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of Transportation

**Federal Railroad
Administration**

Integrated Railway Remote Information Service (*Inte*RRIS®) — Pilot Project

Office of Research and
Development
Washington, D.C. 20590

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Draft Report

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13. ABSTRACT

TTCI via the FRA was tasked by the Congress of the United States to demonstrate the feasibility of using and linking defect detector systems across North America to develop a national database that will enable the railroad industry to engage in predictive maintenance (processes that allow maintenance scheduling when equipment is idle or already in the shop). These detectors measure equipment performance parameters such as the forces between the wheel and rails. The Integrated Railway Remote Information Service, InteRRIS®, an Internet-based system, designed and developed by TTCI, was used to aggregate, interrogate, and store data from field-deployed detector systems. A key task under the program was the determination and implementation of appropriate access to a National Rail Corridor Vehicle Performance Database (VPD), which would draw performance-based data from InteRRIS® for FRA and railroads responsible for the safe operation of cars and locomotives as needed to enable effective performance-based safety monitoring. The VPD has been populated with data from a number of Truck Performance and Wheel Impact Load Detectors in order to capture representative and geographically diverse traffic from freight, mixed freight/commuter/passenger lines, and hazmat lines. The AAR and FRA have a mutual interest in promoting the implementation of performance-based maintenance through the deployment of a wayside detector network with the necessary database to monitor all cars so that preventive action can be taken. This detector network hopes to reduce the necessity to visually inspect cars and locomotives thereby focusing efforts on making repairs. This could greatly enhance the efficiency with which railroads make safety critical repairs. Such tools, with detector data in a central database, should they prove feasible, could eventually lead to the development of performance-based inspection standards.

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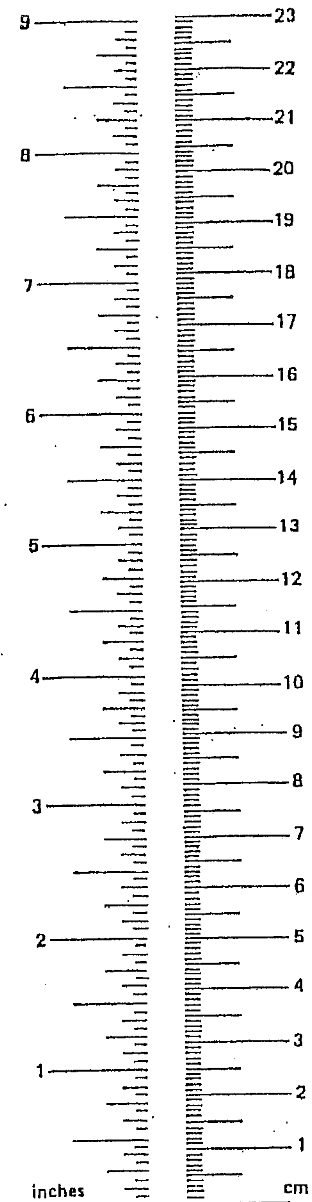
METRIC CONVERSION FACTORS

Approximate Conversions to Metric Measures

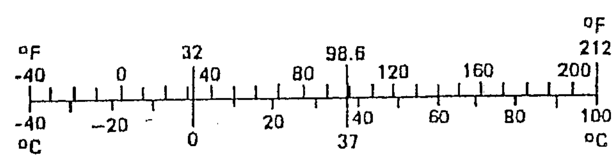
Symbol	When You Know	Multiply by	To Find	Symbol
	LENGTH			
in	inches	*2.50	centimeters	cm
ft	feet	30.00	centimeters	cm
yd	yards	0.90	meters	m
mi	miles	1.60	kilometers	km
	AREA			
in^2	square inches	6.50	square centimeters	cm^2
ft^2	square feet	0.09	square meters	m^2
yd^2	square yards	0.80	square meters	m^2
mi^2	square miles	2.60	square kilometers	km^2
	acres	0.40	hectares	ha
	MASS (weight)			
oz	ounces	28.00	grams	g
lb	pounds	0.45	kilograms	kg
	short tons (2000 lb)	0.90	tonnes	t
	VOLUME			
tsp	teaspoons	5.00	milliliters	ml
Tbsp	tablespoons	15.00	milliliters	ml
fl oz	fluid ounces	30.00	milliliters	ml
c	cups	0.24	liters	l
pt	pints	0.47	liters	l
qt	quarts	0.95	liters	l
gal	gallons	3.80	liters	l
ft^3	cubic feet	0.03	cubic meters	m^3
yd^3	cubic yards	0 76	cubic meters	m^3
	TEMPERATURE (exact)			
°F	Fahrenheit temperature	5/9 (after subtracting 32)	Celsius temperature	°C

* 1 in. = 2.54 cm (exactly)



Approximate Conversions from Metric Measures

Symbol	When You Know	Multiply by	To Find	Symbol
	LENGTH			
mm	millimeters	0.04	inches	in
cm	centimeters	0.40	inches	in
m	meters	3.30	feet	ft
m	meters	1.10	yards	yd
km	kilometers	0.60	miles	mi
	AREA			
cm^2	square centim.	0.16	square inches	in^2
m^2	square meters	1.20	square yards	yd^2
km^2	square kilom.	0.40	square miles	mi^2
ha	hectares (10,000 m^2)	2.50	acres	
	MASS (weight)			
g	grams	0.035	ounces	oz
kg	kilograms	2.2	pounds	lb
t	tonnes (1000 kg)	1.1	short tons	
	VOLUME			
ml	milliliters	0.03	fluid ounces	fl oz
l	liters	2.10	pints	pt
l	liters	1.06	quarts	qt
l	liters	0.26	gallons	gal
m^3	cubic meters	36.00	cubic feet	ft^3
m^3	cubic meters	1.30	cubic yards	yd^3
	TEMPERATURE (exact)			
°C	Celsius temperature	9/5 (then add 32	Fahrenheit temperature	°F



Executive Summary

This pilot program the United States Congress funded as a year-mark represents a public/private cooperative effort to accelerate the introduction of wayside detectors on routes that will have the greatest safety impact. The program called for utilizing InteRRIS® to set up a Vehicle Performance Database for the Federal Railroad Administration (FRA) for its research needs in assessing the safety benefits of a national database to hosts data from wayside defect detectors. *Inte*RRIS® provides a proactive central database that will enable railroads and other car owners to effectively monitor degradation of vehicle performance over time using data from wayside (or onboard) detectors. Estimates suggest significant safety benefits, if the technology performs as expected.

Railroads are consistently exploring the use of advanced technology to improve safety. The integrated use of detectors using InteRRIS® shows promise of significant safety advancements for the industry and public. InteRRIS® is an Internet-based system designed to aggregate, interrogate, and store data from field-deployed detector systems. InteRRIS® is capable of applying intelligence to collected data, which results in actionable information to customers. Such information includes exception reports to reduce accidents, vehicle condition reports to support preventative maintenance, and maintenance advice designed to increase the overall efficiency of railroad operations.

The pilot program has used data from existing Wheel Impact Load Detector (WILD) units and Truck Performance Detector (TPD) units. The addition of four additional TPD units was seen as a necessary step in assuring data from rail corridors that represented a geographic and commodity mix to be incorporated in the program. The additional four TPD's, which were co-funded by the individual railroads, included traffic patterns and commodity types that included high tonnage, hazardous materials, and passenger service.

The implementation of the Vehicle Performance Database (VPD) should allow the FRA to study the feasibility of linking and using data from a suite of national detectors to enhance the safety of rail operations and to promote preventive and predictive maintenance practices.

The two major tasks of the program have been successfully completed:

- Support of the purchase and installation of four TPD systems, one each on BNSF, UP, CSXT, and NS
- Implementation of a VPD that FRA personnel can access for the feasibility study and research activities. Examples of the feasibility of applying corrective actions based on a national database have been provided. In addition, examples of applying predictive analysis tools have also been addressed.

This pilot project has produced a set of tools that will enable the rail industry and the FRA to apply statistical analysis to performance data from defect detectors across the United States. The feasibility of applying statistical process control to performance data shows promise and further research is recommended in applying the methodology for predictive maintenance techniques.

Performance-based data from InteRRIS® has been used to produce the VPD. This database is comprised of specific vehicle-type data (e.g., hopper car, boxcar, coal gondola, tank car) and specific corridor-based data (all four corridors in which the new detectors are installed and any other that are chosen to include existing TPD and WILD detector units). This data enables statistical process control and other statistical analyses to be used for safety research by the FRA.

