with little or no diagnostic, or even operational adjustment, capability. Car-level monitoring has not progressed to an integrated system in the transit railcar industry. This subsystem could provide data to assist in both fault identification and fault diagnosis.

Table 2 presents a summary of the efforts to categorize rail transit vehicle systems. Preliminary categorization and initial site visits identified widely different diagnostic needs during different phases of the repair efforts. The isolation and identification of faults are different during revenue operations, vehiclelevel troubleshooting, and component checkout. These differences result in the use of different diagnostic techniques. This delineation of differences has resulted in structuring of the vehicle categorization to differentiate the three levels of fault

TABLE 2. Vehicle System Characterization

SYSTEM/ SUBSYSTEM	REVENUE SERVICE LEVEL			
	Equipment Type	Failure Consequence	Complexity	Diagnostics
Propulsion	Power Contactor Cam Controller, PCBs Cam Controller, μP Solid State, μP	Moderate Delay Minor Delay Minor Delay Minor Delay	Simple Moderate Moderate Moderate	Indicator Indicator μP, Indicator μP, Indicator
Friction Brakes	Pneumatic PCBs μP	Major Delays Moderate Delay Moderate Delay	Moderate Moderate Moderate	Visual & Air Leaks Indicators μP, Indicators
Auxiliary Electrical 1. Train Control	Relay Relay, μP	Moderate Delay Minor Delay	Moderate Simple	Vehicle Inoperable μP, Vehicle Inoperable
2. High Voltage	Power Switches	Major Delay	Simple	Self-Indicating
3 Auxiliary Voltage (M/A, Inverter)	PCBs	Minor Delay	Simple	Self-Indicating
4. Low Voltage (Xfmr, Batt, Char, Conv)		Minor Delay	Simple	Self-Indicating
Doors	Relays, PCBs Relays, μP	Moderate Delay Minor Delay	Simple Simple	Fault Indicators μP, Fault Indicators
HVAC	PCBs μP	Reduced Quality Reduced Quality	Moderate Moderate	Passenger Passenger
Communications		Moderate Delays	Simple	System Inoperable
Auto Train Cont	ATO, PCBs ATO, μP ATP, PCBs ATP, μP	Moderate Delay Moderate Delay Major Delay Major Delay	Moderate Moderate Moderate Moderate	No Auto Operation No Auto Operation No Vehicle Operation No Vehicle Operation

μP	— Microprocessor control	Cam Tester	— Special function tester
PCB	— Printed circuit board control	Test Box	— Input external signals and exercise system
Test Setup	— PCB repair, setup test equipment, and checkout card	Autotester	— μP PCB repair, complexity leads to more intense test setup

Source: Ray Oren

isolation: revenue service level, vehicle level, and back shop level.

Revenue service level applies to faults occurring during operations or revenue service. The goal is to minimize disruption to service. The diagnostic need is to quickly ascertain which system has failed, how it affects passenger safety, and what actions are necessary to continue revenue operations. A measure of the fault identification and repair function in this mode is the amount of time the revenue service is disrupted.

Vehicle-level diagnostics refers to the period from when a fault has been reported and the vehicle has been assigned to the shop up to the time it has been returned to service. The goal is to repair the vehicle and return it to service as quickly and as accurately as possible. The maintenance requirement is to efficiently identify the failed lowest LRU. Diagnostic needs are an accurate report of the failure and a rapid, comprehensive, well-structured system checkout procedure. The measure of maintenance and fault diagnosis capability is the time to return the vehicle to service and the number of indeterminate failures.

Back-shop-level diagnostics refers to repairs on components that have been removed from the vehicle and repaired on the bench. The maintenance and diagnostic needs are more complex: rigorous component checkout and alignment procedures are necessary. Again, the measure of maintenance and fault diagnosis capability is the time to repair, but separating this effort from the total repair is often difficult. An in-depth description of the railcar systems is provided in Appendix A.

Vehicle System Evaluation. A methodology for evaluating vehicle systems is presented, which is based on equipment reliability and maintainability. The vehicle system components and reliability data are developed for a composite or generic vehicle representative of the heavy rail transit operators visited. Appendix B characterizes heavy, light, and commuter rail systems.

All the transit-operating authorities have Maintenance Information Systems (MISs) in use for reporting maintenance

TABLE 2. Vehicle System Characterization (continued)

SYSTEM/ SUBSYSTEM	VEHICLE LEVEL			
	Equipment Type	Failure Consequence	Complexity	Diagnostics
Propulsion	Power Contactor	Vehicle Inoperable	Simple	Wiring Diagram
	Cam Controller, PCBs	Vehicle Inoperable	Moderate	Cam Tester, Schematics
	Cam Controller, µP	Vehicle Inoperable	Moderate	µP, Cam Tester, Schematics
	Solid State, µP	Vehicle Inoperable	Complex	µP, Schematics
Friction Brakes	Pneumatic	Vehicle Inoperable	Moderate	Piping
	PCBs	Vehicle Inoperable	Moderate	Piping and Schematics
	µP	Vehicle Inoperable	Moderate	µP, Piping, Schematics
Auxiliary Electrical 1 Train Control	Relay	No Lead Vehicle	Moderate	Fault Ind., Schematics
	Relay, µP	No Lead Vehicle	Moderate	µP, Schematics
2. High Voltage	Power Switches	Vehicle Inoperable	Simple	Schematics
3. Auxiliary Voltage (M/A, Inverter)	PCBs	Vehicle Inoperable	Moderate	Schematics
4 Low Voltage (Xfmr, Batt, Char, Conv)		Vehicle Inoperable	Simple/ Complex	Schematics
Doors	Relays, PCBs	Veh. Inop., or Reduced Quality	Moderate	Fault Indicators, Schematics
	Relays, µP	Veh. Inop., or Reduced Quality	Moderate	µP, Fault Ind., Schematics
HVAC	PCBs	Reduced Quality	Moderate	Fault Indicators, Schematics
	µP	Reduced Quality	Moderate	µP Schematics
Communications		Reduced Quality or No Lead Vehicle	Simple	Schematics
Auto Train Cont.	ATO, PCBs	No Lead Vehicle	Moderate	Schematic, Test Box
	ATO, µP	No Lead Vehicle	Moderate	µP, Schematic, Test Box
	ATP, PCBs	Vehicle Inoperable	Moderate	Schematic, Test Box
	ATP, µP	Vehicle Inoperable	Moderate	µP, Schematic, Test Box

µP	— Microprocessor control	Cam Tester	— Special function tester
PCB	— Printed circuit board control	Test Box	— Input external signals and exercise system
Test Setup	— PCB repair, setup test equipment, and checkout card	Autotester	— µP PCB repair, complexity leads to more intense test setup

Source: Ray Oren

activity and providing vehicle and component histories. A common feature of these MISs is their uniqueness to the property where they are installed. Although the basic purposes of the MISs are similar, the structure for coding vehicle components and the availability of reports is different. Some MIS vehicle codes are such that the components can be associated with the major vehicle systems and assemblies. WMATA uses such a coding system, which is similar to many military and aircraft code structures. Even within this structure, however, there are some codes that are based on the physical location of the components. Propulsion system components, for example, are coded with truck equipment. This location-type of coding is more apparent at PATCO. Some of the structuring is also based on the trade performing the repair. In some MISs, not necessarily represented by the sites visited, the equipment-coding structure is based on the initial inventory control system implemented, and the system association is to original equipment suppliers. Appendix C provides samples of data retrieved from several transit authorities.

The extent and use of the MIS vary widely from property

TABLE 2. Vehicle System Characterization (continued)

SYSTEM/ SUBSYSTEM	BACK SHOP			
	Equipment Type	Failure Conseq.	Complexity	Diagnostics
Propulsion	Power Contractor Cam Controller, PCBs Cam Controller, µP Solid State, µP	Component Lost Component Lost Component Lost Component Lost	Simple Moderate Complex Complex	Rebuild Test Setup Autotester Autotester
Friction Brakes	Pneumatic PCBs µP	Component Lost Component Lost Component Lost	Simple Moderate Complex	Rebuild Test Setup Autotester
Auxiliary Electrical 1. Train Control	Relay Relay, µP	Component Lost Component Lost	Simple Complex	Rebuild Autotester
2. High Voltage	Power Switches	Component Lost	Simple	Rebuild
3. Auxiliary Voltage (M/A, Inverter)	PCBs	Component Lost	Moderate	Test Setup
4. Low Voltage (Xfmr, Batt, Char, Conv)		Component Lost	Moderate	Test Setup
Doors	Relays, PCBs Relays, µP	Component Lost Component Lost	Moderate Moderate	Test Setup Autotester
HVAC	PCBs µP	Component Lost Component Lost	Moderate Complex	Test Setup Autotester
Communications		Component Lost	Simple/ Complex	Autotester
Auto Train Cont.	ATO, PCBs ATO, µP ATP, PCBs ATP, µP	Component Lost Component Lost Component Lost Component Lost	Moderate Complex Moderate Complex	Test Setup Autotester Test Setup Autotester

µP	— Microprocessor control	Cam Tester	— Special function tester
PCB	— Printed circuit board control	Test Box	— Input external signals and exercise system
Test Setup	— PCB repair, setup test equipment, and checkout card	Autotester	— µP PCB repair, complexity leads to more intense test setup

Source: Ray Oren

to property. For any individual operating authority, a great deal of data is available for history and trend analysis. However, there is no easy way to make an industrywide comparison.

Reports from two of the sites visited were used to develop a generic vehicle performance matrix, which is shown in Table 3. The breakdown of the vehicle systems and components is the same as in Table 2, where the vehicle systems characterization was reduced to a generic vehicle by selecting the configuration of various systems. As an example, the propulsion system configuration is a solid-state, microprocessor-controlled system with electromagnetic contactors. The friction brake system is electropneumatic with microprocessor control, doors are a relay-based control system, and the HVAC is printed circuit board controlled. These systems are similar to a WMATA fleet because the WMATA reliability data were used to generate the service portion of the performance matrix. Although this makes the matrix resemble that of the WMATA fleet, it is only a snapshot in time. The resulting tabled data are consistent with an intuitive opinion for the magnitude and order of the vehicle system failures. The failure rate data can be reexamined for different system configurations, such as a cam-controlled propulsion system.

As mentioned, the Field Service Report (FSR) section of the fleet performance matrix was developed from a WMATA report. The report did not include data on the repair effected: it reports incidents charged against various vehicle components or assemblies. The assignment of an FSR incident to a category listed in the matrix (e.g., Microboards) was made when the WMATA coding structure clearly indicated that the incident was identified to that level. Incidents in the report shown against upper level assemblies were assigned to the No Defect Found (NDF) category. Some judgement was applied here as to what may or may not be a line replaceable or repairable assembly. Normally, an operating authority does not indicate as large an NDF category as the matrix shows. The NDFs may indicate that a specific fault was not uncovered for the incident.

TABLE 3. Generic Fleet Performance

System Name	Field Service Report Per 1,000 Hours				Time Per Incident			Time per 1,000 Hours		
	NDF	Vehicle	Back Shop	Operations	Service Delay (minutes)	Vehicle MTTR (hrs.)	Back Shop MTRR (hrs.)	Service Delay (minutes)	Vehicle Repair (hrs.)	Back Shop (hrs.)
PROPULSION	0.900			1.147	1.000	1.800		1.147	1.987	
Remove & replace, adjust		0.205								
Microboards			0.014				8.000			0.114
Relays, contactors			0.016				3.000			0.048
Amplifier			0.013				4.000			0.051
FRICTION BRAKES	0.272			0.562	5.300	2.000		2.979	0.994	
R&R, Adj. - Val., flys, snsrs, sw.s and Mech.		0.225								
Microprocessor boards			0.003				8.000			0.020
Pnuematic valves			0.063				3.000			0.188
AUXILIARY ELECTRIC										
TRAIN CONTROL	0.102			0.146	0.460	1.500		0.067	0.191	
Circuit breakers & switches		0.025								
Relays & contactors			0.019				3.000			0.057
HIGH VOLTAGE	0.337			0.786	0.460	1.500		0.361	1.159	
Fuses, valves, switches, cabling		0.436								
Contactor			0.013				3.000			0.039
LOW VOLTAGE	0.013			0.081	0.290	1.500		0.023	0.077	
R&R - relays, semiconductors, fuses		0.038								
PCB boards			0.030				4.000			0.118
DOORS	0.403			0.481	3.910	0.900		1.882	0.433	
R&R and adjust - relays and switches		0.078								
nil			0.000							
HVAC	0.338			0.726	0.000	2.120		0.000	1.212	
Mechanical R&R		0.234								
PCB boards & relays			0.155				3.000			0.464
COMMUNICATIONS	0.152			0.261	0.000	0.900		0.000	0.155	
R&R, cabling		0.021								
Radio, amplifier			0.088				4.000			0.353
AUTO-TRAIN CONTROL	0.303			0.631	3.270	1.770		2.063	1.046	
R&R, relays, cabling		0.288								
PCBs			0.040				4.000			0.161
CAR BODY	0.537			1.606	0.000	2.000		0.000	2.643	
Mechanical, windows, switches		0.784								
Valve, gauge, display, amplifier			0.263				3.000			0.790
Power supply, CPU board			0.008				4.000			0.031
Electromechanical PCB			0.014				3.000			0.041
TRUCKS, SUSPENSION & COUPLER	0.181			0.266	0.000	3.000		0.000	0.798	
Mechanical R&R		0.085								
nil			0.000							
Total number of failures per 1,000 operating hours =	6.69225									
Total service delays (minutes per 1,000 operating hours) =	8.523									
Total repair time (hours per 1,000 operating hours) =	13.167									

Source: Ray Oren

The lower lever assignments of incidents do indicate a definitive action against a specific component.

The FSR section of the matrix is read slightly out of normal reading order to enable subsequent automatic spreadsheet calculations. The total number of FSR incidents is that show in the Operations column. Since these are service failures, theoperation department sees all the failures. These total failures are assigned to the remaining categories. For example in the

Propulsion System, these are NDF, Remove & Replace, Microboards, Relays, and Amplifier.

The Time per Incident portion of the Fleet Performance Matrix was developed in a different manner. The Service Delay section is based on BART's monthly operations report. The BART service delay data were restructured to be similar to the structure of the generic vehicle systems. As with the reliability data, it is only a snapshot, not necessarily a stable statistical sample. It is believed, however, to be reasonably representative of normal service delays.

Mean Time to Repair (MTTR) was not available as part of any operating authority's MIS. The values used in the matrix are based on a review of a number of vehicle technical specifications. MTTR values are specified in some vehicle procurements and are warranted and demonstrated by suppliers. The values are, at least, an agreed-upon target. A review of maintainability analyses and demonstration reports for a specific vehicle procurement was also accomplished. The values shown are consistent as a set: they may be lower than what an operating authority experiences. If time is reported to the MIS, the authorities do not separate administrative time from repair time. Back shop MTTRs are estimates based on knowledge of the repair procedures and discussions with supervisors during the site visits.

The Time per 1,000 Hours column is a product of failure rate and average repair time expressed as a function of 1,000 hours of vehicle operation. The values in the Service Delay column (under Time per 1,000 Hours) is a multiplication of the total number of FSRs (in the Operations column) with the Service Delay per incident (under Time per Incident). Vehicle repair time (under Time per 1,000 Hours) is a multiplication of the sum of NDFs and vehicle FRSs with the vehicle MTTR per incident. The Back Shop Repair (under Time per 1,000 Hours) is a multiplication of the FSRs in each back shop category with the back shop MTTR per incident.

The matrix can be used to evaluate railcar systems for prioritization in application of AI diagnostic techniques. The car body, friction brake, and propulsion systems rank high in maintenance requirements. The car body system, probably because of its passenger interface, requires the greatest maintenance effort for reported incidents. The friction brake system causes the longest service delays. The propulsion system is second in maintenance effort, but has a very large number of NDFs. The number of NDFs, the amount of maintenance required, and the opinion of the transit maintenance managers that the propulsion system should be the initial focus for improved diagnostics place the propulsion system at the highest priority.

ARTIFICIAL INTELLIGENCE TECHNIQUES USED FOR DIAGNOSIS

Literature Search

Information is available about various AI techniques used or proposed for diagnosis. A descriptive word search of the INSPEC data base using the key words "Artificial Intelligence AND Diagnosis" resulted in 591 citations. Although a few of these citations were of popular media reporting on advances in this area, the vast majority were technical papers reporting theoretical, prototypical, or operational aspects of using AI in diagnosis. Table 4 lists the primary domains reported.