The VPD is a summary or reduced subset of the raw detector data. Detector data is processed monthly to reduce it to a statistical summary level. This data reduction will allow data aggregation to the corridor-level by all pertinent, independent variables.

North American railroads have invested a considerable amount of capital funds and technical resources in wayside detection systems. The wayside systems are capable of providing data that allows preventive maintenance by removing equipment that exceeds set defect parameters or AAR standards. By using a national database, this function is further optimized and leads to reduced train stops and promoting proactive planning.

Another benefit of a national database is in the development of predictive maintenance tools. These tools need a historic time-based condition and defect database of components. By applying degradation analysis, the wear and failure modes of components can be established. Knowing the failure modes allows the equipment to be maintained without service failures and service interruptions. InteRRIS® and VPD play a significant role in making preventive and predictive maintenance possible.

TABLE OF CONTENTS

List of Figures

List of Tables

1.0 INTRODUCTION AND BACKGROUND

As requested by the United States Congress, the Federal Railroad Administration (FRA) undertook a pilot project to conduct a feasibility study using and linking defect detector systems across the United States to develop a database to enable the railroad industry to engage in predictive maintenance. These detectors measure equipment performance parameters such as the forces between the wheel and rails. The specific language used in the Congressional request was as follows:

> "...includes $2m for a pilot program of the Integrated Railway Remote Information Service at the Transportation Technology Center. This pilot program is expected to enjoy substantial industry matching contributions. It is designed to demonstrate the feasibility of using defect detectors across North America. These detectors will measure safety parameters such as the forces between the wheel and rails, and physical condition of axle bearings on rail vehicles. The Integrated Railway Remote Information Service is an Internet-based system designed to aggregate, interrogate and store data from these field-deployed detector systems.
>
> "The conference agreement provides $1m for the integrated railway remote information service instead of $2m as proposed by the Senate."

The AAR and FRA should benefit from performance-based maintenance, reduction in the stress state of the railroad, and improvements in railroad safety through the deployment of a wayside detector network that would enable railroads to monitor all cars for defects and take preventive action. The stress state of the railroad relates to forces imparted by rolling stock on the infrastructure. The detector network can be expected to reduce the necessity to visually inspect cars and locomotives, thereby focusing efforts on making repairs. This could greatly enhance the efficiency with which railroads make safety critical repairs. Such tools, with detector data in a central database should they prove feasible, could eventually lead to the development of performance-based inspection standards.

There are four basic approaches that can reduce the stress-state at the wheel/rail interface: (1) lower steady state lateral loads, (2) lower vertical input loads, (3) lower wheel/rail contact stresses, and (4) reduce adverse vehicle dynamic behavior. Figure 1 shows lateral force (in kips) performance measured in curving by a Truck Performance Detector (TPD). The three distributions to the left are for three groups of a similar fleet of cars, which are identical except for different trucks under each of the three segments. The right-hand distribution represents data from a track strength-testing vehicle such as TTCI's Track Loading Vehicle. The data demonstrates the force required to displace the railhead laterally about 0.5 inch (13 millimeters) with the shaded area indicating situations where the loads imparted by the trucks will create accelerated degradation of the track structure. In this example, choosing the left most truck design over the other two would represent a design solution to reducing the stress state of the railroad.

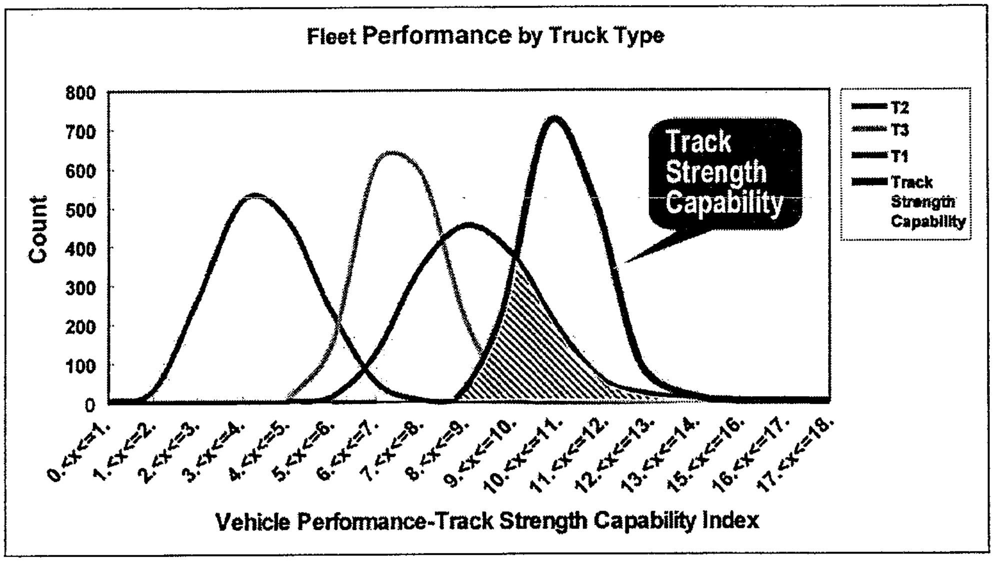


Figure 1. Stress State Reduction by Design

Reductions in any or all of the stress-generating parameters will reduce the energy into the contact patch and consequently reduce the wear and tear of the track structure. TTCI has researched the implementation of a number of solutions to reduce the stress state of the wheel/rail interface, which includes acceleration of the deployment of detector network systems.

Accompanying the technological changes directed at lowering the stress state are changes in maintenance strategies that are designed to ensure that adverse vehicle conditions are identified and rectified. Some of these maintenance strategy changes will most likely rely on car owners taking proactive steps to correct problems before they reach levels where they adversely affect the stress state of the railroad (and for that matter, the stress state of the rail vehicle).

Typically, freight traffic originates at manufacturing plants, mining locations, and ports and moves through corridors (traffic lanes), some of which are high density. One of the tasks under this pilot project was to identify high-density corridors (traffic lanes) for the purpose of equipping these corridors with condition monitoring sites. These sites were used to determine the "health" of cars and locomotives and to report this information to the operating railroad and a central safety database. The Integrated Railway Remote Information Service (*Inte*RRIS®*), an Internet-based system designed and developed by Transportation Technology Center, Inc. (TTCI), was used to aggregate, normalize, interrogate, and store data from field-deployed detector systems. For the purpose of the feasibility study two detector types were included: (1) the Truck Performance Detector (TPD) and the Wheel Impact Load Detector (WILD).

The TPD systems identify railcar truck-suspension systems that do not perform optimally in curves. Poor curving performance may result in derailments due to wheel climb, track gage spreading, rail rollover, and track panel shift. Poor curving also contributes to wear on special track work, wheel profile and flanges, and rail. The safety of rail operations can be improved

* *Inte*RRIS® is a registered software and database product of Transportation Technology Center, Inc., a wholly owned subsidiary of the Association of American Railroads (AAR).

through performance-based preventive action. This improvement comes from identifying poor performers so that preventive maintenance can be implemented before a derailment risk exists. A TPD can indicate poor truck curving performance by measuring lateral loads, vertical loads, and angle-of-attack (AOA) — and the corresponding derived values like lateral over vertical (L/V) force ratios.

The WILD systems have been in use nationwide for over 10 years and are deployed at over 60 sites in North America. WILD systems identify defects on the tread of each wheel passing the site by providing a measure of the impact force generated by slid flats, shells and spalls, and out-of-round wheels. The Association of American Railroads (AAR) has conducted research and tests to correlate impact forces to defect types and severity. Over time, wheels with tread defects can damage rail welds, concrete ties, and track and bridge components. Removal of "high impact" wheels reduces this damage, which, if undetected, could lead to derailments.

2.0 OBJECTIVE

The objective of this feasibility study was to use data from vehicle defect detectors, stored in a common national database, to measure safety parameters, such as wheel/rail forces, to support preventive and predictive maintenance practices. The national database that was used was based on *Inte*RRIS® which lends itself to notification of the performance of equipment and facilitates maintenance planning.

To meet the objectives, several tasks were undertaken and accomplished by TTCI. The two major tasks were:

1. Initiate, facilitate, and supervise the purchase and installation of four TPD systems, one each on the property of the four U.S. Class I railroads (BNSF, CSXT, NS, and UP). The addition of four TPDs was seen as an essential step to capture representative and geographically diverse traffic from freight, mixed freight/commuter/passenger lines, and hazardous materials lines.

2. Develop a National Rail Corridor Vehicle Performance Database (VPD) to host data from the four new TPD systems, selected existing TPD systems, and selected existing WILD systems.

Other related sub-tasks accomplished were:

1. Facilitate development of performance requirements for TPDs based on experience, recommendations of the Truck Performance Research Consortium (TPRC), and public comments from interested stakeholders.

2. Determine the technical feasibility and implementation of predictive maintenance criteria using developed algorithms based on previously collected data and data from the newly installed/identified cooperative sites (TPD/WILD).

3. Determine and implement appropriate access to the National Rail Corridor VPD, which will draw performance-based data from *Inte*RRIS®. This data can be accessed, as needed, to enable effective performance-based safety research.

3.0 PROCEDURES

3.1 Track Performance Detectors: Prepare and Publish Requirements, Invite Public Comment, and Hold Town Meeting

TPD systems identify railcar truck-suspension systems that do not perform optimally in curves. Poor performance can result in derailments due to wheel climb, gage spreading, rail rollover, and panel shift. In addition, poor curving can contribute to excess fuel consumption, wear on special track work, wear on wheel tread and flanges, and rail. By identifying the poor performers before they cause derailments, the safety of rail operations can be improved. A TPD can indicate poor truck performance by measuring lateral loads, vertical loads, and AOA (and the corresponding derived values like L/V ratios). Since the premise of this pilot project was to use data from TPDs installed on a national level, any new TPDs were to comply with the same site characteristics as those already installed and sending data to *Inte*RRIS®.

As part of this FRA project, TTCI facilitated the formation of an industry Technical Advisory Group (TAG) to establish minimum site and performance guidelines for the purchase and installation of four TPDs. Because TTCI elected to be one of the suppliers of TPDs, TTCI did not participate as a member of the TAG. The TAG consisted of personnel from the railroads and FRA. The TAG used the Truck Performance Research Consortium (TPRC) recommendations as the basis to produce the guidelines.[1]

Site characteristics, including curve requirements and track construction details, were defined. The data communication and transfer of the data to *Inte*RRIS® were specified and the requirements were published by the TAG for public comment. The TAG convened a public town meeting for discussion of the requirements, which was revised as appropriate after receipt of comments after the town meeting.

3.2 Corridor Selection and Prioritization

TTCI built upon previously collected railroad car movement data to identify high-density rail traffic lanes where potential TPD units could be located. Additional data was collected as required to complete the corridor site selection. Sites were prioritized to include as many cars and car types as possible. Cars carrying hazardous materials were given "extra weight" for site selection purposes. Data from existing TPD/WILD sites were incorporated into the pilot project provided they conformed to the TPD site requirements (per the TAG) and the site's owning railroad agreed to participate in the pilot project.

3.3 Procurement of TPD including Hardware/Software Acquisition and Installation/Implementation

The TPD hardware/software and installation were procured by the individual railroads in accordance with the Federal Acquisition Regulation. The TPD systems procured were required to meet the minimum requirements as per the TAG. As was agreed to in the contract with the FRA,

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[1] In 2000, TTCI successfully managed and participated in the TPRC, a program for the rail industry that produced a standard for a typical TPD site and recommended criteria requirements for removal of poor performing trucks for the typical three-piece truck design used in North America.

each of the railroads was awarded $100,000 towards the installation of a TPD. TTCI managed the disbursement of the $100,000 to the railroads upon the successful approval of each of the TPD sites by the TAG.

3.4 Site Installations on Railroads and Data Start-Up

The TAG established a checklist for the approval process of each of the TPDs. The approval process included a site inspection by a fair and unbiased person who submitted the checklist to the TAG. Agreements with the operating railroads were reached for providing all relevant data to support the inspection and completion of the checklist. The startup data consisted of up to 10 separate train lists from each site. In addition, data from each of the trains included the measured values for the locomotives and cars within each train. The data from each train was provided in a format compatible with *Inte*RRIS®.

The cooperating railroad contributed hardware to include Automated Equipment Identification (AEI), bungalows, power, and communications. The TPD equipment became a part of the railroads fixed assets and was owned by the cooperating railroad. For the duration of this project, the TPD was maintained and kept operational by the cooperating railroad.

3.5 Process Data from All Available Sites and New Data from New Sites to Support the Feasibility Study

Raw data from individual sites was processed to determine integrity and then entered into the database (InteRRIS®). Performance-based data from InteRRIS® was used to produce the VPD, the only database provided to FRA as a deliverable under this agreement. The VPD provides specific car type data (hopper car, boxcar, coal gondola, tank car) and specific corridor-based data (comprised of data from the four corridors where the new detectors are installed and any other that were chosen to include existing TPD and WILD detector units). While the aggregate data of the VPD supports a higher-level fleet performance characterization, analysis of certain performance indicators requires individual car series specific data. An underlying intent of the VPD's aggregation of data is to leave individual vehicles anonymous. In order to accommodate car series-specific access, a solution is to represent the data by a *unique alias* of specific car series. As an example, a boxcar series CSXT000000 to CSXT111111 can be represented as B123000000 to B123111111. By accessing the same car series data over a period of time and detectors/corridors the FRA will be able to:

- Assure data reliability and repeatability,
- Establish different distributions per car series and service (passenger, hazmat, etc.),
- Assure data can be normalized if needed,
- Agree with use of data for better fleet management, efficient operations, and reducing derailment risks, and
- Report to Congress on the value/return on their investment for the Pilot Program and potentially request future funding.

A number of car series were selected, representing at least six UMLER Equipment Type Codes (UMLER is an industry reference file that provides information regarding the type of vehicle — hopper car, box car, etc.). Approximately 10,000 vehicles per car type are accessible via the alias or pseudo ID, if the car type has that many vehicles within it.

Under the 10 target car types (Table 1), random road marks were selected. All vehicles under that mark were assigned an alias. The random selection/assignment process was repeated until at least 10,000 vehicles were identified for each selected type.

Table 1. Proposed Car Types for FRA Pseudo-Access

Target UMLER Equip. Type Descriptions	UMLER Equip. Type Codes
Equipped Box Cars	A
Unequipped Box Cars	B
Covered Hopper Cars	C
Equipped Gondola	E
Flat Cars	F
Unequipped Hopper	H
Gondola Car – GT	J
Equipped Hopper	K
Passenger	M
Tank Cars	T

These types represent 2703 reporting marks and 756,080 individual vehicles as candidates for pseudo-car access.

3.6 Provide Support Data to FRA to Conduct Technical Feasibility for Report to Congress

The FRA will use this final report in preparing a report to Congress. Additional information was provided by TTCI to the FRA in support of an independent economic evaluation of using a national database of defect detection information.

4.0 RESULTS

4.1 Site Selection and TPD Implementation

A Town Hall Meeting was held August 29, 2003, at the Marriott Hotel in Pueblo, Colorado, to discuss TPD requirements under the FRA program and to hear all public comment. This meeting was chaired by Mr. Jon Jeambey of the TTX Company and directed by the TAG made up of participating railroad representatives and FRA. As the meeting began, TTCI indicated that the TAG was responsible for the conduct of the Town Hall Meeting and that TTCI was present at the meeting in the capacity of a potential TPD vendor.

The meeting and subsequent discussions resulted in a document of site guidelines produced with input from all TAG members and TPD vendors. The following are the guidelines that were published and distributed to all TAG members, TPD vendors, and the FRA:

TPD Track Geometry Recommended Site Selection Criteria:

1. Site must be located in a reverse "S" curve, separated by tangent track.
2. Radius of curvature for the two curves must be greater than 3 degrees and up to and including 6 degrees.
3. Length of curves must be nominally 400 feet minimum.
4. Length of tangent must be 400-2,000 feet for monitoring bi-directional traffic. For monitoring traffic predominately in one direction, shorter tangents may be used provided the measuring location is nominally 200 feet from the previous spiral and nominally 100 feet from the end of tangent track in the direction of monitored traffic.
5. Route must be made up of track Class 3 or better.
6. Grade must be level within 0.5 percent (preferred) and no more than 1.0 percent. For sites in the range of 0.5-1.0 percent, monitored traffic must be predominately ascending. Analysis must be provided to verify that steady-state longitudinal train forces are less than 150,000 pounds and do not skew the lateral rail force data.
7. Undulating terrain with transitioning "in-train" longitudinal buff/draft forces should be avoided.
8. Rail, crosstie and subgrade structure must be consistent throughout TPD site and the track maintained at Class 4 or better.
9. Road crossings or special track work within site should be avoided.
10. Consistent train handling practices should be maintained: avoid locations associated with routine train starts/stops or other air brake applications.