TABLE 4. Domains Represented in the Literature of AI Approaches to Diagnosis

Telecommunications	Spacecraft
Nuclear Power	Utilities (nonnuclear)
Chemical Production	Computers
Health Care	Electronics
Automobile Production	Vehicle Monitoring and Diagnosis
AI in Diagnosis (theory)	Other

Source: Ian Mulholland

The systems targeted for diagnosis using AI techniques within the domains listed in Table 4 included electrical, electronic, mechanical, biological, chemical, and behavioral (in the physical sense). Additionally, combinations of the systems were also candidates for the AI techniques and these included complete systemwide diagnosis. Some of the reports explicitly stated that the approach described was domain and system independent. Even most of the reports of techniques that used specific domains and systems as examples stated that the techniques could be used across other domains and systems. There were few reports describing transit, transportation, or railcarlike vehicles used as target systems of the AI technique. Even so, the techniques described for other industrial domains seem completely appropriate for the transit railcar domain. The techniques described fell into the categories of expert systems, case-based reasoning (CBR), model-based reasoning (MBR), artificial neural networks (AANs), computer vision (CV), fuzzy logic systems, and knowledge-based systems (KBSs). Many of the reports discussed combinations of the techniques. Each of the individual techniques was often discussed in terms of its strengths and weaknesses, the knowledge available to support it, the data type (symptoms) required to drive the technique, how the technique was to fit into the diagnostic process, and aspects of its implementation. The bibliography of material reviewed is given in Appendix E. References are for material that provided substantial information on the subject.

Al Techniques Reported

Expert Systems. Rule-based expert systems were reported on extensively, both as stand-alone diagnostic systems and in combination with other AI techniques. Most of the systems described were ideas for either an approach or a prototype system. Few of the systems would be considered to be operational; they were reported as being used mainly as a technician's aid to help novice maintenance personnel identify a problem. It some cases they were used directly in a monitoring program. The expertise used in the development of the system came from current experts who had extensive experience with the system. The data used were generally the behavior of the system, which ranged from specific performance data at the component level to broad status at the subsystem level. Expert systems were considered in the reports to be fairly mature technology and were believed to be useful in the maintenance domain. It was emphasized in several reports that the capability of the expert system to archive expertise for use by novice personnel is important. Additionally, it was deemed crucial that the system be able to explain its conclusions as a mechanism to increase its credibility as well as to train novice personnel. It was noted, however, that the expertise needed to develop the rule base had to exist in an experienced person; thus the expert system approach to diagnosis would have difficulty with a new system. It was also admitted that rule bases that become large can be inflexible, unpredictable, and cumbersome to use.

An example of a rule-based expert system used for diagnosis is that of the CLEAR system (Hughes 1991). CLEAR monitors the communications between a primary satellite and a relay satellite, alerts the satellite analyst to any problems, and offers advice on how to correct them. It monitors more than 100 realtime performance parameters that represent the condition and operation of the spacecraft's communications with the relay satellite. CLEAR has approximately 165 rules and isolates 75 problems.

Case-Based Reasoning. CBR is a fairly recent AI approach to attacking problems. There has been only limited investigation into using CBR for diagnostic uses. CBR stores previous cases of correct diagnosis (and possibly common incorrect diagnosis) with the related symptoms and allows for quick access to those cases by attempting to match current symptoms with the set of stored symptoms. The data used for the symptoms can be at any level for which previous data were used in the cases. If the CBR system cannot exactly match the input symptoms, it can modify the case closest to the input. If that result is correct, it will maintain the modified case and in effect "learn" a new case. In addition to being fast and using previous knowledge, CBR also has the advantage of being usable on a new system without previous diagnostic knowledge. Since the CBR system can "learn," its performance will increase as it continues to function. CBR can be profitably combined with other techniques for performing diagnosis. One such combination reported by Karamousiz and Feyock (*2*) uses MBR in which aircraft engine failures were diagnosed. For some applications, MBR is computer intensive; and because it generates the hypotheses and conclusions from the beginning for each situation, the process may take longer than necessary. By combining CBR with the MBR system, a first look can be made to the CBR to determine if this situation has occurred before. If it has, then the determination is very quick; if not, then the MBR portion of the system can do its function. The current belief is that CBR holds promise for diagnosis; however, there is little operational experience with it.

Model-Based Reasoning. From the amount of recent publications concerning MBR, it would appear that this AI technique is the current favorite in the diagnostic world. Both the National Aeronautics and Space Administration and Department of Defense have done extensive work in this area. Much of the work reported has been theoretical; however, some prototypes have been developed along with a few operational systems. At least one vendor has developed an MBR diagnostic shell. The models used in this approach range from complex mathematical models such as those used during the design phase (e.g., satellites) to "qualitative" models that depict structure and function at a fairly high level. Especially important in this approach is a "causal" model, which indicates the causal relationships between components. These models can be developed from schematic or functional diagrams of the systems, along with an understanding of how the system functions. The system can be modeled at whatever level of detail is appropriate for performing the diagnosis. The MBR technique then uses the system behavior to determine if a fault exists and to develop candidate causes for the fault. The MBR technique was shown to be appropriate for continuous monitoring of systems, but has been used operationally as a technician's assistant. Because existing diagnostic expertise is not required, the MBR can be used on new systems. Additionally, this technique shows good flexibility in response to changes in the system, and MBR diagnostic techniques can provide good explanations to users. Finally, an advantage to this approach is its capability to find faults that were not previously expected from the system. MBR systems do require, however, a considerable amount of effort to develop and ensure accuracy of the model, depending on the level of diagnosis required. Additionally, it is possible that running the model would require considerable computer resources, depending on the size and detail of the model.

FIS, an MBR diagnostic program reported by Pipitone et al. (*3*), was developed by the Naval Research Laboratory. The goal was to develop a program that could be used on many different electronic systems by providing a general fault isolation shell that employs a common knowledge acquisition and representation scheme. This scheme was a model of the system being diagnosed. It was realized, however, that there would still be a different model for each system, so FIS supported the concept of reuse knowledge modules. In essence, the reuse knowledge module represents a specific component or function and can be reused in any model at any location where that component or function should appear. A simple on/off electrical switch is an example. Once the switch is modeled, the switch module can be used anywhere in the full model or in another model where a similar switch is needed. After building a library of knowledge modules, many different models can be constructed by combining these modules in different ways.

Artificial Neural Networks. ANNs have become popular in recent years and are well represented in the literature about AI and diagnosis. ANNs seem well suited for use in diagnosis because they can find patterns in complex data. These patterns can be used to distinguish between properly functioning components and systems and those that are malfunctioning, even if the differences are fairly subtle. Additionally, ANNs can learn and increase their accuracy and ability to discriminate as they function. Most of the reports in the literature about ANNs in diagnosis were theoretical or proof-of-concept descriptions. Little discussion was presented on how the ANNs would fit into a diagnostic system beyond the designation of a component or system as functioning properly or improperly. There was discussion of using the output of the ANN as an input into another AI-based system (e.g., expert system). Much of the discussion concerned the amount and kinds of training data needed to set up the ANNs so that a high level of accuracy would be achieved. It was stated by many that the initial training set would not have to be large if the ANN were set to learn through its functioning process. A concern was expressed about the inability of ANN to explain to a technician how it arrived at its conclusion.

A pilot project, reported by Jones and Plummer (*4*), in the application of ANNs in transit railcar diagnostics was performed on a converter. A simulation of a converter was used to accumulate the data necessary to train the ANN. The ANN was to correctly categorize the waveforms from the converter associated with component variations. The simulation produced 10 faults in 5 areas. The first approach was to have one ANN identify all the faults. The result was a 22 percent error rate. The approach was then changed so that one ANN was used to identify the area (out of five areas) of the fault and then another ANN to identify the fault within that area. The result for this approach was only a 4 percent error rate.

Computer Vision. The CV approach to diagnostics was described in several reports dealing with medical imagery. CAT scans, x-rays, and MRI scans were the primary imagery input into the CV programs. The medical diagnostic domain is producing and using greater quantities of imagery data and has an acute need for automated preprocessing (prescreening) of imagery data. The CV approach requires special equipment for acquiring the image, mass storage media for storing the imagery, and powerful computers for processing the data. Although there was some allusion to using CV in manufacturing quality control and nonmedical diagnosis, there were no direct reports found in that area.

Fuzzy Logic. Although the literature discusses the use of fuzzy logic in reference to data values used in ANNs, expert systems, and other AI techniques, there were very few reports focusing on fuzzy logic in diagnosis. Traditionally, maintenance specialists have had to deal with a mixture of precise component threshold values, as defined by the manufacturer, and imprecise values, as developed by experience doing diagnosis and repair. Fuzzy logic provides for imprecise values for measurements such as high, low, warm, and hot. The fuzzy logic approach can support values in ANNs, expert systems, MBR, or any other AI approach.

One approach to using fuzzy logic in diagnosis was in a report by Bocklisch *(5),* which described the method of clustering important features of a system being diagnosed to reveal the differences between the normal (nominal) system and a system with various faults. The features are sets using fuzzy values determined either by an expert or by some data reduction/classification algorithm. This approach allows for a much broader capability to determine a partially faulted (degraded) system then some more traditional methods.

Knowledge-Based System. Within the realm of KBSs reported is one developed by the U.S. Army. It is based on procedural activities resembling a troubleshooting decision tree: in fact, it is the troubleshooting functional charts that support the creation of this system. Maintenance personnel are very familiar with this type of approach; it can be used with ease and is relatively simple. It can be used at any level for which there are troubleshooting charts. The primary use for this system is as a technician's assistant. It is fairly easy to modify this system; however, care must be taken to ensure the accuracy of the decision tree, as well as the descriptive nature of each decision point. The Army, using a commercial shell, developed the Turbine Engine Diagnostic application, which provides Army mechanics with engine maintenance procedures in a step-by-step fashion. Information in the form of hints, prompts, and graphical representations is presented to the mechanics. Reports and parts-ordering paperwork are also developed in this system.

Completeness and Accuracy of Al Techniques

The majority of the literature discusses the AI techniques in terms of stand-alone processes. There is some discussion, however, of combining AI techniques; an AI system that uses two or more AI techniques in conjunction is termed a hybrid. Often this is done in order to take advantage of certain strengths. The earlier discussion of CBR and MBR is an example. In some cases, one AI technique can be used as an overall control mechanism (e.g., an expert system) and another technique (e.g., ANN) can process specific components and provide input to the control mechanism. Perhaps one of the most compelling reasons to use a hybrid system is the increase in the amount (and possibly accuracy) of diagnosis performed by the system. The literature contains some general discussion of what the researchers believe would be the level of completeness and accuracy of specific AI techniques in performing diagnosis on the research or prototypical systems. However, there were no data on or discussions of the completeness and accuracy of fully operational systems. Additionally, there were few improvement statistics cited; that kind of data can be developed through recording the results of operational systems over time. To estimate the potential for completeness and accuracy of an AI technique in diagnosis would require extensive knowledge-engineering activity. Knowledge engineering identifies the knowledge available to drive the AI technique. Assessing the extent of knowledge available to support the technique in performing diagnosis and comparing that extent with the success the human expert currently has with that knowledge would give a fair approximation of how well that AI technique would perform (if properly implemented). For example, if an expert used only if-then rules in performing diagnosis of a system and that resulted in a 90 percent successful diagnosis, then an expert system alone could be expected to perform at least that well (the system could theoretically perform better than any one expert if the rule set were developed from multiple experts). However, if the expert was found to use additional knowledge in the form of cases or pattern recognition (which is usually the case), then a rule-based expert system alone would not be sufficient. Using human experts as a standard would indicate that no one approach (i.e., AI technique) would be sufficient to completely solve the diagnostic problem.

The literature discusses criteria for selection of particular AI techniques in terms of knowledge available for the AI program, what data were used as input to the program, the primary function the AI program was to perform within the diagnostic process, and what implementation features were important to the developers and users. Since most of this work can be considered research or prototypical development, instead of operational implementation, the selection criteria were not concerned with the issue of which AI technique would provide the best overall solution in supporting the diagnostic process.

Comparison of Al Techniques

A summary of the AI diagnostic techniques is given in Table 5. Although these techniques are applicable to most diagnostic problems, each technique has its own strengths and weaknesses. All the AI techniques listed in Table 5, with the exception of CV, use symptom data as input. These data are primarily the same data that a human expert would use to perform diagnostics, although ANNs can use raw symptom data that are not used by a human. The CV approach uses imagery data that have been digitized. Additionally, except for CV, there is available commercial software for each of the AI techniques. This software is for the shell of the system: that usually includes the computer-user interface, the processing or inference engine, and the supporting software. To create a viable diagnostic system, the user would have to develop the knowledge base and interface it with the shell. Some of the commercial software shells have incorporated the AI techniques into a diagnostic-directed program (e.g., MBR shell that is designated as a diagnostic program). Others are generic shells related to the AI technique (e.g., expert system shell). Even the generic shells, however, could be successfully developed to support the diagnostic domain. The computer vision approach does have some commercial software available; however, the application to diagnostics would take much more effort than the other approaches.

ARTIFICIAL INTELLIGENCE TECHNIQUES AND RAILCAR SUBSYSTEM CORRELATION

Criteria

An analysis was performed to correlate AI techniques with railcar subsystems. The information gathered during the site surveys and the AI diagnostic techniques literature search were used to relate the various AI techniques with the railcar subsystems. The goal is to develop an understanding of how well each AI technique would function against each railcar subsystem. That information can be used as criteria for recommending implementation of specific AI techniques against individual railcar subsystems. Additionally, recommendations for further research can be derived from information about how AI techniques function on the specific subsystems.

Reducing cost and increasing accuracy of diagnostics requires the application of effective AI techniques to the railcar subsystems. The railcar subsystems differ not only functionally, but also by how the subsystems operate and are diagnosed. Because no one AI technique can solve the diagnostic problems for all railcar subsystems, it is necessary to understand how each AI technique can contribute to the diagnosis of each railcar subsystem.

Most of the railcar systems are composed of a combination of mechanical, electrical, and electronic functional types of subsystems and components. The amount of each of these functional types varies within the system. Additionally, each system varies in complexity and difficulty to diagnose. AI techniques, even those used primarily in the diagnosis domain, are not tied in any primary way to those functional types of subsystems and components. Instead, AI techniques attempt to emulate the different human problem-solving approaches. As described in the background section, each particular AI technique can be associated with a specific human problem-solving approach or activity.

Human experts bring to bear on each diagnostic situation all their problem-solving techniques. It is true, however, that some of the approaches are used more often with some of the railcar systems, depending on the experience and knowledge of the human expert. For a system with which the experts have a great deal of experience, they may use generalized rules as the primary diagnostic approach, perhaps remembering specific past cases as an added technique. For a new and complex system, the experts may have to rely on schematics and their knowledge of how the system works to track down faults. The experts do not rely on only one approach to diagnosis for any system.

To correlate AI techniques to railcar subsystems, the attributes in Table 6 were used. Many of the AI techniques can use varying kinds or levels of symptom data. For example, rule-based expert system programs could potentially use highlevel symptom data associated with the physical behavior of complete components or functional portions of the subsystem or fine-grained symptom data such as would be provided by a microprocessor. Each of the AI techniques, however, is used most often with specific kinds or levels of data.

Each AI technique is constructed around a specific kind of knowledge. For example, it is difficult to build a procedural KBS if no procedures exist; therefore, the knowledge of the railcar subsystem in the form required by an AI technique must exist for that technique to be viable against that particular subsystem.

Diagnosis of a subsystem or component may require an explanation to be accepted. This is particularly true for complex subsystems that have a large number of potential faults. For an AI technique to be effective in such a case, the technique

TABLE 5. Comparison of AI Diagnostic Techniques

	KNOWLEDGE USED	LEVEL OF SYSTEM SUPPORTED	IMPLEMENTATION USES	LEVEL OF OPERATIONAL MATURITY	STRENGTHS	WEAKNESSES
EXPERT SYSTEMS	If-Then Rules	• System and Subsystem Interactions	• System/Subsystem Monitoring and Evaluation • Technician's Assistant	High	• Lots of Operational Experience • Institutionalize Expertise • Explain findings	• Requires existing expertise • Can become complex and cumbersome • Identifying rules can be difficult
CASE-BASED REASONING	Previously Analyzed Data (Known Cases)	• System and Subsystem Interactions	• Technician's Assistant	Medium	• Can begin with little knowledge • Can learn • Fast • Explain findings	• Must have some beginning cases • Little operational experience
MODEL-BASED REASONING	Models/ Schematics	• System and Subsystem Interactions • Able to Easily Move Through Multiple Levels	• System/Subsystem Monitoring and Evaluating • Technician's Assistant	Medium	• Does not require existing diagnostic expertise • Can find unexpected results • Flexible to change • Explain findings	• May require extensive computer resources • Requires model development
ARTIFICIAL NEURAL NETWORK	Previously Analyzed Data (Performance Data Sets)	• System and Subsystem Interactions • Data Producing Component	• Component/ Subsystem Evaluation • Input to Wider Level Technique	Medium	• Can begin with little knowledge • Can identify complex data patterns • Can learn and tune automatically • Fast	• Cannot explain findings • Requires past performance data sets
COMPUTER VISION	Past Images	• Component	• Identification of Components Physical Status	Low	• May be only way to assess certain components automatically	• Complex • Large computer resources required • Little operational experience
FUZZY LOGIC	Expert Understanding of Data Values	• Any Level	• Support of Other Techniques	Low	• Supports other techniques • Uses terms humans understand	• Little operational experience in diagnostics
KNOWLEDGE-BASED SYSTEM (PROCEDURAL)	Troubleshooting Procedures	• System and Subsystem Interactions	• Technician's Assistant (Troubleshooting)	Medium	• Simple • Low cost in resources	• Limited in capability to known procedures

Source: Ian Mulholland

TABLE 6. Criteria for Correlation of AI Technique to Railcar Subsystem

Subsystem Attribute	AI Technique Attribute
Symptom Data Available	Symptom Data Required
Knowledge Available	Knowledge Required
Explanation Required	Explanation Capable
Complex	Able to Handle Complexity

Source Ian Mulholland

would have to be able to explain its logic in arriving at its answer. Of course, that explanation would have to be in terminology that the maintenance personnel understand. In other cases, simply the determination that a component is bad (e.g., a line replaceable component) is sufficient.