TPD Site Measurements

1. AEI integrated collection system.
2. Six cribs (load measuring locations) minimum, two per track section: entry curve, tangent, and exit curve.
3. Measure lateral and vertical forces acting on each rail at each crib.
4. Wheelset (AOA) by one or both alternative methods:
    a. Determined by measured force on rail at each crib.
    b. Determined by wheelset displacement measured on tangent track section and to include wheelset-tracking position.
5. Two cribs per section must be spaced nominally 6 feet apart and located at least 200 feet from spirals.

TPD Site Data Generation:

1. Car, truck and wheel identification.
2. Vertical force on rail from each wheel.
3. Lateral force on rail from each wheel.
4. L/V ratio from each wheel.
5. Truck side L/V from each side of each truck for each track section.
6. AOA of each wheelset.
7. Data file to include location, date, time, direction, axle count, and train/vehicle speeds.
8. Computational speed to be sufficient to prevent lost data or missed trains passing site.

TPD Site Data Accuracy Requirements:

1. Lateral forces accurate within ±5 percent of applied load from 2,000 pounds or greater.
2. Vertical forces accurate within ±3 percent of applied load from 2,000 pounds or greater.
3. L/V accurate within ±5 percent (.95 to 1.05 L/V) for equal vertical and lateral loads applied simultaneously at each crib of 1,500, 5,000, and 10,000 pounds.
4. System may not generate alerts for high L/V for lateral forces below 1,500 pounds.
5. Wheelset AOA accuracy:
    a. Force on rail indicated AOA ±0.5 milliradians.
    b. Wheelset displacement indicated AOA ± 0.5 milliradians.
6. Maintain/provide calibration records for TPD site (1-year calibration cycle, minimum, with 10,000 pound minimum lateral load and 25,000 pound minimum vertical load).
7. TPD data system health to be monitored and alarm sent for out-of-service failures.
8. Output data to be monitored by statistical process control techniques and reported to host railroad. Host railroad to provide a report to the FRA/TPD TAG by the end of 2003 regarding any significant statistical variations in the lateral load, vertical load, and AOA data from each TPD co-funded by the FRA.

9. Data integrity must be verified prior to communication to *Inte*RRIS® and suspect records are to be labeled as such in accordance with the *Inte*RRIS® data interface format.
10. TPD records are also to be verified by *Inte*RRIS® prior to entry into its database. The TPD supplier is to provide a record validation methodology to be used by *Inte*RRIS®.

TPD Site Data Storage:

1. Site must be able to store data from most recent 100 trains in the event of communications outage.

TPD Site Hardware:

1. Option of rechargeable-battery powered with solar or wayside power for recharging.
2. Bridge circuit to signal conditioner cable length must be no more than 100 feet.
3. Sensors, cables, and enclosures must be able to withstand harsh railroad environment.
4. Lightning protection, power surge protection, and proper grounding are required.
5. TPD electronic component hardware must have an operating temperature range of -40°C to +55°C.
6. TPD supplier must provide the host railroad with TPD data system parameters:
   a. Sample rate(s)
   b. Filter cut-off frequency
   c. Individual bridge gain(s)
   d. System gain
   e. Signal/Noise ratio
   f. Operating temperature limits

Each of the cooperating railroads has installed and calibrated one TPD (Figure 2) for evaluating vehicle-curving performance.

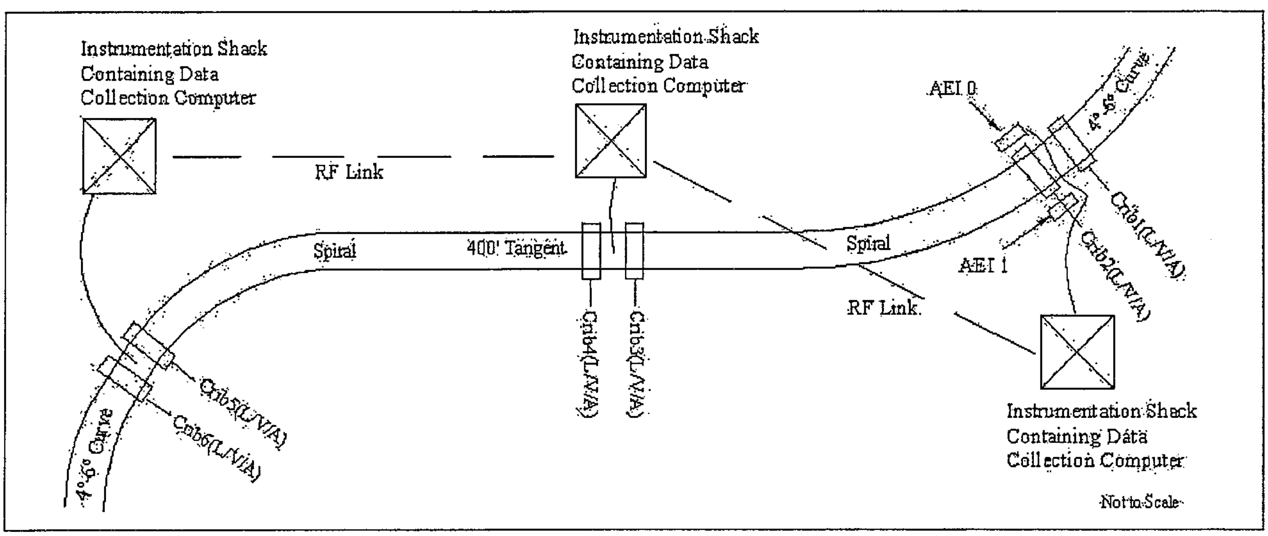

Figure 2. Typical TPD Site Layout

The four sites that were established and are functional have the following characteristics and adhered to the guidelines per the TAG.

Site 1. Norfolk Southern:

Location: Central Division, CNO&TP 2nd district, Double track installation, Milepost 152.8, near Science Hill, Kentucky.

Traffic: Key hazardous materials route. 77.2 MGT per year, approximately 33 train passes per day.

Site 2. Union Pacific:

Location: Evanston Subdivision, Track 2 (eastbound), Milepost 947.4, Near Ecko, Utah.

Traffic: Premium service intermodal route. 39 MGT per year, approximately 19 train passes per day.

Site 3. CSX Transportation:

Location: Carfax, Virginia, Milepost

Traffic: Mixed freight route. 38 MGT per year, approximately 17 train passes per day.

Site 4. Burlington Northern Santa Fe:

Location: Chriesman, Texas, Milepost 169 , 50 miles southeast of Temple, Texas.

Traffic: Heavy tank car traffic/hazardous materials and freight route. 51 MGT per year.

Figure 3 shows the detector installation sites. TPDs are designated as "T," WILD as "W," and acoustic bearing detectors as "B.

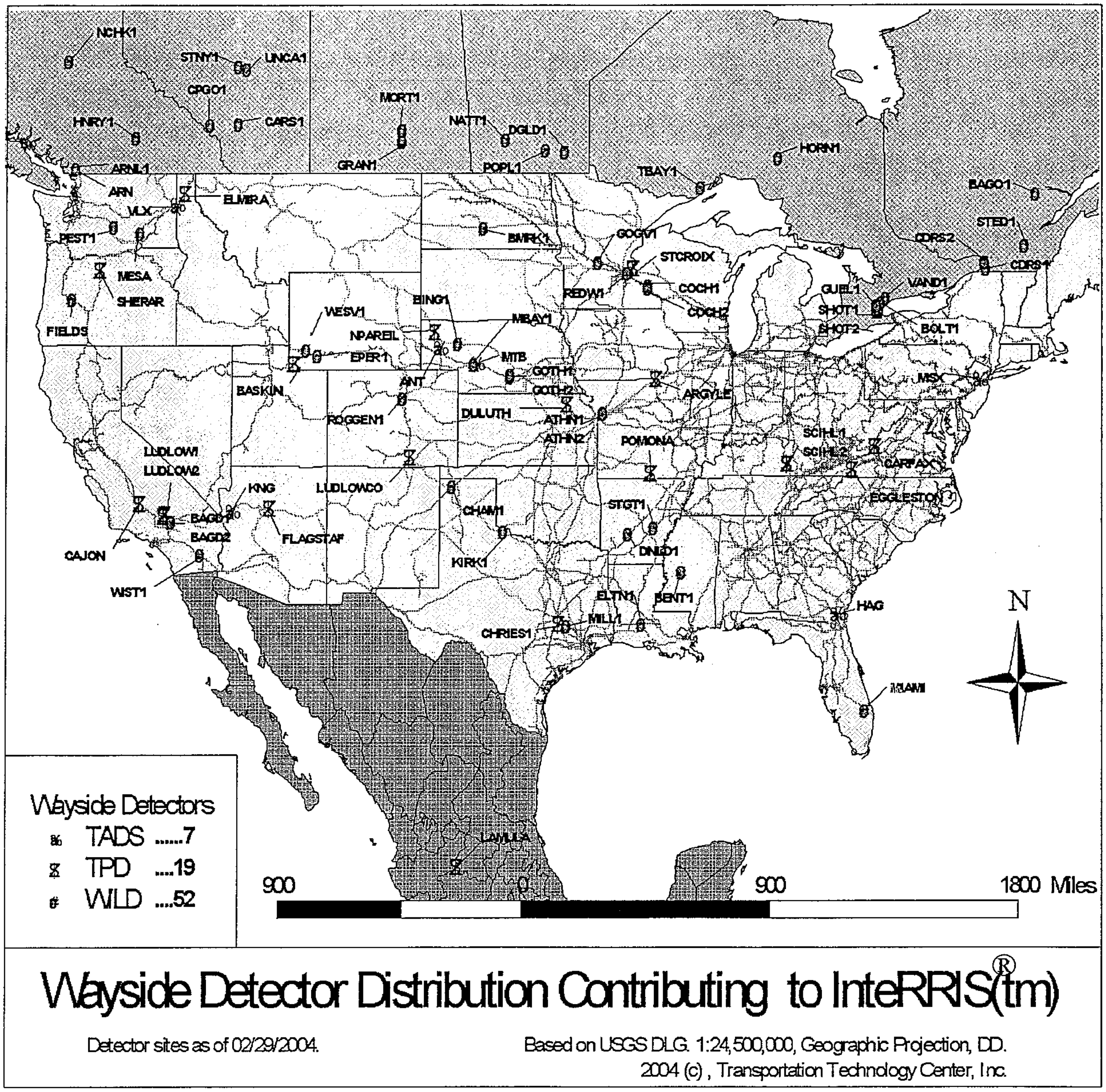

Figure 3. Detector Installation Sites

4.2 Vehicle Performance Database (Process and Host data from all available sites and new data from new sites)

4.2.1 Overview

The VPD was provided to the FRA for accessing data from a suite of existing and four new TPD systems for evaluating the feasibility of using a national database to improve safety and enhance maintenance practices. The VPD has been designed to provide performance-monitoring data from WILD and TPD sites based on selected car types and car series.

All possible car marks were compiled from the UMLER database and categorized by vehicle alpha-type code. Eighteen possible codes exist. The 10 target vehicle types represent over 95 percent of the possible vehicles.

The *Target* vehicle types were probability sampled to produce the minimum 60,000 vehicles to be assigned pseudo IDs. With this method, every observation in the population has a known probability of being selected into the sample. As part of this step, the number of vehicle types was reduced to six (Table 2).

Table 2. Final Car Types Used for FRA Pseudo-Access

Used UMLER Equip.Type Descriptions	UMLER Equip. Type Codes
Covered Hopper Car	C
Flat Car	F
Gondola Car – GT	J
LW/LP Intermodal Car	Q
Stack Car	S
Tank Car	T

The final set of pseudo-access vehicles represents 121 marks and 108,273 individual vehicles. If a mark was selected, all vehicles under that mark became part of the sample subset, thus producing a pool of greater than 60,000 individual vehicles.

Using this approach, the standard *Inte*RRIS® vehicle access interface could be used with virtually no changes. This interface enables not only basic vehicle data access but also Event-Tracking™ for custom event criteria monitoring, reporting, and auto-notification. This access is for wheel impact load and truck performance detectors. The detector type to be accessed is selected upon login. (Note: The ORD office of the FRA reiterated that the data and associated analysis would not be used for regulatory purposes.)

This data enables statistical process control and other statistical analyses that lend to conducting safety research by the FRA.

4.2.2 Data Processing and Retention Requirements

The VPD is a summary or reduced subset of the raw detector data, which is processed monthly and reduced to a statistical summary level. This data reduction allows for data aggregation to the corridor level by all pertinent independent variables. The data processing follows a two-step approach:

1. Computes and accumulates all derived measurement types for all vehicles.
2. Compiles these results plus all measured values by breakout category into distribution bins of 1,000 parts (n-tiles) per each unique combination of all pertinent independent variables. This will support distribution statistics for percentiles with precision of ±0.05 percent.

The data is processed and organized as follows:

1. Computation and Accumulation
    a. Derived measurements are computed, either at the detector or by *Inte*RRIS®.
        i. TPD: L/V ratio, truckside L/V, axle sum L/V, net axle L/V, light wheel in truck ratio, heavy wheel in truck ratio, wheel vertical/truck sum vertical ratio.
        ii. WILD: Wheel dynamic vertical, wheel dynamic ratio, light wheel in truck ratio, heavy wheel in truck ratio, left-to-right truck imbalance ratio, left-to-right vehicle imbalance ratio, fore-to-aft vehicle imbalance ratio.
    b. Measured values are those that are directly reported by the detectors but are not based on regular mathematical computations involving any other directly measured value. These values may be derived by complex analytical algorithms based on advanced instrumentation and/or signal processing techniques. All force measurements are in units of kips with AOA in milliradians. Ratios have no unit.
        i. TPD: Lateral force, vertical force, AOA.
        ii. WILD: Maximum vertical wheel force, average vertical wheel force, average lateral wheel force.
    c. Data comparisons between different accumulation levels are not valid, although mathematical relationships may be evaluated.
        i. Wheel: Values referring to a single wheel.
        ii. Axle: Values derived from both wheels as a complete axle. Not computed if required values for either wheel are missing.
        iii. Truck side: Values referring to and derived from all wheels on a single side of the truck (half of the wheels or all wheels on the same side of that truck). Not computed if required values for any wheel are missing.
        iv. Truck: Values referring to a complete truck and derived from all wheels on the truck. Not computed if required values for any wheel are missing.
        v. Vehicle: Values referring to a complete vehicle (all wheels on the vehicle). Not computed if required values for any wheel are missing.

2. Data Compilation

   a. All measured values and derived measurements are grouped by categories that distinguish unique performance conditions. These categories are made up of each unique combination of all pertinent independent variables and accumulation levels, broken into 1,000 uniformly distributed accumulation bins. The count of the number of instances included in each bin is recorded along with the range of values (minimum-maximum) bounding the bin.

   b. Categories: The pertinent accumulation levels are as described above. The performance conditions primarily depend upon the type of detector, although some conditions (e.g., end leading or speed) are common.

      i. TPD: end leading, car side, rail, curvature, crib, leading or trailing (axle or wheel), speed, vehicle type (equipment type code) and corridor.

      ii. WILD: end leading, speed, vehicle type (equipment type code) and corridor.

   c. Base Categories: The highest-level categorization will be by detector type, detector site, and month.

3. High-Level Accumulation.

   a. Vehicle Type: Vehicle type is designated as the single letter Equipment Type Code, as designated by UMLER. Currently there are 26 unique codes. The subcode values are retained and can be isolated in the output. The results from a subcode-based query are entirely dependent on whether data exists for that type at the queried category and/or accumulation level. Note: Future development could allow offline (batch-mode queries) breakdowns of the full 4-character, alpha-numeric Equipment Type Code.

   b. Detector Type: Currently, WILD and TPD types of detectors are accommodated.

   c. Month: Data reductions are accumulated on a monthly basis.

   d. Site: Each detector site (a single-track data collection system) is accumulated discretely.

   e. Corridor: Sites are identified as being included in one or more corridors, (i.e., Hazmat, passenger, mixed, or freight).

The raw data aggregation results will be retained for at least two full months. These may occasionally be recomputed. Detectors do not always provide timely reporting of data due to communications problems. Should a significant portion of data from a particular network or corridor experience a delay in processing by *Inte*RRIS®, the subsequent monthly processing may be re-run for the affected site or sites. This will alter performance data summaries for the corridor including those sites.

4.2.3 Data Output Requirements

Output from the VPD follows the regular file download conventions of *Inte*RRIS®.