Some AI techniques can handle complex subsystems better than others. For example, expert systems have been found to have difficulty in dealing with complex systems that require many rules. Alternatively, MBR systems are designed to handle complex systems well.

Correlation

Table 7 lists the AI techniques (with the exception of CV) evaluated in this study and the transit railcar systems to which the AI techniques may be applied. The entries in the matrix specify the relative potential performance of an AI technique against the railcar subsystem. Any of the AI techniques have the potential of being applied to any of the railcar systems; however, some of the techniques are best used with specific systems.

An expert system is appropriate to use on railcar systems for which experience has been used by human experts performing diagnosis. The expert system will be composed of rules derived from the diagnostic expert, and the input data will be symptoms of the faulted railcar system. In general, neither the diagnosed railcar system nor the symptom data should be too complex.

TABLE 7. Matrix of Railcar Systems and AI Techniques

RAILCAR SYSTEM	EXPERT SYSTEMS	MODEL-BASED SYSTEMS	ARTIFICIAL NEURAL NETWORKS	FUZZY LOGIC	KNOWLEDGE-BASED SYSTEM (PROCEDURAL)	CASE-BASED REASONING
PROPULSION	FAIR	GOOD	FAIR	FAIR	FAIR	FAIR
FRICTION BRAKES	GOOD	FAIR	FAIR	FAIR	GOOD	GOOD
AUXILIARY ELECTRIC	FAIR	GOOD	GOOD	FAIR	FAIR	FAIR
DOORS	GOOD	FAIR	FAIR	FAIR	GOOD	GOOD
HVAC	FAIR	GOOD	FAIR	FAIR	FAIR	FAIR
COMMUNICATIONS	FAIR	GOOD	GOOD	FAIR	FAIR	FAIR
AUTO-TRAIN CONTROL	FAIR	GOOD	GOOD	FAIR	FAIR	FAIR
CAR BODY	GOOD	FAIR	FAIR	FAIR	GOOD	GOOD
TRUCKS, SUSPENSION & COUPLER	GOOD	FAIR	FAIR	FAIR	GOOD	GOOD

Source: Ian Mulholland

CBR diagnostic programs can be used on any railcar system for which previous diagnosis has been performed and the information of those cases recorded. Even for systems where little previous information has been recorded, CBR programs have the capability to learn and improve their performance as they function. CBR programs are fast, use previous experience, and are able to relate the current situation to the previous ones.

MBR diagnostic programs would be especially useful for complex railcar systems or where there are systems interacting with each other. In these kinds of systems, the symptomatic data may be subtle or indirect: as, for instance, when one component's failure causes the symptoms to show up in another component. Additionally, since the basis for an MBR program is a model of the railcar system that can be derived from schematics or computer-aid design data, the MBR program is especially useful when there is little diagnostic experience due to the newness of the railcar system.

ANNs can perform pattern recognition on complex data of the type produced by such electronic systems as Printed Circuit Boards (PCBs), as well as symbolic data. ANNs can be effective for situations even where it is difficult for a human expert to determine the difference between the output of a good electronic component and a degraded one. The ANN has to be trained using data reflecting good and degraded components; however, the ANN has the capability to continue to learn and improve its performance as it does its diagnostic job.

As stated in the background section, CV approaches attempt to emulate the vision capability of the human expert. Although this approach appears to have some potential for use in railcar diagnostics, little work has been done using CV in the diagnostic domain in other industries (with the exception of the medical domain). With the lack of background research in CV diagnostics and with the requirements for specialized equipment such as cameras and special image-processing hardware, it is currently unknown if CV would be appropriate for use in the diagnosis of any railcar systems. The CV category has been left out of Table 7.

Fuzzy logic can be applied as part of any diagnostic system. Its use allows familiar terminology for data values to be used in the expert knowledge. Additionally, fuzzy logic provides for understanding the degradation (partial failure) of the railcar system and can be used anywhere precise threshold values are not needed. The level of operational maturity for fuzzy logic use in diagnosis is still low. The extent of the contribution that fuzzy logic can provide to diagnosis is unknown.

A procedural KBS can be used on any railcar system for which there is procedural expertise. If human experts have developed diagnostic procedures such as reliable troubleshooting decision trees, which, if followed, will lead to correct diagnosis, then that procedure decision tree can be automated.

Operational Requirements

Inspection of Table 7 reveals that the criteria used (listed in Table 6) did not result in very good discrimination for selecting specific AI techniques for use on particular railcar subsystems. In fact, any AI technique has the potential of working on any railcar subsystem. The primary criterion that could have made the ranking of AI techniques to railcar subsystems possible was found to be beyond the scope of this effort. That criterion was the level of completeness and accuracy that each AI technique provides to each railcar subsystem. As described earlier, determining or estimating how much an AI technique would contribute to the completeness and accuracy of diagnosis in a particular railcar subsystem would require an extensive amount of effort. The selection of specific railcar subsystems and AI techniques for inclusion in a recommendation for implementation will require using other criteria.

Instead of just focusing on the applicability of an AI diagnostic

TABLE 8. Operational Requirements

Program must work well on high-priority railcar subsystems
Program must be cost-effective and be able to be implemented without long delays
Program must be able to interface with other AI techniques, computer programs, or data sources (e.g., electronic technical manuals)
Program must be user friendly for both development and end use
Program must be able to be implemented Incrementally
Program must be able to explain its conclusions
Program must be able to perform the function of advising technicians in the diagnostic process

Source: Ian Mulholland

technique against each railcar subsystem, criteria were developed in response to the operational needs of the properties as determined in the site surveys. Table 8 lists those needs as they relate to a diagnostic AI program (AI technique or techniques implemented in a computer program).

As explained in the findings from the site surveys, the propulsion system was designated by most maintenance managers as being the system they believe should be the priority candidate for advanced diagnostics. This is supported by the very high percent of incidents with no defect found, as listed in Table 3. The AI program implemented must be able to function on the propulsion system.

A large cost of implementing an AI program relates to development of the shell. If the shell has to be developed from scratch or customized extensively, then the cost will be much higher than if the shell has been commercialized and available at reasonable cost. Therefore the shell for the AI program should be Commercial Off-the-Shelf (COTS) software. Additionally, COTS AI shells allow for the quick implementation of an initial AI system. An economic analysis was performed and reported in the next section.

Properties want as much capability in the program as possible. This means the ability to increase completeness and accuracy of diagnosis by adding additional AI techniques to the core program. Just like a human expert who uses all the problem-solving techniques possible, a viable AI program will do the same. The usability of the program will also increase if it is able to interface to other computer programs and data sources. A capability of interfacing to and using historical maintenance data would be extremely useful, as would the ability to display technical drawings when appropriate.

The AI program must be easy to use, and have terms the user understands. Knowledge engineers, domain experts, and computer programmers must be able to easily enter knowledge and data and test the system during development. Maintenance personnel and managers must be able to use the program without being required to have special skills or learn new terminology.

Reducing developmental risk and allowing improvement through lessons learned can be supported by a program that can be implemented incrementally. It is important that each increment of the program be useful on its own, as well as adding to the functionality of the whole program.

The success of an AI diagnostic program will depend, in large part, on the credibility the program has with the maintenance personnel. The ability of the program to explain how it arrived at its conclusions will improve that credibility. There are some important additional benefits of being able to explain its logic process: during the testing of new knowledge, the explanation function can be of tremendous help; additionally, novice maintenance personnel can use the AI program to help them learn new diagnostic skills.

Most maintenance personnel, as described in the site survey section, believe that installing the AI program to directly assist the maintenance specialist during diagnosis should be the first step in implementing this technology. This "technician's assistant" would not only provide recommendations as to the fault, but could also display technical text and drawings and provide recommendations for repair. It was also considered important, especially by maintenance managers, that such an AI program could help the technician accomplish all the required diagnostic steps to ensure that a false fault was not found and "fixed" and the railcar released just to be returned later. Finally, the technician's assistant could help efficiently document the diagnostic (and possibly maintenance) process.

The ultimate goal may be to install AI computer programs on board the railcar to automatically monitor, detect, and identify faults; however, most maintenance specialists believe that a program used by them during the diagnostic process is the best way to start. This approach will help them become comfortable with the technology and provide stimulation for eventually placing these techniques in a more automated location.

ECONOMIC ANALYSIS

Cost Model and Calibration

This section discusses the use of the cost model reported by Moutoh and Elms *(6), Cost Savings Potential from Improvement in Railcar Reliability and Maintainability,* and its calibration. As the title implies, this model was developed for the express purpose of evaluating potential cost savings from improvements in maintainability or reliability. The model comprises three separate but related modules: operations, maintenance, and capital costs. All three of these areas can benefit from improvements in maintenance diagnostic procedures; hence the model is well suited for use in this project.

Each cost module develops an annual incremental cost reduction based on postulated improvements in reliability, expressed as Mean Time Between Failures, and improvements in maintainability, expressed as MTTR. The reliability values used are those developed for the vehicle subsystems evaluation as described in Table 3. These reliability values are representative of a composite heavy rail transit fleet. The purpose of the analysis is to evaluate the effect of incremental changes in the MTTR; a significant portion of the repair time is the time to diagnose the problem.

A detailed description of the model is found in the referenced document. The model requires calibration for the specific operating property because it accounts for different operating and maintenance structures and uses actual annual costs as a base. The costs used to calibrate the model were developed in a manner similar to the way the reliability values were developed. A generic operating property was characterized from the data in the American Public Transit Association's (APTA) Annual Financial Statistical Reports of 1992. This generic property was assumed to have a fleet size of 600 vehicles. The values used are presented below.

The following terms and values are taken from Table 3 as input variables for calibrating the cost model:

Number of failures per 1,000 hours	6.69225
Service delays (minutes per 1,000 operating hours)	8.523
Repair time (hours per 1,000 operating hours)	13.167

The model variable for Annual Operating Cost (Co) is taken from the APTA Financial Report 1992, and is equal to $63,065,446. Annual Corrective Maintenance Cost (Ccm) is $16,254,926. Annual Corrective Spare Parts Cost (Csp) is $4,768,111. These values are one-half the total vehicle maintenance and spare parts costs reported for the same property. Annual Operating Hours (Hs) was taken from APTA Operating Statistics for the same property, and are 1,498,740 hours. The average number of cars in a train (No) was set at 6 cars. An annual operating schedule of 18 hours per day, 7 days a week, yields a schedule operating hours per car per year (hs) of 6,570 hours.

The MTTR Line Service, in hours (R1) is equal to 0.021226 hours. It is Service Delay in hours divided by Number of Failures (both per 1,000 hours). The Mean Time Between Failures (Fs) is equal to 149.42658 hours. This is the inverse of the Number of Failures per 1,000 hours. The Total Number of Failures (Nf) is 10,029.943. This is the Number of Failures per 1,000 hours times the Annual Operating Hours (Hs) divided by 1,000. The Repair Time is divided by Number of Failures (both per 1,000 hours) to yield the MTTR (Rs) of 1.9674997 hours. The Mean Time to Restore (shop time) (Rm), is estimated to be 8 hours: this is shop turnaround time and includes actual repair time. The Annual Maintenance Cost is Cm.

The Annual Fleet Capital Cost is Ec. The Cost per Vehicle (Cv) used in the model is $1,000,000. A discount factor (crf) of 10 percent discount for 30 years was calculated, and the value is 0.057309.

All the cost modules use a ratio expression for improvements to reliability and maintainability. The improvement in reliability is expressed as Pf. Pf is the ratio of the increased time between failures divided by the base failure rate. For the Operating Cost module, these values are the Service Delay failures. For the Maintenance and Capital Cost modules, these are the equipment failure rates. Maintainability is Pr for the Operating Cost module and Prs for the Maintenance and Capital Cost modules. Pr is the decrease in time to return the line to service divided by the base time. Prs is the decreased time to repair the system.

Operating Cost Module. The expression for the change in annual operating cost due to an improvement in reliability, Pf, and maintainability, Pr, is

Delta(Co) = Co*{(Pf + Pr)/(1 + Pf)*(No*R1/Fs)}

Evaluating the variables yields

Delta(Co) = (Pf + Pr)/(1 + Pf)*53750.68

Maintenance Cost Module. The expression for the change in annual maintenance cost as a function of Pf and Prs is

Delta(Cm) = Nf*{Ks*Rs*(Pf + Prs)/(1 + Pf) + Kp(Pf/(1 + Pf))}

where

Ks = Ccm/Ds
Ds = Nf*Rs
Kp = Csp/Nf

Evaluating: Ks = 823.7053
Kp = 475.38771
Delta(Cm) = 16254926*(Pf + Prs)/(1 + Pf) + 4768111.5*(Pf/(1 + Pf))

Fleet Capital Cost Module. The expression for the change in annual fleet capital cost as a function of Pf and Pr is

Delta(Ec) = Cv*Hs*(crf)/hs*{No*R1/Fs + Rm/Fs} *(Pf+ Pr)/(l + Pf)

where

Rm/Fs = 0.053538
*No*R1/Fs* = 0.0008523
*Cv*Hs*(crf)/hs* = 13073256

and, therefore,

Delta(Ec) = 711058.31*(Pf + Pr)/(l + Pf)

Economic Analysis

The cost model developed and described above is used to illustrate a few diagnostic improvement strategies. These strategies include a system to improve the diagnostic time for PCB repair, a system to improve the ratio of NDFs, and a system to improve individual vehicle systems. The model was exercised postulating various levels of improvements. The annual cost

TABLE 9. All PCB Repair Time Improvement

Reduction Repair Time (percent)	Annual Corrective Maintenance Cost Reduction (dollars)	Annual Corrective Maintenance Cost Reduction (percent)
0.00	0	0.00
6.25	61,494	0.29
12.50	122,987	0.59
18.75	184,481	0.88
25.00	245,975	1.17

Source Ray Oren

TABLE 10. Microprocessor Board Only Repair Time Improvement

Reduction Repair Time (percent)	Annual Corrective Maintenance Cost Reduction (dollars)	Annual Corrective Maintenance Cost Reduction (percent)
0.00	0	0.00
6.25	10,339	0.05
12.50	20,678	0.10
18.75	31,017	0.15
25.00	41,356	0.20

Source Ray Oren

TABLE 11. All PCBs But Microprocessor Board Repair Time Improvement

Reduction Repair Time (percent)	Annual Corrective Maintenance Cost Reduction (dollars)	Annual Corrective Maintenance Cost Reduction (percent)
0.00	0	0.00
6.25	51,155	0.24
12.50	102,309	0.49
18.75	153,464	0.73
25.00	204,619	0.97

Source Ray Oren

reductions were tabled, and graphed, and are presented as follows.

Printed Circuit Boards

The first case examines the use of a system that would improve the repair of PCBs by improving the time to diagnose a problem. A maximum of 25 percent of the current repair time was set as the limit of expected improvement. Postulated new MTTRs were entered in the cost matrix, and the resultant annual costs are shown in Tables 9 through 13.

TABLE 12. Communication PCB Only Repair Time Improvement

Reduction Repair Time (percent)	Annual Corrective Maintenance Cost Reduction (dollars)	Annual Corrective Maintenance Cost Reduction (percent)
0.00	0	0.00
6.25	27,236	0.13
12.50	54,472	0.26
18.75	81,708	0.39
25.00	108,945	0 52

Source Ray Oren

TABLE 13. ATC PCBs Only Repair Time Improvement

Reduction Repair Time (percent)	Annual Corrective Maintenance Cost Reduction (dollars)	Annual Corrective Maintenance Cost Reduction (percent)
0.00	0	0.00
6.25	12,422	0.06
12.50	24,844	0.12
18.75	37,267	0.18
25.00	49,689	0.24

Source Ray Oren

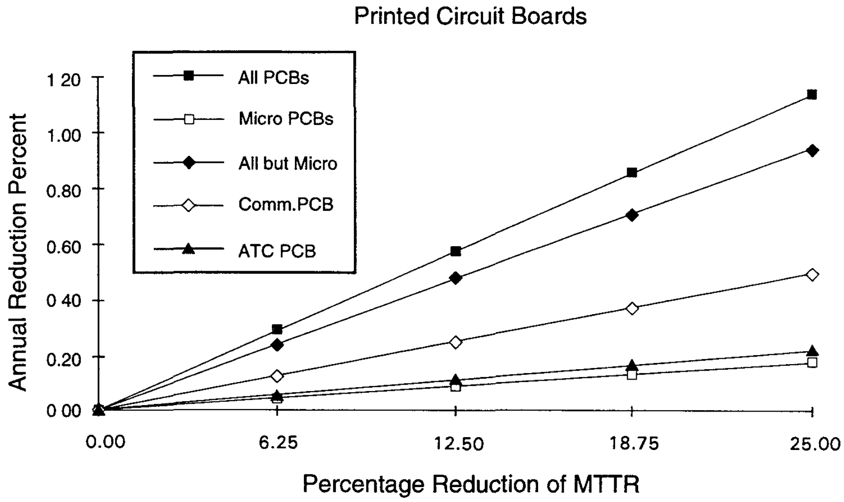
The tabled data are shown in Figure 1. The figure shows that a system that can be applied to improving the repair times for all printed circuit boards, if it can reduce repair times by 25 percent, has the potential of reducing annual maintenance costs by nearly 1.2 percent.