1. Display Output.
   a. Query Input. The default query will return all vehicle performance summary data for the current month. The output will not subgroup and subtotal by the various accumulation and categorical levels as this is critically dependent upon the sort order of the output. The default order is from highest to lowest accumulation level. However, certain accumulations do not occur in a logical order or hierarchical subset relative to each other. Truck side and axle level accumulations are not comparable data. While both are subsets of truck level accumulation and both accumulate wheel level data, truck side and axle accumulations are independent in accumulation order.
      i. Base Input: Required basic input constraints will exist for detector type, site and month, or range of months.
      ii. Percentiles: Default percentile accumulations for output area — the maximum resolution of 1,000 bins or 0.1 percent increments. Selecting an abbreviated or summary form of output may reduce these.
      iii. Statistics: Basic statistics are: minimum, maximum, and mean. These are optional outputs depending on the output (summary or detail).

   b. Output Format: A summary of returned records are viewable online via the web-based interface. The user may choose to submit the query for full output and download or edit the query.
2. File Output (downloadable data file).
   a. Query Input: This input is the same as for direct displayed queries.
   b. Output Format: All file output is provided as a comma-delimited (csv) text file. All percentiles and statistics are automatically provided in the output. The data will be in clean tabular format (one header row begins the output) without subtotals or totals. An overall record count retrieved will be indicated for the number of components (e.g., wheel, axle) returned for the query.
   c. Download/Direct Save: The request will be queued and the user notified via e-mail when the file is ready. The web browser's save-to-disk function is called by the website when the user is ready to download the data file from InteRRIS®. Users may choose the location/name to which the data file is saved on their own hard drive.
3. Automated Report. These reports are set up on an as needed basis.

a. Direct Send: If the anticipated data is of reasonable size (less than 1 Mb in file size), it can be attached to an e-mail notification.

   b. File Transfer Protocol (FTP) Retrieval: If the data to be returned is greater than 1Mb, the file will be stored and the user notified via e-mail when the file is ready. The user will use ftp to retrieve the data file from InteRRIS®.
   c. Data Structure, Interface, and Output Design Requirements

The final design and implementation of the VPD must generally support the listed requirements, as described above. Variations in functionality may result due to unanticipated requirements or technical constraints. The overall capabilities for information reporting remain. Query or output flexibility may be constrained due to processing limitations and the ability to retrieve and compile large volumes of data within a reasonable amount of time. Automated, periodic reports can be staged to run at appropriate reduced-load intervals. Interactive queries to the VPD are potentially complex and therefore will be staged in a process queue as a FIFO (first-in-first-out) request and are limited to certain standard outputs or predetermined blocks of data (e.g., a single month for all sites or a single site for several months, but not all months for all sites in a single query). A general objective is to produce summary data in a format compatible with standard, high-end statistical analysis software. This is in contrast to attempting to produce comprehensive statistical analyses online where the balance of reasonable performance *and* complete statistical evaluation are difficult to achieve.

Figure 4 shows the various levels of the VPD structure as described in subsection 4.2. Figure 5, 6, and 7 show examples of the screen shots of VPD.

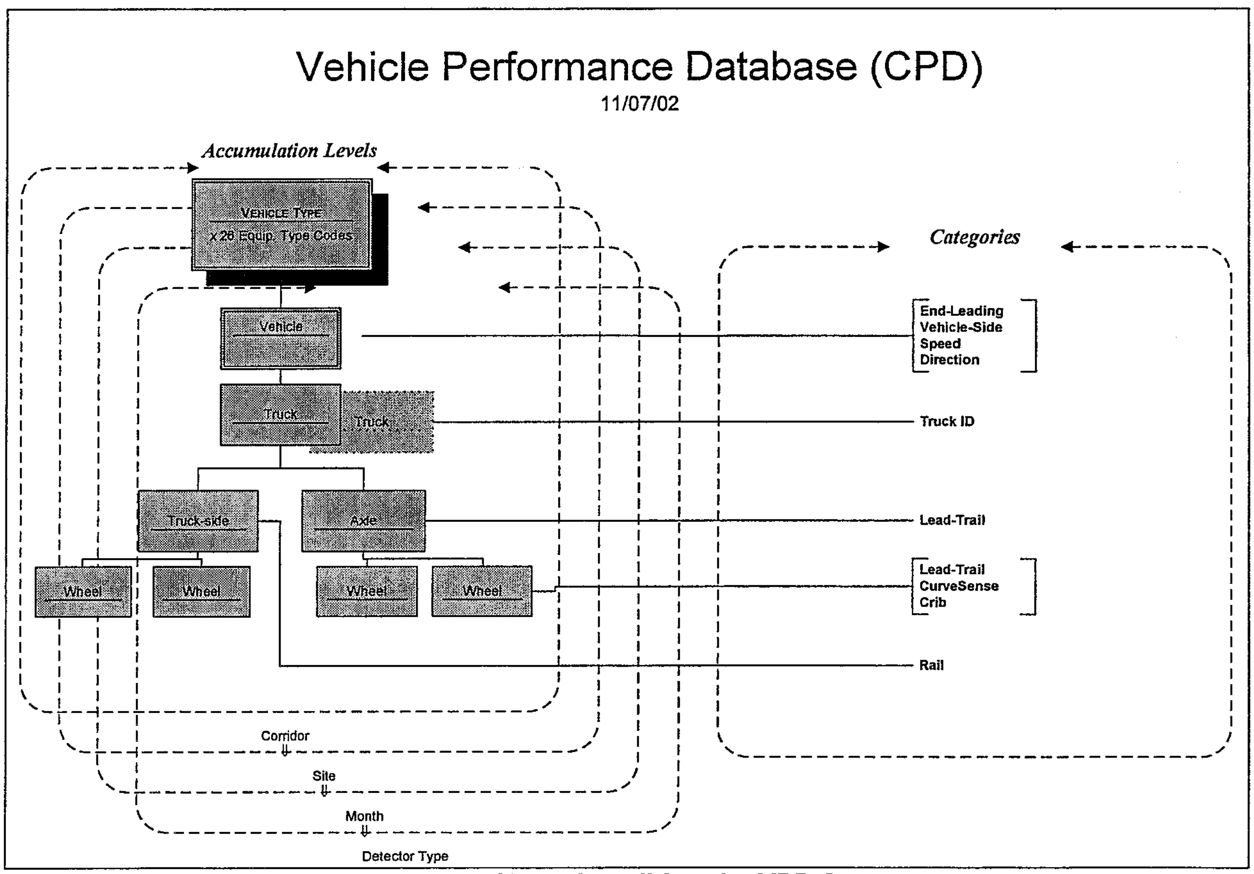

Figure 4. Flow Chart describing the VPD Structure

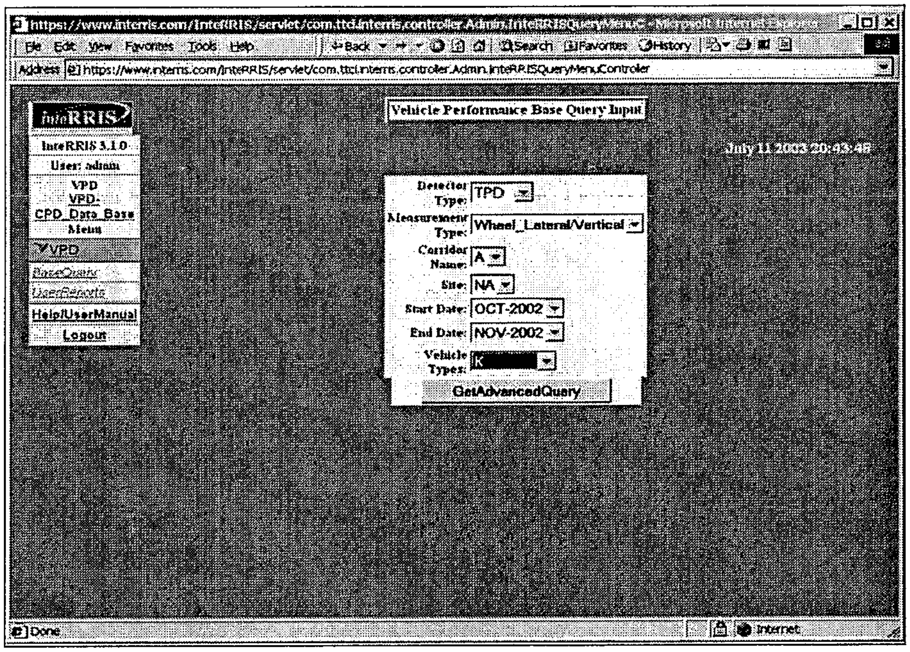

Figure 5. Query Input Screen for TPD data in VPD

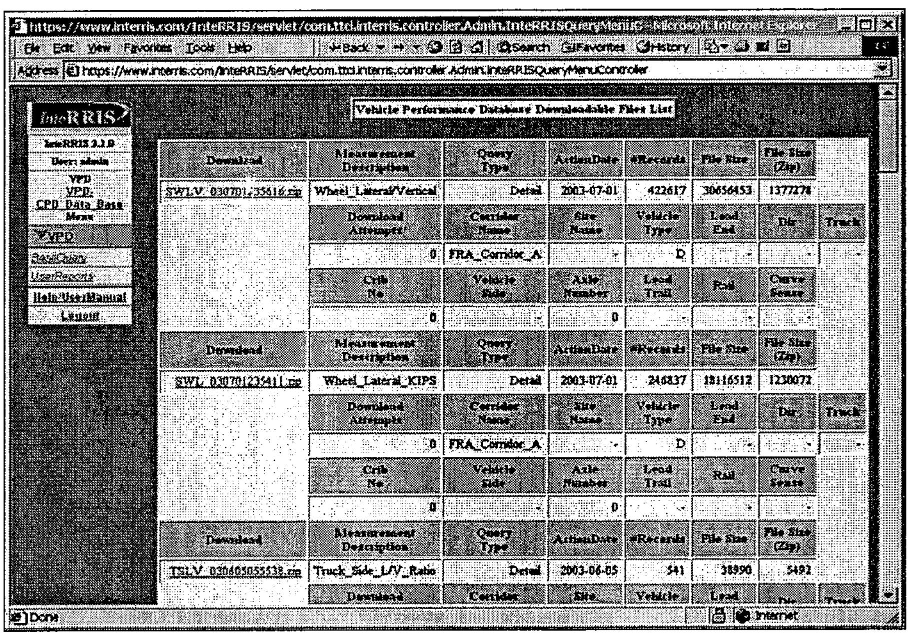

Figure 6. Screen Capture of Advanced Query Output for TPD Data in VPD

month	site_id	corridor_name	lead_end	direction	truck	crib_no	car_side	axle_no	lead_trail	rail	curve_sense	car_type	avg_speed	lat	wheel_cnt	ntile
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	40	5.57	1	885
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	39	5.65	1	888
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	40	6.51	1	916
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	38	6.55	1	917
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	39	6.8	1	924
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	41	6.82	1	925
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	40	6.91	1	927
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	41	7.9	1	949
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	35	10.64	1	983
1-Oct-02	87	FRA_Corridor_C	B	A	A	1	L	3	L	H	L	H350	38	-1.09	1	89

Figure 7. Example of Output for a WILD Data Query

4.3 Use of *Inte*RRIS® Truck Performance Data for Performance-Based Maintenance

4.3.1 Background

The objective of the work reported here is to demonstrate that a nationwide network of wayside truck performance detectors and a central data warehousing system such as *Inte*RRIS® can enable performance-based car maintenance. It is intended to show that trends in car performance can be identified and that predictions can be made of when cars require maintenance.

The objective is not to generate new performance indicators or measuring techniques, but to identify where such additional work is required.

4.3.2 Problem Definition

Wayside detectors, such as hotbox detectors, WILD and TPDs, are currently used for exception reporting. In its simplest use, a wayside detector will raise an alarm whenever an axle box temperature, wheel impact, or truck performance indicator exceeds a predetermined threshold. The offending item is then removed from service at the earliest opportunity.

A more sophisticated use of wayside detector data would be to monitor the changes of data with time and to predict when an alarm condition will be reached. Figure 8 shows an idealized plot of truck performance against time. The vertical axis is some measure of performance (e.g., L/V ratio or AOA) for which a high number means bad performance.

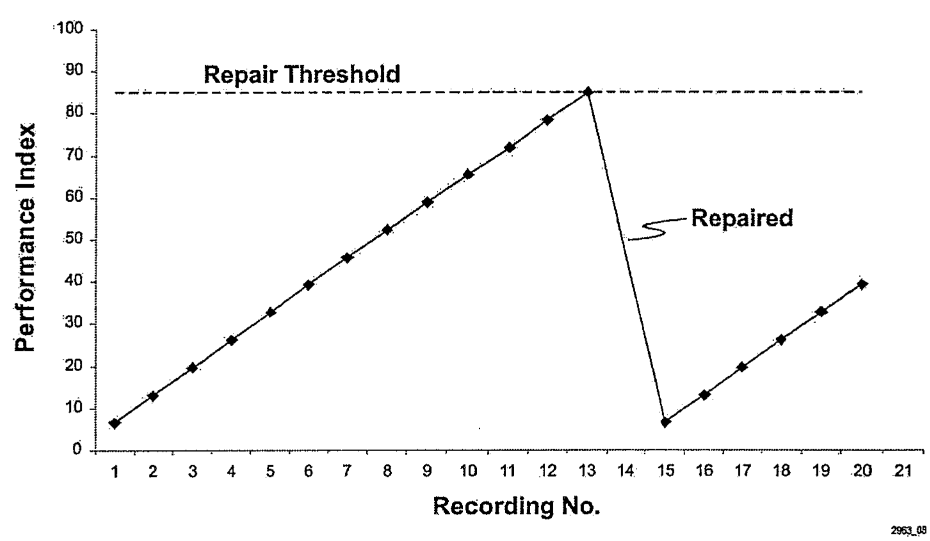

Figure 8. Idealized Deterioration and Improvement Behavior

In Figure 8, truck performance is seen to have deteriorated linearly with time. When it reached a specified threshold (recording No. 13) the truck was maintained or repaired, after which its performance improved. The truck's performance then continued to deteriorate in the previous manner until the last recording (No. 20). By extending the deterioration trend line, it is possible to predict when the truck will next need to be maintained or repaired.

This example has introduced three important parameters:

1. The deterioration rate, which quantifies the rate of change of performance with time. If performance data shows a trend, then it will be possible to calculate the deterioration rate.
2. The improvement in performance after maintenance or repair.
3. A maintenance threshold, which could also be called a specification limit, alarm level, or intervention level.

Predictive maintenance is possible if all three parameters are known. The time until the next maintenance can be calculated from the current performance level, the deterioration rate, and the maintenance threshold. The period between maintenance can be calculated from the deterioration rate and the maintenance improvement.

Thus, showing that this data enables deterioration rates, maintenance improvements to be found, and sensible maintenance thresholds to be set answers the question of whether truck performance data can be used for predictive maintenance. The data analysis described in subsection 4.3.3 attempts to show this possibility.

When real-world truck performance data is studied, the idealized pattern shown in Figure 8 is often difficult to recognize. This is because there are many sources of variation in the data that tend to move the data points away from a straight line and make the data seem random. Table 3 shows some of the sources of variation in truck performance data.

Table 3. Some Sources of Truck Performance Variation

Source	Description
Speed	The car will not always pass the detector at the same speed.
Load	The car may be empty, loaded, or partially loaded. The load may be centered or offset.
Direction	On single-track lines, the car may pass the detector in either direction.
Train Handling	The train may be braking, coasting, or accelerating.
Leading or Trailing	Regardless of the direction of travel the A- or B-end of the car may be leading.
Rail Lubrication	If lubricators are installed, they may or may not be working.
Weather	Rain on the rails or high winds can affect truck performance.
Curvature	Curvature may vary from one TPD site to another.
Track Maintenance and Deterioration	Truck performance can be affected by vertical and lateral rail profiles.
Vehicle Maintenance and Deterioration	Truck performance deteriorates with time and is improved by maintenance.
Rail Profile	Wheel/rail contact geometry affects truck performance.
Wheel Profile	Wheel/rail contact geometry affects truck performance.
Instrumentation Drift	Truck performance detectors use strain gage circuits, which can change their output with time.
Detector Accuracy	The detector may not measure a truck's true performance.
Detector Type	Different detectors may give different performance for the same truck.

Two sources of variation listed in Table 3 are of interest to the present study: vehicle deterioration and maintenance. Identifying these specific variations among all the other sources is a challenge that lies ahead.