Improving No Defects Found (NDFs)

The cost model was used to evaluate the effect of reducing the number of NDFs by 5 percent. If the number of NDFs is reduced by 5 percent in each of the vehicle systems, the net annual cost reduction is $576,000, which includes reduction in operating costs and fleet capital costs, as well as maintenance costs. This dollar value would only relate to an operating authority similar in size to that of the model variants. The percentage of annual maintenance cost reduction is 2.6 percent.

Individual Systems MTTR Improvements

The model was next used to examine the effect of improvements in the MTTR of each individual vehicle system. Reduced repair times at the vehicle level were entered and the resultant annual maintenance cost reductions in percent are tabulated in Table 14. Figure 2 presents a simple bar chart comparing the



Source: Ray Oren

Figure 1. Annual Maintenance Cost Reduction for Improvement in PCB Rapair Time.

TABLE 14. Vehicle Systems MTTR Reduction

Reduction in Mean Time to Repair (percent)	Reduction In Annual Maintenance Cost (percent)								
	Propulsion	Friction Brake	Train Control	High Voltage	Low Voltage	Doors	HVAC	Comm.	ATC
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6.25	0.71	0.35	0.07	0.43	0.03	0.16	0.44	0.06	0.38
12.50	1.43	0.73	0.14	0.85	0.06	0.32	0.89	0.11	0.77
18.75	2.20	1.08	0.21	1.28	0.08	0.48	1.33	0.17	1.15
25.00	2.92	1.46	0.28	1.70	0.11	0.64	1.78	0.23	1.54

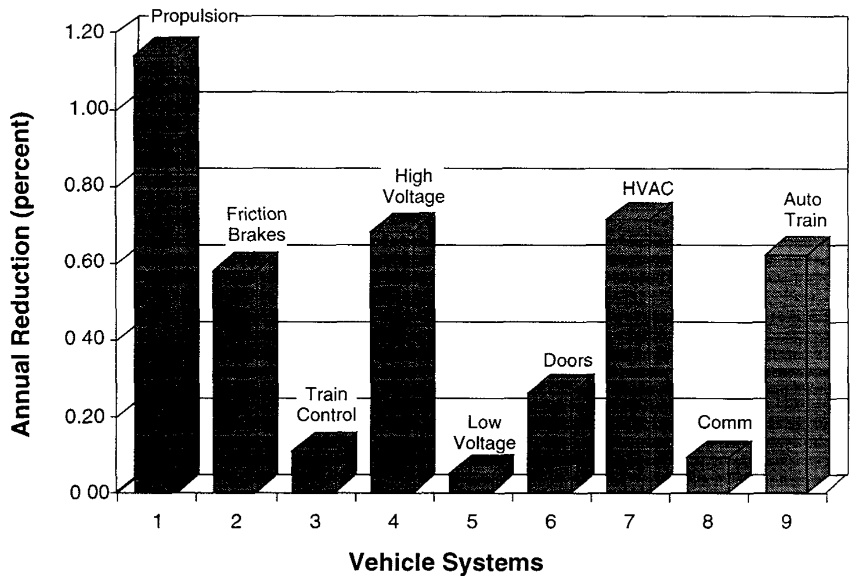
Source Ray Oren

annual maintenance cost reductions in percent possible with a 10 percent reduction in individual systems' MTTR.

Model-Based Al System for the Propulsion System

A model-based system is proposed as a diagnostic tool for the propulsion system including the traction motors, gearboxes, power switchgear, and control logic units. The initial cost estimate for the system is $120,000. That cost includes a COTS shell, initial development of the base system by a contractor, training and follow-up consultation, and cost of a transit authority's maintenance specialist. Reviewing the value used in the cost model, there would be 1,719 propulsion system failures in a year. With a 5-day work week, this is 6.6 failures per day. Ignoring multiple shifts, eight workstations should be provided.

At $6,500 a workstation, an additional $52,000 is added to the system cost estimate. This is a total of $172,000 for an operating authority of the size similar to that of the cost model. The cost model uses an annual corrective maintenance cost of $21,073,038. The cost of the proposed diagnostic tool is 0.82 percent of this annual corrective maintenance cost. The diagnostic tool only has to provide a 7.2 percent reduction in the propulsion system MTTR to pay for itself out of cost savings in 1 year. A 7.2 percent reduction in the propulsion MTTR, moving from 1.8 to 1.67 hours MTTR, is less than the postulated limit of a possible 25 percent improvement used in the above sensitivity exercises. The MTTR is composed of actual repair time and diagnostic time. As mentioned earlier, there are no operating statistics on how much of an MTTR is repair and how much is diagnostic time. One approach to determining



Source Ray Oren

Figure 2. Annual Maintenance Cost Reduction for a 10 Percent Reduction in System **MTTR.**

how reasonable a 7.2 percent reduction in the propulsion system MTTR requires examining the average MTTR. Assume for this example that, on the average, the 1.8 hour MTTR is split equally between repair and diagnostic time, i.e., 54 minutes for each. To achieve an average MTTR of 1.67 hours, retaining the same repair time, the diagnostic time would have to be reduced to 46.2 minutes (54 + 46.2 minutes = 1.67 hours). This is only a 15 percent reduction in average diagnostic time. This seems to be a reasonable possibility.

The useful life of this AI system is based primarily on the use of the propulsion system modeled. The AI system will not have to be replaced unless a different propulsion system is used. Updates to the AI system could occur because of slight modification to the propulsion system or additional diagnostic knowledge emerging.

BARRIERS TO IMPLEMENTATION

Introduction

The implementation of AI technology in the transit railcar diagnostic process will require support from several sources: maintenance operational support, systems support, personnel support, and financial support.

The maintenance operational environment and procedures have to be structured to promote and support the inclusion and use of the AI technology. Maintenance managers need to develop required procedures that ensure the collection, storage, and use of appropriate historical data necessary to support the AI techniques used. Additionally, training for personnel who will be involved in the AI technology should be developed and promoted. Support that may have a profound effect on the success of introducing this new technology is management proponancy.

System support is necessary to provide the equipment and information for the maintenance personnel to effectively and efficiently use the AI diagnostic capability. System and component suppliers can play an important part in this support. A well-designed and integrated system can substantially increase the overall use of the AI program.

The capability and desire of the transit railcar maintenance personnel is crucial to the successful implementation of this technology. The injection and use of AI technology in this domain require that maintenance personnel be capable and comfortable in using computers and software. Additionally, since maintenance experts will also be involved with helping to develop and maintain this diagnostic system, they have to be able to interface and use the more sophisticated development capability of the AI software.

The implementation of any new technology will, of course, require financial support, and in the current environment of tight budgets the implementation cost must be visible. To take full advantage of the capability of AI diagnostic techniques will require financial support for computer equipment, software, development expertise, training, and system support.

Maintenance Operational Support

Most AI techniques use historical data to support or drive their approach. In some techniques, the data are used directly, as with CBR, and with others the data are modified, such as rule development for an expert system. In all techniques, the content and accuracy of the historical data are important.

In the transit railcar maintenance environment, this data can be potentially located in two places. First, as the AI program is exercised it will collect and store localized data. The localized data will be derived only from the problem being diagnosed at that moment. Additionally, historical data can be stored in a centralized data base receiving data from all operational, diagnostic, and maintenance sources within the facility or authority. This second data location is currently being used by most transit authorities. However, as described in the section on current diagnostic practices, many maintenance personnel do not feel that the historical data in their MIS data base are sufficient to support diagnosis in great detail. Expansion of the data in the MIS data base will help to support the AI diagnostic program.

The AI program implemented will determine the content and form that both the localized and centralized data need to have in order to support the techniques in the program. The content and form requirement for both sets of data will best be designed as the AI program is developed in the specific diagnostic environment.

Maintenance operational procedures will have to be established that encourage or require maintenance personnel to collect, record, and save into the central data base the specified historical data. Although none of the AI techniques evaluated in this study are required to use the data from the centralized data base, that kind of data can improve performance of the AI program.

The implementation of an AI computer program will require a training module to be established directed toward its use. Railcar transit authorities that intend to help develop and maintain the AI program will also have to train the individuals charged with those tasks. Most of the training requirements will be for end users.

The AI diagnostic training module can well be incorporated with diagnostic training, and can even use the AI program itself. The AI program implementation details will determine the level of training necessary. A program having an intuitive interface that is couched in terms that maintenance personnel are comfortable with will require less training than will a more obscure program. It is important to understand, however, that the use of an AI program requires a somewhat different approach in training. Computer training of conventional software generally assumes that the software, if properly used, will generate a correct answer that the user can accept. AI programs, however, generate the best solution possible from the evidence available. That solution is not guaranteed to be sufficient. The maintenance specialist must be trained to use the information provided by the AI program as advice and use the explanation capability of the program if there is a question about the output.

A management proponent to support the inclusion of AI technology in transit railcar maintenance is important. AI technology is not well understood by many people and it is often considered a threat, although attempts have been made to implement AI approaches in different domains. It was believed that some of the difficulties encountered were because of the characteristics and terminology used with these approaches: phrases like "expert in a box" and "intelligent machine" conjure up images of workers being replaced by automation. In most cases, AI technology would be used to improve the performance of maintenance personnel; it is important that there is a management proponent to help explain this to the maintenance personnel.

Discussions with managers and personnel at the railcar maintenance facilities indicated general support for the requirements listed above. There was some concern, however, about the ability to effectively implement procedures to consistently collect, record, and store the historical diagnostic and maintenance data at the level needed by the AI program. Some of this concern related to the system support required to store and use the data; this will be discussed in more detail in the next section. Another concern, however, was with the discipline needed by the maintenance personnel to perform this level of data collection. This problem can be mitigated through a combined development of operational procedures and an AI program that makes it easy for the personnel to collect and store the needed historical data.

None of the operational problems listed would preclude the successful implementation of an AI diagnostic program. If attention is focused upon these, however, the program can be more readily accepted and used to good effect. It was believed by most of the maintenance managers and specialists that an AI diagnostic program would be readily accepted by most people (regardless of their jobs) if the program truly helps to relieve the diagnostic problem.

System Support

Implementation of an AI diagnostic program requires equipment, software, and information support. Computer equipment, sensors, data bases, technical publications, and supporting software need to be able to interface, allowing efficient transfer of information and data for the AI program. Such an integrated system would considerably increase efficiency.

In such a system, computer equipment such as laptops or workstations, and their support peripherals, will be used as the primary interface between the maintenance specialists and the AI program. Data related to specific subsystem failures will be entered into the AI program by the maintenance specialist or directly by downloading event logs from the subsystems. Event data logging requires equipment sensors with monitoring and recording software.

The maintenance specialist will receive information or advice from the AI program through the user interface. Useful additional information in the form of data from external databases and technical publications (e.g., manuals and schematics) could be accessed through the diagnostic program. Finally, the generation of reports and the archiving of diagnostic and maintenance activities could be accomplished from the diagnostic program.

The equipment, data, and activities discussed above describe the system support required for an efficient and effective diagnostic system. The critical attribute is the integration of those things. Equipment, software, and data bases need to be compatible and allow easy communication; these capabilities are important for achieving the highest potential of the AI approach, but railcar transit authorities do not have the support system architecture in place to allow easy integration of the necessary items. There is movement toward developing more capability in computer equipment, data bases, and technical publications; however, the overall integration of these is lacking. Several transit authorities are proceeding to install their technical publications in electronic media, and some suppliers of subsystems are including event logging in their systems. Although these activities will help support the AI diagnostic program, a fully integrated system would be superior. The AI program can perform its function in a stand-alone mode; however, the complete potential could only be met with a fully integrated system.

Personnel Support

The introduction of an AI diagnostic program into the transit railcar maintenance facility will require that maintenance personnel acquire certain skills and accept a different approach to performing diagnostics. The capability of the personnel to learn these skills and the readiness with which they accept the AI program will, in large part, determine the program's success. Maintenance personnel will be using the computer that hosts the AI program. The specific skills required by the program depend on which AI approach is taken and how the interface is implemented. The more user friendly the program is to the maintenance personnel, the fewer computer skills will be required. Those computer skills required to support the AI diagnostic program will be useful in other computerized functions in the maintenance process and will add benefits independent of the diagnostic capability.

Acceptance of the AI diagnostic program will be determined primarily by the level at which the program helps the maintenance specialist perform the job. If the program is easy to use and the specialist becomes more efficient in performing diagnoses, acceptance will follow. Maintenance managers believe that personnel will accept and use an AI diagnostic program if the program is easy to use and works well. Even in transit authorities where union labor practices dominate, it is believed that such a diagnostic program would be accepted.

Financial Support

The cost of implementing an AI program is an important issue for transit authorities. Hardware, software, training, and consulting costs, along with the cost of maintenance personnel participating in the system development, will compose the initial cost of the system. Additionally, an ongoing cost is that related to maintaining the knowledge base and upgrading the program. Funding the support system necessary to allow the AI program to reach its highest potential could be substantial. There would be cost for integrating the separate data and information sources with the program to allow easy communication of information. Another cost would be the design and installation of railcar subsystem sensor equipment, along with the monitoring and recording of equipment and software.

Incremental implementation of the AI program will allow the cost to be spread across funding periods. The cost could also be shared across transit authorities as the AI program is portable with only marginal costs to adapt to each authority (assuming the authorities have similar railcar systems). Additionally, the payback period should be relatively short.

As described in the economic analysis section, the cost of initially implementing the AI programs (with the exception of the computer vision approach) can be paid back easily within 1 year.

CHAPTER 3

APPLICATION

INTRODUCTION

Artificial Intelligence (AI) techniques can be applied to transit railcar diagnostics in a cost-effective manner. The AI techniques have been shown to be viable diagnostic approaches in many equipment and process areas within various domains. Research, prototype development, and operational development has occurred and produced successful results in applying these AI techniques to the diagnostic process. The objective of this chapter is to discuss the initial application of a specific set of AI techniques to a transit railcar subsystem.

The application of AI diagnostic technology into the transit railcar domain should result in improved diagnostics and reduced overall maintenance costs. AI-based computer programs, however, are often viewed differently by personnel than are conventional programs. Additionally, the development of an AI program requires participation by end users to a much greater extent than does that of conventional software programs. The AI diagnostic program initial implementation, therefore, should be highly visible and done in such a way as to reduce risk and concern.

The objective of the initial application of the AI diagnostic program should be to demonstrate its capabilities in the railcar maintenance environment. The use of the program will aid the diagnostic process and reduce the associated costs, while at the same time inform and educate maintenance personnel and transportation managers about the use and benefit of AI technology.

This chapter will discuss the initial implementation of an AI diagnostic program and the criteria for selecting the railcar subsystem to be used. A hybrid AI program and its attributes are discussed. Use of the AI program in the diagnostic operational process along with its overall advantages is described. This is followed by the issues and recommendations relating to the implementation of the AI program. The final section of this chapter concerns applications that can add to the capability of the initial AI program.

RAILCAR SUBSYSTEM

The propulsion subsystem including the traction motors, gearboxes, power switchgear, and control logic units, described in the Vehicle System Evaluation section presented earlier, was given the highest priority for initial application of AI technology to the diagnostic process. Most of the maintenance managers surveyed felt that increasing the diagnostic capability on the propulsion subsystem would provide a high initial benefit of reducing overall maintenance costs. The high overall maintenance effort required for propulsion and a large number of No Defects Found (NDFs) were cited as reasons for recommending the propulsion subsystem. Since NDFs may be indicative of difficulties in diagnosing the propulsion subsystem, they may be a good indicator of achieving increased diagnostic capability. Of course, decreased overall maintenance time (in which diagnostic time is included) would also be a good indicator of its success.

Using the propulsion subsystem for the initial application of the AI diagnostic program has other benefits. Because the propulsion subsystem is complex, being composed of electrical, mechanical, and electronic components, an AI diagnostic program applied to the propulsion subsystem will show the capability of the program to deal with complexity and with the variation of components.

Much knowledge exists to support the development of an AI program for diagnosing the propulsion subsystem. In addition to maintenance manuals and troubleshooting charts, detailed schematics and functional flow diagrams exist. There are also experts in the propulsion domain who have extensive knowledge of the diagnosis of propulsion.

Finally, the propulsion subsystem has a history of technological progression. Manufacturers are improving the propulsion subsystem and implementing data logging into the newer versions. The manufacturers already have data collected, which may be used in supporting the development of the AI program. If the ultimate goal is to develop an on-board automated diagnostic capability, data logging will be essential.

Al DIAGNOSTIC PROGRAM

The AI techniques that drive the diagnostic program must effectively work with the propulsion subsystem. All of the techniques have the potential of functioning to some degree against the propulsion subsystem, however, as shown in Table 7, model-based reasoning appears to offer the most potential. As described in Chapter 2, because the AI techniques are not tied to the railcar subsystems in any fundamental way, the application of the techniques will be determined primarily by the operational needs of the properties.

Applying a computer technology that is new to the railcar maintenance environment will develop concerns about the technology's capability to cost-effectively increase diagnostic performance and meet the operational requirements. These concerns may be even greater for AI technology, but can be mitigated by using a program that is very visible to the transit authorities. Applying the AI program initially to the high-level requirements of propulsion subsystem diagnosis, and then having the program evolve to finer levels of detail as needed, will provide great flexibility and better demonstrate the program capabilities. Early review and evaluation of the program and its capabilities will provide the necessary visibility to the program and the development process. By including maintenance experts and end users in the development process, the operational issues will be addressed and each expert or user will have a stake in the success of the program.

The AI program that best meets the needs and the operational requirements, as defined in Table 8, will be a hybrid combination of AI techniques. Eventually, the program may use most of the techniques discussed in this report. That would ensure that the maximum amount of knowledge available would be put to use. The initial program, however, should use MBR as its core. An MBR program will provide for application to various levels of detail in a complex system; this allows the program to be incrementally implemented and evolve over time. Additionally, the MBR program can explain its findings in terms familiar to maintenance personnel. An MBR program used as a core will provide the framework on which to add other capabilities. Using a functional model of the propulsion subsystem allows the developers and users to follow the way the subsystem is used in developing diagnostic processes.

In addition to the MBR core, an expert system capability should be added to the initial implementation of the AI program. The expert system will allow for use of the extensive knowledge that already exists among the propulsion experts. The expert system should be integrated with the MBR so that rules can be used anywhere appropriate. Use of a commercial shell that has already integrated the MBR approach with an expert system capability would provide a cost-effective approach. There is at least one commercial product (I-CAT developed by Automated Technology Systems Corporation of Hauppauge, New York[1]) meeting this criteria (see Appendix D for more commercial products). It would be also possible to integrate an independent MBR product with an expert system product to create an enhanced capability.

DIAGNOSTIC FUNCTION

The application of an AI diagnostic program could occur at several locations in the diagnostic process. The first application, however, should be as a "maintenance assistant." Implementing the initial AI diagnostic program as an assistant to maintenance personnel, as many maintenance managers have requested, has many advantages. A maintenance individual who is required to interface with an AI program based on the MBR and expert system approach will be exposed to how the propulsion subsystem operates and how experts perform diagnosis on propulsion. This will help train personnel and keep maintenance personnel current in technology.

The AI program must establish a standard diagnostic procedure that will ensure that the maintenance individuals perform the activities needed to reduce the problem of quitting after the first obvious fault is found. This will help reduce the number of times a vehicle or subsystem has to be diagnosed for the same problem (i.e., repeat failures).

A maintenance assistant program will be highly visible and can be used or observed by anyone, thus allowing maintenance personnel and managers to evaluate the capabilities of the program in performing diagnosis. The explanation facility of the program will lend credibility to using AI technology and will naturally lead to the identification of other approaches to support the diagnostic program.

Finally, if the program is implemented with the capability to perform report generation, it can help the maintenance specialist perform a more thorough job of documenting and storing the diagnostic and maintenance activities. Such a capability may be very welcome to maintenance individuals and allow for more standardization of maintenance reporting. More detailed information can be automatically included in the report thus making the report more useful.

IMPLEMENTATION

One of the most important implementation details required for a successful AI program is the early inclusion of the end users. A program that serves as an assistant to maintenance personnel will have to provide an interface that is user friendly and capable of supporting the activities needed. The only way to achieve this is by including as many of the potential end users--from novices to experts--in the development process as soon as possible. Traditionally, in the development of the human interface in computer programs, end users are interviewed about how they would like to see the interface function. This is necessary since it is critical that end users begin to actually exercise the interface as early in the development process as possible. This concept of rapid prototyping of the interface function will help create an interface which is user friendly.

Most commercial AI shells support rapid prototyping of the interface. Another important interface attribute that some commercial off-the-shelf AI shells support is the ability to easily customize the interface for each maintenance individual. Individuals have different preferences and capabilities, and interfaces that can easily be adapted in real time to an individual's preference will promote use of the program.

In addition to end users being involved in development of the interface, propulsion experts need to be involved in development of the knowledge base. These experts should be drawn from different sources if possible; for example, the lead maintenance individual at the authority and a field service engineer of the propulsion system. A propulsion diagnostic program based on the MBR approach requires models of the propulsion subsystem, some of which can be developed from schematics of the subsystem. The schematics can be input into the program manually or from computer-aided design files if they are available. The model of the propulsion subsystem can be entered at any level of detail appropriate to the diagnostic needs. For example, to demonstrate capabilities, some portion of the model can be entered at a high functional level, while another portion can be entered in detail. The detailed portion can now be diagnosed down to that level of detail. The ability to enter

[1]The Transportation Research Board, the National Research Council, the Federal Highway Administration, the American Association of State Highway and Transportation Officials, and the individual states participating in the National Cooperative Highway Research Program do not **endorse** products or manufacturers Trade or manufacturers' names appear herein solely because they **are** considered essential to the object of this report

different levels of detail is another way of incrementally implementing this approach.

Other models may have to be entered to fully support this program. For example, a casual model may be of use. A propulsion diagnostic expert will have to help develop this model. The propulsion expert will also have to work with a knowledge engineer to develop diagnostic rules in the form that the expert system can use. The diagnostic rules in the expert system should be integrated into the AI program such that the rules can be used at specific locations within the models as the MBR process is being used.

The railcar subsystems that interface with the propulsion subsystem and are effected by or affect that system need to be included in the AI program to some level. For example, the ATC and Friction Brake subsystems may need to be modeled, perhaps as only a single functional box, with appropriate diagnostic rules attached to them. This will allow the diagnostic program the ability to suggest that what appears to be a propulsion fault may actually be associated with an interfacing subsystem.

The diagnostic program is a good place to integrate other supporting capabilities. The inclusion of technical manuals and drawings in electronic form can be very helpful to the maintenance personnel. The section of the manuals and drawings associated with the model components should be accessible to the maintenance specialist from those specific model locations. For example, if the specialist requests a technical drawing while viewing the portion of the model that represents the power cam controller, then the appropriate power cam controller drawing will appear.

Interfacing the AI diagnostic program to the maintenance data bases (MIS) would be helpful: access to the historical data in the data bases would allow review of the maintenance background of the propulsion subsystem by the maintenance specialist. Additionally, the AI diagnostic program could directly enter its results into the data base. Developing an interface between the diagnostic program and the data bases may not be a trivial task, but it should be considered.

FOLLOW-ON APPLICATIONS

The initial AI diagnostic program will provide substantial improvement to the propulsion subsystem diagnostic capability. The program can be expanded to a greater level of detail in the propulsion models or to other railcar subsystems. Additionally, other AI techniques can be added to the program, thus adding diagnostic capability.

The initial AI diagnostic program will not be able to diagnose all problems with the railcar subsystems. Adding other AI techniques may better diagnose certain components: for example, an Artificial Neural Network (ANN) program may be developed to diagnose certain electronic components such as Printed Circuit Boards (PCBs). The ANN may perform the diagnosis on the PCB much more efficiently than developing the model of the PCB down to the level of the components on the board. The ANN program could be integrated into the initial AI program so that the ANN would perform its function when requested by the AI program and return its conclusions to that program.

The determination to increase the level of detail of the models and perhaps add more rules, extend the model to other specific railcar subsystems, or add other AI techniques to perform additional diagnosis will depend upon the specific additional diagnosis desired. There will be a point at which the resources required to implement the process will exceed the benefit from the additional diagnosis. This point of diminishing returns will be different for every subsystem or component type to be diagnosed and every approach taken.

CHAPTER 4

CONCLUSIONS AND SUGGESTED RESEARCH

CONCLUSIONS

Initial Implementation

This investigation has shown that transit railcar diagnostics can benefit from application of Artificial Intelligence (AI) techniques. The process of diagnosis currently being performed by human experts can be enhanced by the addition of an AI program used to assist the expert. With the exception of computer vision, all the AI techniques discussed in this report are capable of supporting the AI diagnostic program. Using a model-based reasoning approach as the core of the initial AI program provides the functioning information of the railcar subsystem upon which to expand and build an effective diagnostic program.

Quantifying the cost-to-benefit ratio is extremely difficult. The complete cost of diagnosis is hard to determine, as is the incremental cost for diagnosis on all different components, in all different situations. The benefit from a potential AI diagnostic program is difficult to quantify because of the effort required to estimate the accuracy and completeness of the diagnosis that could be done by the program.

The actual cost of diagnosis in the transit railcar maintenance process can only be estimated. The various transit railcar authorities do not have a standard maintenance data collection methodology. The maintenance data stored includes diagnosis, replacement, and repair times (and other time) without specification. The diagnostic time is lost in the total time. Additionally, some diagnostic time may not be reported at all. For example, time spent following a false diagnostic trail will occasionally not be reported if it did not lead to the difficulty found in the system and reported by maintenance personnel.

The benefit that any particular AI technique or hybrid set of techniques can have in performing diagnosis is also difficult to quantify. One reason is the structure of the diagnostic problem. The diagnosis of railcar subsystems involves the evaluation of large numbers of variables (e.g., components, subcomponents, input values, and symptoms) and combinations of these variables. Human experts have handled this problem to date because of their ability to quickly reduce the problem space by using their experience or training. An AI program could do the same thing. Determining or estimating the size of the problem space and how well an AI program (or human) would function in that problem space is very difficult. Determining how well an AI diagnostic program would perform could be done, but the cost would be high. *In fact, the cost of implementing an AI program would probably be considerably less than the cost of estimating the accuracy and completeness of an AI diagnostic program.*

Even though determining a cost-to-benefit ratio is difficult, determining that it is cost-effective to implement an AI diagnostic program is not. As detailed in the Economic Analysis section of this report, the initial implementation of an AI program used to perform diagnostics on the propulsion subsystem would be less than 1 percent of the annual corrective maintenance cost.

Program Acceptance

The majority of the maintenance personnel in the transit railcar authorities surveyed would use a properly implemented AI diagnostic program. The critical factors for acceptance are the ease of use of the program and how well it helps maintenance personnel perform their job. Although most current off-the-shelf AI shells provide good interfaces for the end users, the development of the diagnostic interface must be carefully implemented.

The implementation of the AI diagnostic program is expected to encounter some barriers. However, none of these should prevent the successful application of this technology. Although the program can stand alone and be effective, providing support in the maintenance operations and support systems areas will increase the usefulness of the program.

Future Systems

The initial implementation of an AI diagnostic program should be the first step in a process of adding advanced technology to the diagnostic and maintenance process. The ultimate goal, as expressed by many individuals with interest in railcar maintenance, is the development of an on-board system that will automatically monitor and predict faults before they occur, or detect and identify faults after they occur. The information would then be communicated to the operator with suggestions for appropriate action. The diagnostic information could also be transmitted to a maintenance specialist or stored for easy retrieval by the maintenance personnel.

The goal of an advanced on-board diagnostic system is attainable. The steps to reach this goal include incremental improvement to the initial diagnostic program, development of an integrated support system, development of an on-board diagnostic system architecture, and determination of the predictive approach. These steps require additional research.

SUGGESTED RESEARCH

Introduction

The research recommendations are intended to increase diagnostic capability and support eventual implementation of on-board automatic diagnosis. The research falls into five areas: (1) a prototype AI diagnostic program, (2) the architecture necessary to improve the initial AI program capability, (3) the on-board AI diagnostic system architecture, (4) the placement of on-board sensors to support the on-board diagnostic system, and (5) the evaluation of AI predictive techniques to support the on-board diagnostic system.

Prototype Al Diagnostic Program

As discussed in Chapter 3, AI technology is sufficiently mature to be implemented in the transit railcar maintenance domain. The initial implementation should be accomplished as a prototype using a Commercial Off-the-Shelf (COTS) shell. This approach will allow rapid prototyping to be accomplished so that the diagnostic program will benefit from support by the maintenance personnel.

Organizations that successfully develop AI programs to an operational level often do so through a prototype version. This allows the organization to try various concepts with some flexibility. Using a COTS shell allows easy change of the Human-Computer Interface (HCI) and the knowledge base. If the prototype version is sufficient then it naturally becomes the operational version. If, however, the prototype version will not support the operational requirements, a new HCI and knowledge base are developed that allow the prototype to quickly transition to the operational version. New hardware and COTS software are not usually required.

The prototype implemented should follow the program described in Chapter 3. A combination of MBR and expert system used on the propulsion subsystem will provide the best combination for the prototype. This system will translate well to an operational system and then potentially to the advanced onboard monitoring system.

Support System Architecture for Initial Al Diagnosis Program

Information technology has evolved to the point where increases in productivity can be realized by a well-designed information system architecture. Such an architecture supporting the diagnostic and maintenance process could add substantially to the overall productivity of maintenance personnel. The communication of information between data bases, diagnostic programs, knowledge bases and technical publications, test equipment, sensor packages, and even training systems can help the maintenance organization increase capability and reduce cost.

This report has discussed the benefits of supplying historical maintenance information to the AI diagnostic program for use in its processing. The ability of a maintenance specialist to quickly access technical manuals and drawings was also discussed. There are a few more advanced capabilities that could be developed through the support system.

An advanced AI diagnostic program could use information in independent knowledge bases, technical manuals, and schematics by accessing them directly. By having a set of knowledge bases and a series of technical manuals and schematics on line that could be accessed by an AI program, the program could adjust its diagnosis to the subsystem of interest.

Communication between test equipment and the diagnostic program could provide greater efficiency. The AI diagnostic program can specify which tests to perform along with the test parameter values, and receive results that can then be used in the program.

Finally, self-contained training programs can use the AI diagnostic program and the support system to help train novice maintenance personnel. Such a program could use AI to help determine the best training approach and process for each individual. The program would then use the same knowledge bases and supporting data for training. The AI diagnostic program could be used to train individuals; however, the process of performing diagnosis and the process of training someone to perform diagnosis are different.

It is recommended that research into the support system architecture should be undertaken to develop the elements of the system, how each should function, the contribution to the maintenance process of each function, and the cost to implement such an architecture.

On-Board Diagnostic Architecture

An on-board diagnostic system that continuously monitors the system and predicts or identifies faults could have a major impact upon both railcar maintenance and operations. Such a system would be composed of sensors located at required monitoring points, one or more processors to host the program, data storage capability, and communication capability.

The AI approach to performing diagnosis for the on-board system may be different from that used at the maintenance facility. One major difference may be a requirement for the on-board system to learn. As the system will be mostly automatic, it may have to make self adjustments, either in finetuning the program so as not to produce false alarms or in learning new faults.

The diagnostic system would be able to receive a download of information from the maintenance facilities data base providing information on repairs or replacements made to the railcar subsystems. The diagnostic system would be able to perform startup and shutdown diagnosis on command and continuously monitor the systems while the train is in operation. Prediction, or detection and identification of a fault, along with suggested actions would be provided to the train operator on a monitor at the operator's station. Additionally, depending on the nature of the problem, the diagnostic system could communicate directly with the maintenance facility. Alternatively, a maintenance specialist could download the diagnostic information stored on board the railcar.

Research into the on-board diagnostic system should investigate the AI techniques to use, the elements of the system, which railcar subsystems should be monitored, the method and contents of communication, the impact of a system on railcar operations and maintenance, and the cost to implement such a system.

Sensor Placement

The placement of sensors on board to monitor subsystem events can provide important information to the AI diagnostic program (on board or at the maintenance facility). As discussed in this report, intermittent faults are considered a difficult problem. The collection and storage of event information can significantly reduce this problem.

The location of sensors may very well be tied to the data requirements of the AI diagnostic program. These locations may be different from the locations indicated by subsystem suppliers used for subsystem setup.

The research suggested for sensor placement should investigate the type, number, and locations of sensors needed to support the AI program. A trade-off analysis should be performed to investigate the benefit from a large number of sensors versus the cost and complexity of the sensor system.

Al Predictive Techniques

The capability to replace or repair components in a subsystem before they fail can be cost-effective if it is possible to predict with some certainty when that component will fail. Obviously it is not cost-effective to replace a component that was not going to fail. Most preventative replacements are currently made on the basis of statistical probability of pending failure instead of predictive events.

Many AI techniques have the theoretical possibility of performing predictions. The operational implementation of predictive AI techniques, however, is not widespread. The implementation of predictive techniques in an on-board monitoring system could contribute substantially to railcar operations and maintenance activities.

Research into predictive AI techniques and how they could be implemented should be undertaken. Techniques such as artificial neural networks and case-based reasoning have shown promise in using the current state and trend data to predict future states. These techniques, as well as the data required to support them in predicting railcar faults, should be investigated.

APPENDIX A

VEHICLE SYSTEM CHARACTERIZATION

PROPULSION SYSTEM

Purpose

The purpose is to interpret train-lined commands and configure the traction equipment to receive or generate high-voltage power in order to move or slow the vehicle, and to regulate the effort provided to the level commanded.

Equipment Type

The primary equipment associated with the propulsion system is the traction motor. The most common traction motor is a compound wound-direct current motor with series and shunt-wound fields. There are separately excited dc motors. Newer vehicle orders are tending toward ac induction motors. A coupler provides the fixation of the traction motor to a gear box, which provides speed reduction and is fixed to the axle.

Power circuits in the propulsion system are configured using either pneumatics or low voltage to actuate the high-current contactors, usually through interlocking relay logic. Some systems use a cam controller, where a servo motor positions cams to operate the contactors, establishing the power circuit configuration. It is possible that new vehicles may provide the power switching with solid-state, power Silicon-Controlled Rectifiers (SCRs) and power Gate Turn-Off Thyristors (GTOs) to configure the traction system.

Control logic subsystems use low voltage for power and apply discrete components in analog and digital logic schemes, most employing relays, with interlocking contacts as part of the logic system. Interlocking occurs in both the power circuits and the low-voltage control logic. Although these control schemes use a number of control functions, not all points in the logic are readily available for monitoring external to the control process. Microprocessors are being applied to the propulsion control process. This enables the external monitoring of the traditional functions plus much of the process operation. Some event logging is also being requested of the microprocessor control systems.

Indicators/Signals

Usually there is only a single motor overload/shutdown indicator available to the operator, but some older systems have a motor current indicator available. Monitoring voltages and currents at various points in the circuits is possible; availability of signals varies with every car design. On older systems, relay logic is used to control power; fault isolation is accomplished with schematics and electrical meters. On newer systems, a finer control of the level of tractive effort is provided, and some form of discrete analog or digital printed circuit boards is used. The possibility of waveform analysis of SCR/GTOs for impending faults is possible. In current microprocessor systems, there are checks of SCR/GTO limits in the control system routines.

Consequence of Failure

Propulsion systems are sufficiently redundant that, at the most, a minor reduction in performance will occur with the failure of one system in a train. Most systems also have automatic isolation of the failed system, permitting the train to continue revenue operation.

Complexity of System

The system is relatively complex, with multiple circuit paths to arrive at similar power system configurations and a multitude of different power system configurations. Analog signal tolerance levels require judgment to access faults.

Diagnostic Techniques

1. **Revenue Service Level.** Fault isolation is usually an automatic cutout of the failed system. The individual vehicle with the failure is identified by a local indicator

2. **Vehicle Level.** Electronic test equipment, schematics, wiring diagrams and shop manuals containing checkout and alignment procedures are used for fault diagnosis. On older controller equipment, a visual inspection of contactors and listening for air leaks is a first check procedure. For cam controllers, a test box is used to cycle the cam, ensuring cam motor operation and control availability. Low-voltage discrete logic systems require signal tracing for fault isolation. Microprocessor-based controls currently can provide a record of the status of the system at the time of the fault.

3. **Back Shop.** Schematics and shop manuals for PCBs, usually encompassing a complex test setup and alignment procedure, are used. Electromechanical components are fault diagnosed by repair manuals and rebuild kits.

Equipment Location

Traction motors, gearboxes, and couplers are located on the axles. Power switchgear is usually located in equipment boxes under the car body. Control logic units are in electrical enclosures under the car, lockers inside the vehicle, or in a seatwell.

Note: Systems are configured as one propulsion system per car or as two complete propulsion systems per car. A traction motor may be arranged as a monomotor one motor per truck, two motors per truck permanently connected in series, or, two motors per truck with either electrical connection possible.

FRICTION BRAKE

Purpose

The purpose is to interpret trainline commands and, when requested, slow or stop the vehicle, controlling the effort to the level commanded.

Equipment Type

Tread brake units are either pneumatic or hydraulic-actuated units, mounted on the truck frame, which apply a friction pad against the wheel tread. Disk brake units are either pneumatic or hydraulic truck-mounted units that apply a friction pad against a disk, separately mounted on the axles. Some configurations entail a spring-applied, pneumatically released, friction pad arrangement.

Control units in current use are full-pneumatic, electropneumatic, or electronic. In a pneumatic control system, the train control system establishes a trainlined Brake Pipe (BP) pressure as the command signal. Individual pneumatic units, on a per vehicle or per truck basis, monitor the BP and apply or release the air pressure to the individual brake units in response to the variations, both in level and rate of change of the BP. In electropneumatic systems, a discrete component or microprocessor system interprets trainlined low-voltage electrical signals and provides an analog electrical signal to a variable pneumatic valve, which in turn controls pressure to the brake cylinder. A pneumatic panel includes solenoid valves for charging and discharging the brake system air supply and a pressure-actuated mechanical control valve to provide a loadweighing signal. A full electronic control system bypasses the variable pneumatic valves and provides a digital signal to solenoid valves, with pressure feedback, to control brake cylinder pressure directly. Load-weighing and control signal variation is completed in the electronics or microprocessor routines.

Indicators/Signals Available

Usually, there is a train-lined Brakes On signal interlocked to the propulsion system (any Brake Cylinder Pressure [BCP] on train). This is used to prevent moving the train with a brake applied. Brake pipe pressure is presented to operator, and, sometimes, a single-truck BCP is presented. Different systems have fault lights to assist operations in moving a failed vehicle off the line. These are at the vehicle level (All Brakes On, All Brakes Off, System Failure). Some pressure signals are monitored by controllers. Microprocessor controllers monitor enough pressures to isolate faults. Usually, only a few status lights are available in analog electronic controllers.

Consequence of Failure

Friction brake systems are designed to fail to a brakes-on condition. Failures during operation result in a service interruption until the faulted vehicle can be isolated and manually cut out. "Cut out" means different things to different operators. In some cases, a single vehicle may be isolated and continue in revenue service for the remainder of the day. In other cases, the vehicle is isolated, the train is moved to a station, passengers unloaded, and the train is deadheaded to a service area.

Complexity of System

The system is not very complex. Each system, whether per truck or per vehicle, monitors trainlines or brake pipe pressure and responds independently.

Diagnostic Techniques

I. **Revenue Service Level.** Because of redundancy, brake failures in a "failed off' condition may not be detected during normal operation and would have no effect on operation. Brake failures in a "failed on" condition causes operational delays, as noted above. Some authorities have indicators that facilitate operations' ability to isolate the failed vehicle.

2. **Vehicle Level.** Electrical test equipment, schematics, piping diagrams, and wiring diagrams are used to isolate

a failed component. Visual indication of linkage positions and audible leaks are also used.

3. **Back Shop.** Component repair manuals and rebuild kits are used for fault isolation of pneumatic and mechanical components. Discrete analog PCBs are used in electromechanical control systems. Microprocessors are also used.

Equipment Location

Actuators and brake cylinders are on each truck. Air piping is throughout the undercar area. Pneumatic controllers are usually located at the center of the undercar. Electronic control units may be in undercar enclosures or in interior lockers or in a seatwell.

Note: Some friction brake systems are grouped at the vehicle level; others are on a per truck basis for redundancy.

Auxiliary Electric Systems

The auxiliary electric system is separated into four parts below, primarily because of the variations in the manner by which the systems are tabulated in various authorities. The train control system is usually incorporated as part of the propulsion system by most authorities. This is probably due to the propulsion system supplier's providing the first electrical control systems on the vehicles. As the train control system takes on more tasks, such as vehicle and train monitoring, it is being treated separately in accounting and work breakdown structures. All the rail transit vehicles have high and low-voltage systems, some more complex than others. Again, some authorities do not separate the systems; they are accounted for as part of other systems. Auxiliary voltage systems are not on all vehicles, and the voltages used are different for different authorities and times of vehicle procurement.

TRAIN CONTROL

Purpose

The purpose is to determine which of multiple stations in a train is the operating or control station, and, while active, will prevent any other station in the train from gaining control, to establish the mode of operation (manual, automatic, combination), interpret input commands, and establish trainlined commands that can be used by all the other train/vehicle systems as operating commands Newer vehicle procurement includes the task of monitoring train and vehicle system status in the train control functions

Equipment Type

The train control system includes equipment necessary to establish a train control station and to operate the vehicles. There are key-operated switches, large manual and rotary switches with mechanical interlocking to ensure proper operating configuration. These usually interface to low-voltage relays, with interlocking relay logic, again to enforce correct operating configuration. Relays are used in order to provide the power levels to drive the train-length trainline commands. Some of the control circuits are arranged in a fail-to-safe configuration. Microprocessor-based systems are beginning to be applied, but relays are still used in the safety circuits.

Indicators/Signals

Traditionally, there are usually no direct indicators. Indicators of the status of other train or vehicle systems at the operating station are the indication that the control function has been established (e.g., console lights, door status indication, friction brake status).

With the advent of the microprocessor systems, it is possible to monitor switch and relay positions. Monitoring systems, in order to be a diagnostic tool, must include the logic of valid configurations.

Consequence of Failure

Failures usually occur on train setup; therefore, disruption is usually a delay in dispatching a train. For a failure in service, some authorities permit operation from the second car in a train, others remove the train from service. After operational fault isolation, the vehicle is either buried in the middle of a train until maintenance can be performed or it is removed from service. The components of the system are discrete switches and relays. Repairs are either complete part replacement or limited to overhaul kits supplied by manufacturer.

Complexity of System

The complexity is moderate, there are numerous interlocks and circuits to other vehicles in the train These must make complete logical circuits in any train length within the possible train lengths originally defined when the vehicle was procured or modified

Diagnostic Techniques

1 **Revenue Service Level** With loss of control, the quickest operational procedure is to isolate a failed vehicle, operate from another station under severely

restrictive operating rules, off load passengers, and remove the train from service. Some authorities are incorporating bypass and redundant control systems to enable lead vehicle operation using equipment in a remote vehicle.

2. **Vehicle Level.** Circuit schematics, wiring diagrams, and electrical meters are used to trace the failed function.

3. **Back Shop.** Relay and switch repair manuals and kits, essential to a rebuilding process are used in the back shop. Specific failure data are rarely reported.

Equipment Location

Operating switches and controls are located near or at the operator's console. Interior or undercar electrical lockers and seatwell locations house the relay systems.

Note: This system is sometimes grouped with the propulsion system.

HIGH VOLTAGE

Purpose

The purpose is to collect high-voltage power (13 KVac, 750 Vdc) and distribute it to the using vehicle systems.

Equipment Type

Power collection is provided by pantographs, on the vehicle roof, for overhead catenary supplied power and by third-rail shoes, on the truck assembly, for power distributed by a third-rail system adjacent to the running rails. Fuses and high-speed circuit breakers provide system and cabling protection. Manual transfer switches to isolate systems and provide shop power connection are also part of the system. Low-voltage-operated transfer contactors are used to provide alternate power source connections. Transformers and a converter are used to convert 13 KVac to 750 Vdc.

Indicators/Signals

Usually there is no direct indication of correct high-voltage system operation. Sometimes, the line voltage is indicated at or near the operator's console. Propulsion control systems monitor line input voltages and contactor positions, because they are necessary for regenerative braking capability. In traditional relay-logic and discrete-component logic systems, these monitor points are buried in the logic system and not readily available for external monitoring. The availability of these signals is being enhanced with the use of microprocessor control propulsion systems.

Consequence of Failure

Loss of a high-voltage system usually causes an automatic isolation of the affected vehicle from the high-voltage system. Little disruption to revenue operation should occur unless the failure is in the lead vehicle. The failed train would unload passengers and be removed from service at the first station.

Complexity of System

Usually the system is not complex, but dangerous voltage levels may be present.

Diagnostic Techniques

1. **Revenue Service Level.** Usually a loss of all but the emergency vehicle systems is the indication of a fault in the high-voltage system.
2. **Vehicle Level.** Portable electrical test equipment, schematics, wiring diagrams, and shop manuals are used to isolate faults to a component.
3. **Back Shop.** Repair kits and component manuals are used to fault isolate the predominantly electromechanical components. Electrical test equipment, schematics, and checkout and alignment procedures are used to diagnose PCBs.

Equipment Location

All high-voltage systems are isolated from the operator's console and passenger areas. Pantographs are roof mounted; third-rail shoes, some fuses, and cabling are on the trucks; and other equipment is located in undercar equipment enclosures.

Note: Any existing monitoring is part of the train control or propulsion control system.

AUXILIARY VOLTAGE

Purpose

The purpose is to convert primary power (750 Vdc) to an intermediate power level for various vehicle auxiliary systems use.

Equipment Type

Motor alternators are used to provide 115 or 230 Vac; static inverters are replacing motor alternators in this application. Low-voltage-controlled contactors are used to configure the system circuits. Fuses and circuit breakers are included.

Indicators/Signals

Usually, there is no direct indication of a failure to the operator. Operation of auxiliary equipment is a revenue service indicator of auxiliary system operation. The motor alternator is usually an analog PCB control system. Fault indicators are sometimes located on a motor alternator control unit, and sometimes a remote on/off indicator is located on a fault indication panel. The static inverter might have fault indicators and a control system similar to the motor alternator. However, the inverter internal functions would include control of SCRs and GTOs. Static inverters are also being provided with microprocessor control systems.

Consequence of Failure

Loss of auxiliary voltage usually causes only minor service disruptions. The train may continue operation to the end of the run and then be removed from service.

Complexity of System

Complexity varies from simple to moderately complex. Motor alternator systems have discrete-component analog control circuitry. Static inverters contain more complex control functions.

Diagnostic Techniques

1. **Revenue Service Level.** Usually a loss of a using system, such as interior lighting, is the indication of a fault.
2. **Vehicle Level.** Portable electrical test equipment, schematics, wiring diagrams, and shop manuals are used to isolate faults to a component or PCB.
3. **Back Shop.** Repair kits and component manuals are used to fault isolate electromechanical components. Electrical test equipment, schematics, and checkout and alignment procedures are used to diagnose PCBs.

Equipment Location

The power components of the system are located in undercar enclosures. System controls might be in a separate electrical locker, undercar, or in the interior.

Note: 230/115 Vac is used for incremental horsepower motors, fans, and blowers. 115 Vac is used for interior fluorescent lights.

Load management systems are used on some cars to shed inessential battery loads during loss of primary power.

LOW VOLTAGE

Purpose

The purpose is to convert high-voltage input (750 Vdc) to a low voltage (37.5 or 24 Vdc) and distribute it throughout the vehicle, for use in control and indications of various vehicle auxiliary systems, and to provide an alternative low-voltage power source for essential systems in the absence of primary power.

Equipment Type

Static converters, operated directly from the 750 Vdc, provide the low-voltage power. Older systems used a motor generator for this function. For systems with an auxiliary voltage motor alternator, a transformer with a diode bridge provides the low voltage. The system also includes a battery and battery-charging capability.

Indicators/Signals

Usually, no indicators are available to the operator; loss of individual systems is the indicator of a failure. Some vehicles have a low-voltage meter located on a fault panel. Battery chargers monitor charging currents and battery status but only provide an on/off indicator at charger.

Consequence of Failure

Loss of low voltage, if not the battery system, is the same as loss of auxiliary voltage. Battery capacity is sufficient to enable completion of a round trip with all safety and emergency systems functioning. If the loss is the battery, the effect is a shutdown of operations until the faulted vehicle is isolated and the affected train is removed from the operating line.

Complexity of System

This varies from simple to moderately complex. Batteries, some chargers, and circuit breakers and switch-based systems are simple. Motor alternators and motor generators have some analog control circuitry. Static converters and some chargers contain more complex control functions.

Diagnostic Techniques

1. **Revenue Service Level.** Usually a loss of all but the emergency systems is the indication of a fault in the low-voltage system.

2. **Vehicle Level.** Portable electrical test equipment, schematics, wiring diagrams, and shop manuals are used to isolate faults to a component or PCB.

3. **Back Shop.** Repair kits and component manuals are used to fault isolate electromechanical components. Electrical test equipment, schematics, and checkout and alignment procedures are used to diagnose PCBs.

Equipment Location

Motor generators, converters, and batteries are usually located under the car.

Note: The principal users of the low voltage are the trainlined command signals, the power to control systems, the door operators, the running lights, and emergency interior lights. An emergency bus separates distribution for essential battery loads. Low voltage is distributed and shared on trainlines. Battery voltage is sometimes distributed and shared on trainlines. Battery charging is not distributed on trainlines.

DOORS

Purpose

The purpose is to control the opening and closing of the vehicle side doors permitting passenger egress in a safe manner.

Equipment Type

There is a vehicle-level door control system, monitoring trainlines, using relay logic to control local door operations. Solid-state, vehicle-level door control systems are not in wide use. Door operators, at each door location, are pneumatic or electric motors, with door leaf position monitored by microswitches. Local door operator controls may be relay logic or through discrete-component PCBs. Pushbutton control stations are located at motorman's or conductor's station.

Indicators/Signals

At the vehicle level, there is an all-doors-closed trainline. This signal is summed over the train and interlocked with the propulsion system. Near each door operator is a leafclosed and locked indicator. Individual leaf-closed and locked signals are summed by vehicle. Indication of individual faults are not centrally available on train or vehicle.

Consequence of Failure

Failure of the train or vehicle door control system is toward a safe mode (i.e., the train stops or cannot open the doors) and causes operational disruption of normal service. Passengers must be unloaded and the train removed from service. The failure of individual door operators or leaves is still toward a safe mode. Service disruptions are not as severe, because the faulted component can be locked out of service and bypassed. Fault isolation requires walking the length of the train. Depending on the particular operating agency, the train may continue in service or be removed from service when convenient. The net effect is minor delay in service.

Complexity of System

The door control systems are relatively simple. The most complex are the trainline looping circuits that sum door status and the door command trainlines. These must ensure correct-door-side operation regardless of the direction of vehicle travel.

Diagnostic Techniques

1. **Revenue Service Level.** A train level indication of "doors closed" is available to operator. An exterior-located, vehicle-level "doors open" indicator, per car side, is available on some vehicle designs. An interior "door leaf open" indicator is available on some vehicle designs.

2. **Vehicle Level.** Portable electrical instruments, schematics, wiring diagrams, and operating manuals for timing functions are used to isolate door faults.

3. **Back Shop.** Most systems are presently relay logic, in which case component diagnosis is limited to manuals and repair kits. PCBs with discrete-component logic circuits are used in some door operator motor controls. Maintenance manuals and checkout procedures are required for fault diagnoses on these systems.

Equipment Location

Vehicle control is in an interior electrical locker. Door operators and controls are adjacent to door locations, overhead or in side panels. Pushbutton stations are at operator's and conductor's stations; passenger controls are at doorways.

Note: The vehicle door control power system is interlocked with a fail-safe no-motion signal. The doors closed summary is interlocked with train propulsion and brake controls.

HEATING, VENTILATION, AND AIR CONDITIONING

Purpose

The purpose is to condition the vehicle interior to a reasonably comfortable temperature and humidity level.

Equipment Type

There are electrical heater elements, at 750 Vdc and 230 Vac, and ceiling ductwork for air distribution. Air cooling may be provided by modular air conditioning units or splitsystem air conditioning systems. Control is provided by discrete-component PCBs, or, in a few cases, by microprocessor-based controllers.

Indicators/Signals

This varies, but is usually limited to fault indicators on the control unit or remote indicator panel. System diagnostic data are not readily available. Microprocessor control systems are just being introduced in new vehicle designs.

Consequence of Failure

Failure is the loss of heating or cooling. The train is usually continued in service, at least for the completion of the current run.

Complexity of System

The system is moderately complex for newer systems that comprise all three functions, and where the air conditioning equipment includes modulation for partial cooling capacity.

Diagnostic Techniques

1. **Revenue Service Level.** Faults are diagnosed by operator or passenger complaints.

2. **Vehicle Level.** Some systems have fault panels to indicate which portion of a system is not operating. Pressure gauges, electrical meters, schematics, wiring diagrams, and operating manuals are the usual diagnostic means.

3. **Component Level.** Mechanical components are diagnosed by manuals and repair kits. Electrical instruments, schematics, and checkout procedures are necessary for PCBs. Microprocessor controllers are just being introduced to the industry.

Equipment Location

Heater elements are at floor level and in the overhead; heater control is undercar. Modular air conditioner systems are roof mounted. On split systems, the compressor is mounted undercar, and the condenser is in ceiling ductwork. The system control unit is in an interior electrical locker. Temperature sensors are in the duct work or vehicle interior.

Note: Compressor motors and blower motors may be operated at 750 Vdc or 230 Vac.

COMMUNICATION

Purpose

The purpose is to provide the means for a train operator to communicate: (1) to passengers in or near the train, (2) to and from a central command center, external to the train, and (3) to and from an individual passenger.

Equipment Type

Operator's control head with microphone, preamplifier, speaker or handphone, audio power amplifier, VHF radio, and intercom stations are the system components.

Indicators/Signals

The operator might have a radio transmit light.

Consequence of Failure

There may be a disruption of passenger service and delays for authorities that rely on radio communication for operation. PA and intercom failures, unless reported by passengers, are transparent to operations and cause no delays.

Complexity of System

These systems are relatively simple.

Diagnostic Techniques

1. **<u>Revenue Service Level.</u>** Radio faults are found by the failure to communicate. PA and intercom failures would be reported by passengers or found on preventive maintenance inspection.

2. **<u>Vehicle Level.</u>** Schematics, wiring diagrams, and electric meters assist in isolating the relatively few components of this system.

3. **<u>Component Level.</u>** The various system PCBs range from a very simple preamplifier board to a very complex UHF receiving and digital decoding circuit. Radio circuits require a licensed technician for repair.

Equipment Location

The control head is at the operator's station. The power amplifier and radio are in an interior electrical locker or in a seatwell. Speakers are distributed throughout the vehicle. One or two passenger intercom stations are distributed in vehicle.

AUTOMATIC TRAIN CONTROL (ATP, ATO, ATS)

Purpose

The purpose of the Automatic Train Protection (ATP) system is to receive and interpret wayside command signals that are intended to limit the train operation and to monitor the train operation and impose those limits on the train in a fail-safe manner.

The Automatic Train Operation (ATO) system converts the wayside commands provided by the ATP and transmits them to the train control system in a manner to enable the train to operate within the limits commanded.

The Automatic Train Supervision (ATS) system monitors train parameters are important to the train or the transit system operations and communicate those parameters to an external command center.

Equipment Type

Command reception is accomplished by externally mounted antennas. Control systems may be discrete-component PCBs or microprocessors. Interfaces to train control circuits are usually relay logic.

Indicators/Signals

Wayside commands are presented to the operator, as cab signal speed limits. Overspeed conditions are visually and audibly indicated. The ATP system intervenes in train operation on violation of commands. Fault indicators, in discrete systems, vary from none to lights, at the control unit, of the correct operation of specific functions (e.g., command received, commanded decoded, relay picked).

Consequence of Failure

For the ATS, there is no immediate consequence of a failure, although a record of train operation is lost.

For the ATO, the functions of this system are speed maintaining, station stopping, and, sometimes, train start and train routing. Loss of these functions makes the operator establish and use manual vehicle operations. There are no driverless automatic train operations in the rail transit industry yet.

An ATP failure causes the train to stop, disrupting all train operations, until the fault is isolated and overridden or bypassed. Most authorities have very restricted movement requirements until the passengers are unloaded and the faulted train is removed from service.

Complexity of System

The ATS and ATO systems are moderately complex. They contain analog circuits that may be discrete-component PCBs or a microprocessor-based system.

The ATP system is relatively complex. The basic components may be of the same design type as that of the ATS and ATO systems, with the added complexity of all functions being safety related and having to be fail-safe in design.

Diagnostic Techniques

1. **<u>Revenue Service Level.</u>** ATS failures would be found on periodic maintenance or reported by central operations, if monitored.

   Failure of an ATO provided function (e.g., speed maintaining) and the need to revert to manual vehicle operation lead directly to fault isolation of an ATO failure.

   For ATP failures, a loss-of-speed command at the operator's station and a failure of functions provided by ATP are usually sufficient to identify the fault. All faults are to a safe condition (i.e., the train stops and cannot be moved until failure is bypassed).

2. **Vehicle Level.** The safety-related ATP system operation is checked daily. Because of the interrelationship and action of these systems, the ATP, ATO, and ATS systems are usually provided with a special-purpose set of test equipment. This test set provides wayside test-case input functions and monitors vehicle-level response and operation. Faults are either identified directly by the test set or with the additional use of schematics, wiring diagrams, and manuals.

3. **Back Shop.** Component schematics, electronic test equipment, and operating manuals are used to diagnose PCB-level faults.

Equipment Location

Antennas are undercar near running rails or on the side of the vehicle. Control units are in an interior electrical locker or in a seatwell.

CAR BODY

Purpose

The purpose is to provide the transit passenger with a relatively safe and comfortable environment while being transported and to house the equipment necessary to provide that service.

Equipment Type

There is an operator's station with associated equipment. The car body includes passenger seats, windows, and lighting.

Indicators/Signals

Any available indicators are located near the operator's console, but there are no central indicators for broken windows or seats.

Consequence of Failure

Usually, there is no effect on normal service; repairs can be performed after service. Windows are the exception: the vehicle is probably removed from service as soon as possible, causing minor service delays.

Complexity of System

The car body systems are simple. Faults are visually obvious, such as torn seatcovers or broken windows. Lighting circuits are similar to house wiring systems.

Diagnostic Techniques

1. **Revenue Service Level.** A fault is usually visually obvious upon its being reported. Action taken depends on authority operating rules.

2. **Vehicle Level.** Portable electrical meters and wiring diagrams are used for the lighting system.

3. **Back Shop.** Mechanical component rebuilding, including seats, occurs in the back shop area.

Equipment Location

Seats and windows are located throughout the car body interior.

TRUCKS, SUSPENSION, AND COUPLER

Purpose

Their purpose is to carry and guide the car body along the rail system and to provide a means to join separate vehicles.

Equipment Type

This system is composed of wheels, axles, truck assemblies, mechanical and electrical couplers, and pneumatic suspension components.

Indicators/Signals

Usually, there would be only a secondary indication of a failure, such as from the propulsion system failure if it uses load weighing and the suspension system failed. Unusual noise or motion might indicate a truck failure.

Consequence of Failure

A complete failure of one of these systems causes a major disruption of service and loss of the vehicle. Intermittent electrical coupling failures cause minor service delays.

Complexity of System

The systems are relatively simple to diagnose during failure.

Diagnostic Techniques

1. **Revenue Service Level.** Complete failures are visually and audibly obvious. Intermittent electrical coupling failures can be diagnosed only through repeated failure of the systems affected.

2. **Vehicle Level.** Most failures are obvious. There is no direct diagnostic approach available to isolate intermittent electrical coupling failures.

3. **Back Shop.** Mechanical component rebuilding occurs in the back shop area.

APPENDIX B

RAIL TRANSIT SYSTEM CHARACTERIZATION

HEAVY RAIL TRANSIT SYSTEMS

A substantial portion of this project's efforts were directed toward heavy rail transit systems. This is natural because this grouping is the most homogeneous in operations and vehicles, facilitating the ability to characterize and enumerate vehicle systems. This concentration of efforts does not in any manner detract from the applicability of the findings and recommendations of this project. The vehicle systems and components are very similar in all three rail transit operations. Slight variations and adjustments to the project findings would be required for any specific heavy rail system based on fleet size or operational nuances. Similar variations and adjustments would be used to tailor the findings to a commuter or light rail operation. There follows a description of the heavy rail transit systems features used in the vehicle systems characterization and cost modeling, and a brief description of the differences of these features with the commuter and light rail operations.

The largest sector of the rail transit industry is the heavy rail portion. A summary of the composition of this sector is shown in Table B-l, U.S. Heavy Rail Transit System Operations. There are 13 systems operating in the United States, 12 are shown. SCRTD did not have operating statistics for 1992. The data shown are taken from 1992 Transit Operating and Financial statistics from APTA. Total costs are the portion of the system's annual costs for the heavy rail portion, and maintenance costs are annual cost for the heavy rail vehicle maintenance. The AM Peak Fleet number is an indicator of the minimum number of vehicles, with no reserve, required to provide the present service. The column marked Percent Reserve Fleet is a rough indicator of how much of the total fleet could be in the repair pipeline. Maintenance cost per active fleet is the system annual heavy rail maintenance cost divided by the active fleet size. Maintenance cost per AM peak is the same system annual heavy rail maintenance cost divided by the AM peak fleet requirements. Both columns are merely indicators of the per vehicle costs to maintain a rail transit vehicle.

Table B-1. U.S. Heavy Rail Transit System Operations

	HEAVY RAIL COST		FLEET SIZE		% RESERVE	MAINTENANCE COST	
SYSTEM	ANNUAL	MAINTENANCE	ACTIVE	A M PEAK	FLEET	PER ACTIVE FLEET	PER A M PEAK
MARTA	$62,219,155	$7,766,969	238	135	44	$32,634	$57,533
MTA, Blt	$31,620,361	$5,435,944	100	60	40	$54,359	$90,599
MBTA	$241,023,556	$44,618,944	400	312	36	$111,547	$143,009
CTA	$303,557,688	$53,321,844	1205	923	23	$44,250	$57,770
GCRTA	$21,078,587	$4,231,229	60	38	37	$70,520	$111,348
MDTA	$44,152,680	$8,267,229	136	72	47	$60,788	$114,823
NYCTA	$2,372,776,336	$391,799,133	5951	4877	18	$65,838	$80,336
PATH	$135,449,000	$20,418,000	342	297	13	$59,702	$68,747
PATCO	$23,833,752	$3,712,952	121	102	16	$30,686	$36,401
SEPTA	$136,282,441	$16,908,379	372	284	20	$45,453	$59,537
BART	$200,284,150	$43,555,072	581	396	31	$74,966	$109,988
WMATA	$268,900,000	$42,046,075	664	442	36	$63,322	$95,127

Source Ray Oren

Concentration on the heavy rail sector was selected because it represents the most homogeneous type of equipment and operations. Although the age and technology of the vehicles span generations, the vehicles operate in multiple-unit trains over protected rights of way with similar speeds and station spacing. Similar operations and equipment relate to similar maintenance and diagnostic problems.

COMMUTER RAIL TRANSIT SYSTEMS

Commuter rail transit system vehicle fleets vary widely from property to property. Although all operate in multiple-unit trains, some are self-propelled and others are locomotive hauled. Operations are different, with most vehicles making only one round trip per day at high speed and with distant station spacing. Because of this operation, field maintenance must be performed at locations away from a shop support facility. The diagnostic and maintenance concerns are somewhat different from those of the heavy rail systems because of the off-site repair requirements.

LIGHT RAIL TRANSIT SYSTEMS

Light rail systems are also considerably different from heavy rail. Light rail systems, with few exceptions, are smaller fleets. The vehicles are designed to operate in single units on city streets in mixed traffic. This operation, the small fleet size, and the resurgence of this mode of transit has produced a number of small procurements over the past few years. As a consequence, light rail systems have the advantages of not having to be compatible with previous operations and they contain the latest technologies. Foremost in this is the availability of the microprocessor-based controllers with the faultlogging and potential diagnostic capability. The light rail vehicle in Baltimore is 3 years old. A vehicle-level processor is linked to every other control system on the vehicle over a common communication link. The other systems (e.g., brakes, propulsion, HVAC) all report operating status to the vehicle processor. The vehicle processor provides the operator with a vehicle condition display and stores event data upon detection of predefined fault conditions. The Baltimore system is in the process of redefining some of the predetermined fault conditions.

APPENDIX C

MIS SAMPLE DATA

Figures C-l through C-6 provide examples of reports generated from MIS data bases.

Structure for data base:	F:\REL_DATA\MARIS\VEHINC.DBF				
Number of data records:	33693				
Date of last update:	05/04/93				
Field	**Field Name**	**Type**	**Width**	**Dec**	**Index**
1	INCIDENT	Character	8		Y
2	CAR	Numeric	3		Y
3	JUL_I_DATE	Numeric	5		N
4	TIME	Numeric	4		N
5	SYMPTOM	Character	4		N
6	CONSIST	Numeric	3		N
7	DASH	Numeric	2		N
8	LOCATION	Character	3		N
9	DIR	Character	1		N
10	CARS	Character	30		N
11	CONST_SIZE	Character	1		N
12	INC_STATUS	Character	1		N
13	INC_DATE	Date	8		N
14	SPEED	Character	3		N
15	CANC_DISP	Numeric	2		N
16	INC_HRS	Numeric	7		N
17	PRI_DELAY	Numeric	3		N
18	SEC_DELAY	Numeric	2		N
19	DELAYRLOW	Numeric	3		N
20	DELAYRHIGH	Numeric	2		N
21	PRI_OFF	Character	2		N
22	SEC_OFF	Character	2		N
23	USR	Character	2		N
24	USR_NO	Character	2		N
25	DELAY_FLAG	Character	1		N
26	UNKHOMEYD	Character	1		N
Total			106		

Figures C-1. Composite of a Few of BART's MARIS File Structures (page 1 of 2)

Structure for data base:	F:\REL_DATA\MARIS\VEHREP.DBF				
Number of data records:	26211				
Date of last update:	05/04/93				
Field	**Field Name**	**Type**	**Width**	**Dec**	**Index**
1	INCIDENT	Character	8		Y
2	CAR	Numeric	3		Y
3	JUL_R_DATE	Numeric	5		N
4	REP_DATE	Date	8		N
5	REP-DOC-NO	Numeric	2		N
6	REP_CAUSE	Character	1		N
7	REP_SERON	Character	12		N
8	REP_SEROFF	Character	12		N
9	SYSTEM	Numeric	4		Y
10	REP_LABOR	Numeric	4		N
11	REP_LOCAT	Character	4		N
12	REP_DISP	Character	1		N
13	PCT	Character	8		Y
14	REP_EMP	Numeric	5		
Total			78		

Structure for data base:	F:\REL_DATA\MARIS\VEHCOMP.DBF				
Number of data records:	29559				
Date of last update:	05/04/93				
Field	**Field Name**	**Type**	**Width**	**Dec**	**Index**
1	INCIDENT	Character	8		Y
2	CAR	Numeric	3		N
3	SYSTEM	Numeric	4		N
4	CRC_NUMBE R	Numeric	2		N
5	CRC_COMP	Numeric	3		N
6	CRC_TYPE	Numeric	2		N
7	CRC_FAULT	Numeric	4		N
8	CRC_DISP	Character	1		N
9	CRC_SERON	Character	12		N
10	CRC_SEROFF	Character	12		N
Total			52		

Figure C-1. Composite of a Few of BART's MARIS File Structures (page 2 of 2)

SYSTEM DELAY ANALYSIS
FOR: JULY 1993

	EVENTS		DELAYED TRAINS					TRAIN-DELAY	
	TOTAL	RATE	PRIMARY	SECONDARY	TOTAL	RATE	GOAL	TOTAL MINUTES	TREND/COMMENTS
VEHICLE-REVENUE									
DOOR	23	0.16	23	37	60	0.41		511	UNFAVORABLE
ATO	21	0.14	21	11	32	0.22		293	STEADY
PROPULSION	25	0.17	23	24	47	0.32		382	MIXED
AUXILIARY	20	0.14	20	5	25	0.17		224	FAVORABLE
FRIC. BRAKE	20	0.14	19	36	55	0.37		454	FAVORABLE
OTHER REV.	4	0.03	3	15	18	0.12		238	MIXED
TOTAL REVENUE	113	0.77	109	128	237	1.61		2102	FAVORABLE
YARD	5	0.03	5	1	6	0.04		43	UNFAVORABLE
CAR SHORTAGE	0	0.00	0	0	0	0.00		0	STEADY
TOTAL VEHICLE	118	0.80	114	129	243	1.65	1.87	2145	FAVORABLE. EVTS & TRNS 5%-20% BELOW PRIOR 3 MO.
WAYSIDE									
FALSE OCCUPANCY	15	0.10	0	49	49	0.33		450	UNFAVORABLE
ROUTING	2	0.01	0	16	16	0.11		141	FAVORABLE
TRACK MAINT	3	0.02	0	4	4	0.03		48	FAVORABLE
3RD-RAIL	6	0.04	0	10	10	0.07		80	UNFAVORABLE
OTHER: SMOKING TIE, EXP. JOINT	3	0.02	0	5	5	0.03		28	FAVORABLE
TOTAL	29	0.20	0	84	84	0.57	0.69	747	MIXED: EVTS 5% ABOVE; TRNS 32% BELOW PRIOR 3 MOS.
OPERATIONS									
LATE DISPATCH	1	0.01	1	0	1	0.01		5	FAVORABLE
LAYUP/MAKE-BREAK	12	0.08	10	5	15	0.10		103	UNFAVORABLE
T.O., TOWER, CONTR. ERROR	35	0.24	35	19	54	0.37		441	UNFAVORABLE
OTHER: T.OP OPENED STATION	1	0.01	1	0	1	0.01		6	UNFAVORABLE
TOTAL	49	0.33	47	24	71	0.48	0.52	555	UNFAVORABLE: EVTS & TRNS 25%-33% ABOVE PRIOR 3 MO.
CONSTRUCTION									
M-LINE TRN CNTL MOD; M-87	0	0.00	0	0	0	0.00		0	STEADY
VEHICLE ATC MOD	0	0.00	0	0	0	0.00		0	STEADY
TOTAL	0	0.00	0	0	0	0.00	0.44	0	STEADY
MISCELLANEOUS									
PATRON: DISORDERLY/VAND	54	0.37	40	65	105	0.71		969	UNFAVORABLE
PATRON: ILLNESS	2	0.01	2	0	2	0.01		17	FAVORABLE
EVENT CONGESTION	3	0.02	0	9	9	0.06		64	UNFAVORABLE
OTHER: TOXIC CLOUD; ANIMAL ON TRACK	7	0.05	0	78	78	0.53		806	MIXED
TOTAL	66	0.45	42	152	194	1.32	0.62	1856	MIXED: EVTS STEADY, TRNS 31% ABOVE PRIOR 3 MO.
SYSTEM TOTAL	262	1.78	203	389	592	4.02	4.14	5303	STEADY: EVTS 3% ABOVE, TRNS 6% BELOW PRIOR 3 MO.

RATE = EVENTS PER 100 TRAIN RUNS **TOTAL TRAIN RUNS = 14717** **DATA SOURCE: OPERATIONS RELIABILITY** **A-3**

Figure C-2. One Page of a BART MARIS Monthly Report

Run Date: 29Nov93 11:21:23
Beg Date: 10/01/93
Division: WABASH

Repair History Report by Work Order

Page: 1
End Date: 10/31/93

BALTIMORE MTA

Sort Order/Range: (1) Work Order (2) Prob
Beg Range: All R04G
End Range:

FL	Unit ID	Work Ordr	Mechanic	Mileage	Opn-Date	Cls-Date	Problem	System	Defect	Action	Hours	Labor $	Matrl $	Total $
A	112	29448	79908	310400	09/10/93		Prop Sys	T/Motor	LLW	R&R	8:00	130.96		130.96
A	112	29448	79908	310400	09/10/93		Prop Sys	T/Motor	LLW	R&R	8:00	130.96		130.96
								Work Order 29448		**Subtotal>>**	**16:00**	**261.92**	**.00**	**261.92**
A	130	29682	40723	287300	09/27/93	10/14/93	Prop Sys	Propulsn	Tripped	R&R	0:08	2.18		2.18
A	130	29682	40723	287300	09/27/93	10/14/93	Prop Sys	Propulsn	Tripped	R&R	8:00	130.96		130.96
A	130	29682	40723	287300	09/27/93	10/14/93	Prop Sys	Propulsn	Tripped	R&R	8:00	130.96		130.96
								Work Order 29682		**Subtotal>>**	**16:08**	**264.10**	**.00**	**264.10**
A	141	29799	20495	274100	10/06/93	10/14/93	Prop Sys	Propulsn	Electro	R&R	8:00	130.96		130.96
								Work Order 29799		**Subtotal>>**	**8:00**	**130.96**	**.00**	**130.96**
A	166	29817	00610	253800	10/06/93	10/06/93	Prop Sys	Propulsn	Electro	R&R	8:00	130.96		130.96
								Work Order 29817		**Subtotal>>**	**8:00**	**130.96**	**.00**	**130.96**
A	157	29835	40723	292356	10/7/93	10/13/93	Prop Sys	Propulsn	Relay	R&R	8:00	130.96		130.96
A	157	29835	40723	292356	10/7/93	10/13/93	Prop Sys	Propulsn	Tripped	R&R	8:00	130.96		130.96
								Work Order 29835		**Subtotal>>**	**16:00**	**261.92**	**.00**	**261.92**
B	187	29838	79525	263000	10/7/93	10/12/93	Prop Sys	M/C Box	Electro	R&R	4:00	65.48		65.48
								Work Order 29838		**Subtotal >>**	**4:00**	**65.48**	**.00**	**65.48**
A	141	29845	00610	274100	10/8/93	10/09/93	Prop Sys	Propulsn	Electro	Test	2:00	32.74		32.74
A	141	29845	17816	274100	10/08/93	10/09/93	Prop Sys	Propulsn	Electro	Test	8:00	130.96		130.96
								Work Order 29845		**Subtotal >>**	**10:00**	**163.70**	**.00**	**163.70**
A	114	29852	00878	312100	10/08/93	10/13/93	Prop Sys	Propulsn	Electro	Inspect/	8:00	130.96		130.96
								Work Order 29852		**Subtotal>>**	**8:00**	**130.96**	**.00**	**130.96**
A	170	29862	76635	321999	10/11/93	10/11/93	Prop Sys	Propulsn	Fuse	R&R	1:00	16.37		16.37
								Work Order 29862		**Subtotal>>**	**1:00**	**16.37**	**.00**	**16.37**

Figure C-3. MD-DOT Portion of a Cost to Repair Report

RUN DATE: 29NOV93 11:23:59 PAGE: 3
BEG DATE: 10/01/93 END DATE: 10/31/93

DEFECTS ANALYSIS FOR FLEET: A

BALTIMORE MTA

VEHICLES: 72 TOTAL DEFECTS: 116

DEFECT	SYSTEM	OCCURRENCES
SCHEDULED MAINTENANCE	PREVENTATIVE MAINT	20
ELECTRICAL/ELECTRONIC	PROPULSION - GENERAL	11
MECHANICAL	CAR BODY GENERAL	7
INSPECTION	PREVENTATIVE MAINT	6
SCHEDULED MAINTENANCE	TRUCK ASSEMBLY	4
NO DEFECT/ADMINISTRATION	STATIC + DYNAMIC TESTING	4
PNEUMATIC/HYDRAULIC	BRAKES - HPT (ACTUATOR) UNIT	3
ELECTRICAL/ELECTRONIC	COMMUNICATIONS - GEN.	3
PNEUMATIC/HYDRAULIC	FRICTION BRAKES - GEN.	2
PNEUMATIC/HYDRAULIC	CAR BODY GENERAL	2
SCHEDULED MAINTENANCE	A/C SYSTEM -GENERAL	2
SCHEDULED MAINTENANCE	RADIUS ROD ASSY.	2
NO DEFECT/ADMINISTRATION	PROPULSION - GEAR UNIT	2
MECHANICAL	COUPLER - DRAFT GEAR	2
MECHANICAL	COUPLER - GENERAL	2
MECHANICAL	PROPULSION - GEAR UNIT	2
ELECTRICAL/ELECTRONIC	ATP SYSTEM GENERAL	2
ELECTRICAL/ELECTRONIC	PROPULSION - CONVERTOR ASSEMBLY	2
VANDALISM	CAR BODY GENERAL	2
TORN/RIPPED	CAR BODY - SEATING	2
INCORRECTLY ASSEMBLED	ATP SYSTEM GENERAL	1
SYSTEM DEFECT	FRICTION BRAKES - GEN.	1
OIL OR FLUID LEAK	BRAKES - HPT (ACTUATOR) UNIT	1
PNEUMATIC/HYDRAULIC	COUPLER - GENERAL	1
MISCELLANEOUS	PROP - ATO LOGIC MODULE	1
SCHEDULED MAINTENANCE	PROPULSION - TRACTION MOTOR	1
NO DEFECT/ADMINISTRATION	DESTINATION SIGN	1
NO DEFECT/ADMINISTRATION	PROPULSION - TRACTION MOTOR	1
NO DEFECT/ADMINISTRATION	PROPULSION - GENERAL	1
NO DEFECT/ADMINISTRATION	TRUCK ASSEMBLY	1
FLATS	PROPULSION - GEAR UNIT	1
TREAD WEAR	WHEEL/AXLE ASSEMBLY	1
BURNED	ELECTRICAL, GENERAL	1
SEIZED	FRICTION BRAKES - GEN.	1
BROKEN/SHEARED	COUPLER - GENERAL	1
MECHANICAL	DOORS - GENERAL	1
MECHANICAL	PROPULSION - GENERAL	1
BAD P.C. BOARD	ATP CARD FILE ASSY.	1
BAD CONNECTION	PROPULSION - GENERAL	1
BLOWN FUSE	PROPULSION - GENERAL	1
TRIPPED	PROPULSION - GENERAL	1
DEFECTIVE RELAY	PROPULSION - GENERAL	1
BAD CONTACT	PROPULSION - GENERAL	1

Figure C-4. MD-DOT Summary Defect Distribution Report

PORT AUTHORITY TRANSIT CORPORATION
MAINTENANCE INFORMATION SYSTEM

REPORT NAME: COMPPFM
RUN DATE: 08/19/93
PAGE: 1

FROM: 07/10/.93
TO: 08/06/93

CAR EQUIPMENT
COMPONENT FUNCTIONAL PERFORMANCE

CODE	DESCRIPTION	ALL OCCURRENCES	PERCENT OF TOTAL	HOURS OF MAINTENANCE	PERCENT OF TOTAL
4A	STRUCTURAL PARTS	2	0.11	2.00	0.04
4C	COUPLER/DRAW BAR ASSEMBLY	99	5.24	366.30	6.66
4D	WINDSHIELDS AND GLAZING	24	1.27	59.00	1.07
4E	CAR INTERIOR	201	10.63	182.30	3.31
4F	DOORS	20	1.06	67.30	1.22
4G	DOOR OPERATORS	87	4.60	117.00	2.13
4H	CONTROL GROUP - ATO, ATC	27	1.43	96.00	1.75
4N	AIR CONDITION/HEATING	72	3.81	200.30	3.64
4Q	RADIO/PUBLIC ADDRESS	50	2.64	107.00	1.95
4R	BATTERIES/CHARGER	43	2.27	96.30	1.75
4S	CONTACTORS	9	0.48	10.30	0.18
4T	CONTROLLER, MASTER - BUDD	3	0.16	11.00	0.20
4U	LIGHTS	136	7.19	93.00	1.69
4V	DESTINATION SIGN	17	0.90	23.30	0.42
4W	MISC. INTERIOR APPOINTMENTS	9	0.48	12.00	0.22
4Y	RESISTER, GRID	4	0.21	7.00	0.13
42	CONTACTORS	30	1.59	54.00	0.98
43	MAIN CAM ASSY.	92	4.87	341.15	6.21
441	INSPECTION	244	12.90	809.15	14.73
446	CLEANING	12	0.63	8.00	0.15
44	TRUCKS HAND BRAKE SYSTEM	329	17.40	1042.30	18.97
45	BRAKE/COMPRESSOR SYSTEM	80	4.23	217.30	3.95
6R	BRAKE/COMPRESSOR SYSTEM	18	0.95	118.00	2.15
70	FARE COLLECTION	5	0.26	27.00	0.49
	TOTALS	1613	100.00	4069.00	100.00

Figure C-5. PATCO Component Functional Performance Report

System Performance - September 1993

Page 5 of 12

HDWID	NAME	FSRs	FSRs/ MM	6 MO AVG	1 YEAR AVG
3D50099	Misc Semi Conductor Box	0	0.00	0.00	0.05
3D5A000	Heat Sink Module	1	0.61	2.32	2.52
3D5A099	Misc heat Sink Module	0	0.00	0.00	0.05
3D5AA00	Thyristor	0	0.00	0.00	0.05
3D5AB00	Heat Sink Module Diode	0	0.00	0.29	0.14
3D5B000	Commutating Capacitor	0	0.00	0.20	0.25
3D5C000	Commutating Inductor	0	0.00	0.10	0.10
3D5D000	Filter Capacitor	13	7.88	8.40	7.87
3D5D099	Misc Filter Capacitor	0	0.00	0.00	0.06
3D5DA00	Filter Capacitor	1	0.61	0.10	0.21
3D5E000	Gate Pulse Amplifier	0	0.00	0.59	0.51
3D5F000	Thermostat	0	0.00	0.09	0.10
3D60000	Reactor Assembly	0	0.00	0.00	0.05
3D70000	Grid Resistor Assembly	4	2.42	2.13	3.55
3D70099	Misc Grid Resistor Assy	0	0.00	0.00	0.21
3D80000	Blower/Motor Assembly	8	4.85	3.39	5.51
3D80099	Misc Blower Motor Assy	1	0.61	0.30	0.95
3D8A000	Blower Wheel Assembly	0	0.00	0.00	0.05
3D8B000	Blower Motor	1	0.61	0.49	0.56
3D8BB00		0	0.00	0.20	0.26
3D8C000	Blower Filter Assembly	0	0.00	0.21	0.27
3E00000	Friction Brake System	18	10.91	14.24	11.66
3E10000	H1 Electronic Control Unit	9	5.45	9.97	7.62
3E1A000	H1 Electronic Portion	7	4.24	7.09	5.19
3E1A099	Misc H1 Electronic Portion	0	0.00	0.11	0.05
3E1AA00	CPU Board	0	0.00	0.00	0.05
3E1AB00	I/O Board	0	0.00	0.09	0.05
3E1B000	H1 Pneumatic Portion	1	0.61	1.99	1.84
3E1BA00	Pressure Transducer	0	0.00	0.31	0.31
3E1C000	Potentiometer Mtng Brkt Assemb	0	0.00	0.48	0.40
3E1CA00	Rate Adjustment Potentiometer	0	0.00	0.20	0.10
3E30000	J-4 Servotrol Control Unit	6	3.64	3.34	3.26
3E30099	Misc J-4 Servotrol Ctrl Unit	1	0.61	0.10	0.05
3E3A000	S1 Servotrol Control Unit	4	2.42	2.63	2.26
3E3B000	XB-1 Variable Load Valve	0	0.00	0.00	0.10
3E3C000	J-1 Relay Valve Portion	1	0.61	0.10	0.10
3E3D000	N-7-D Magnet Valve	0	0.00	0.41	0.69
3E40000	Brake Status Unit	1	0.61	0.62	0.46
3E4A000	D.C. Plug In Relay	0	0.00	0.22	0.11
3E50000	Transducer Box Assembly	2	1.21	0.20	0.15

Figure C-6. WMATA - Single Page of a Reliability Report

APPENDIX D

POINT OF CONTACT FOR COMMERCIAL Al PRODUCTS

Many commercial AI software products have been produced in recent years. Most of those products are shells based upon one or more specific AI techniques. AI Expert magazine often publishes resource guides in its issues. The resource guides usually focus on one AI technique and provide information on the product, including price and address. Information about specific resource guides can be obtained from the magazine's publisher:

Miller Freeman Publications
600 Harrison St.
San Francisco, California 94107
(415) 905-2200 VOICE
(415) 905-2234 FAX

APPENDIX E

REFERENCES AND BIBLIOGRAPHY

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