4.3.3 Data Analysis

4.3.3.1 Data Sources

Data used in this analysis was derived from the *Inte*RRIS® database. The original sources of the data were the following truck performance detector sites and was recorded during the first 10 months of 2002:

- Flagstaff, Arizona
- Ludlow, California Tracks 1 & 2
- Kingman, Arizona
- Pomona, Missouri
- Argyle, Iowa
- Elmira, Idaho
- St Croix, Minnesota

4.3.3.2 Data Types

The above noted detectors are supplied by two different TPD vendors and have several differences, but both produce the following outputs:

- Date and time of recording
- Car identification (e.g., DTTX056494)
- Axle number
- Axle status as leading or trailing
- Direction of travel
- Train speed
- Vertical force on each rail
- Lateral force on each rail
- Axle AOA (not always available)

Both types of TPDs are installed on reverse curves. One vendor's detector has six instrumented cribs. Two are on one curve; two are on the tangent, and two more are on the other curve. The other vendor's detector has two additional instrumented cribs on the spirals between the curves and the central tangent. In general, the analysis described here used the information from the cribs in the curves.

The raw measurements listed above can be combined to give derived performance indicators. Examples are:

- Single wheel L/V force
- Axle sum L/V force
- Truck side L/V force
- Axlescore[2]
- Gage widening index
- Flange climbing index

Much of the analysis performed in this study used the single-wheel L/V force since this parameter is a good indicator of the potential for flange climbing derailment (assuming that the axle has a positive AOA).

[2] TTCI's "Axlescore," is a weighted combination of lateral loads and single wheel, axle sum, and truck side L/V ratios.

4.3.3.3 Analysis of Single Cars

The first analysis performed was the study of single cars over time — real-world examples of Figure 8. The *Inte*RRIS® database was searched for cars that had been recorded several times over the 10-month monitoring period. Locomotives were excluded from the list. An FCA flatcar (Car X) was chosen at random from the most frequently measured cars for further analysis. At first, only the data from the Flagstaff detector was extracted from *Inte*RRIS®. The measurements from the outer wheel of axle 2 when it was leading at crib 1 are shown in Table 4. The L/V ratios are plotted in Figure 9.

Table 4. Car X, Flagstaff Crib 1, Axle 2 Leading

Date	Lateral Force (kips)	Vertical Force (kips)	L/V
1/27/2002	-1.04	19.0	-0.055
2/11/2002	1.85	16.7	0.111
4/20/2002	1.50	17.0	0.088
5/3/2002	3.00	19.6	0.153
5/9/2002	2.04	17.8	0.114
5/18/2002	4.62	17.3	0.268
5/27/2002	3.32	15.2	0.219
6/2/2002	5.13	16.8	0.305
6/10/2002	-1.06	10.3	-0.103
6/23/2002	3.31	20.8	0.159
6/28/2002	-0.58	23.8	-0.024
7/4/2002	4.56	18.8	0.243
7/10/2002	3.73	21.0	0.178

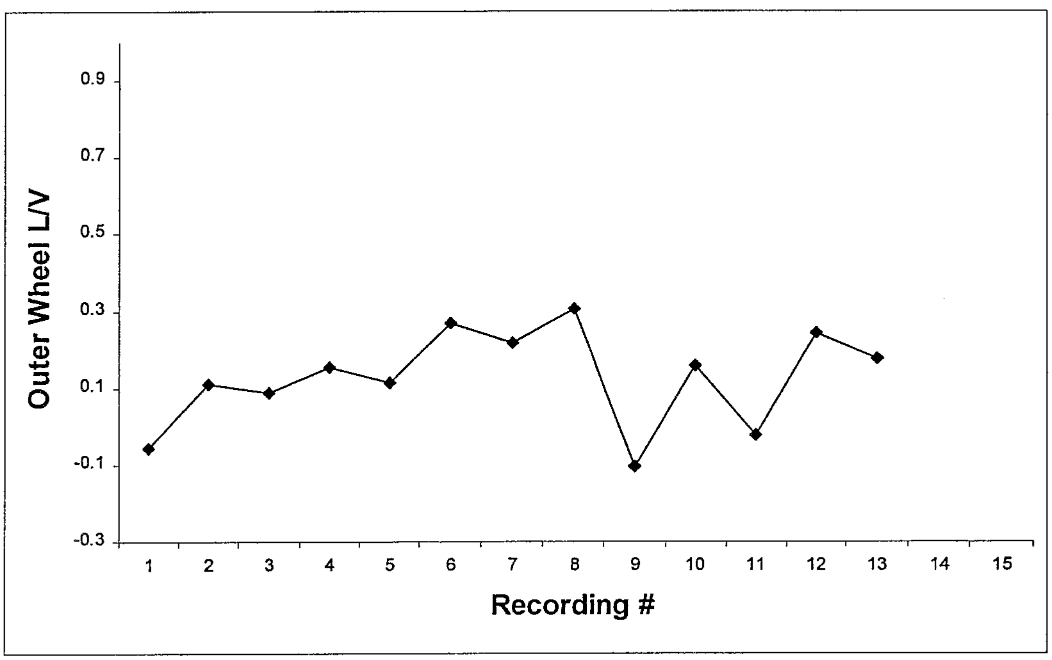

Figure 9. Car X, Flagstaff Crib 1, Axle 2 Leading

The first observation to be made about this data is that it is variable. The lateral and vertical forces were different every time the axle passed this crib; thus, the L/V values were different every time. This is not surprising considering that the speed and load for the car were different for each of the axle passes shown in Figure 9.

It would be tempting to draw a straight line through the first eight data points, and attribute the reduction in L/V from recording 8 to 9 to the result of maintenance. However, this would not be the correct interpretation of the data.

An alterative method of analyzing this data, and one that is very useful when analyzing variation, is Statistical Process Control (SPC). Figure 10 shows the same data as Figure 9 with three lines added.

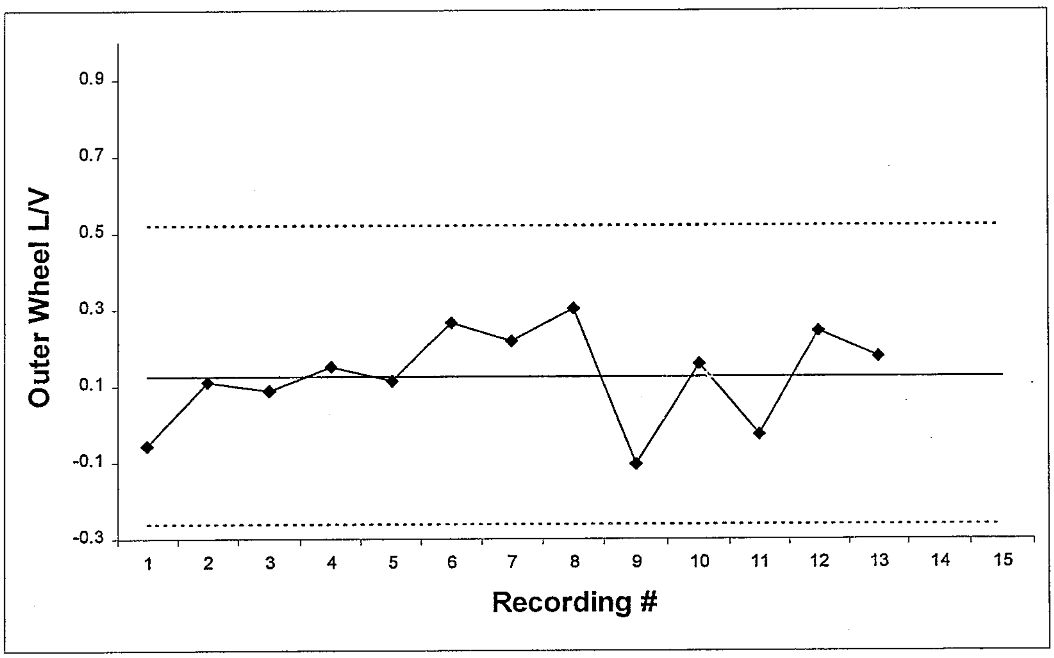

Figure 10. Car X, Flagstaff Crib 1, Axle 2 Leading with Average and Control Limits

The solid line in Figure 10 is the average of the data. The average L/V ratio for the 13 recordings was 0.13. The recordings vary about the average, as would be expected of real world data.

The dotted lines in Figure 10 are known as control limits or natural process limits. They are placed at ±3 standard deviations (±3σ) from the average, where σ is calculated from the available recordings.

The region between the control limits is where recordings of this wheel when leading at this crib were expected to be found. All the recordings made in the monitoring period of 10 months fall in this region. The lines can be extended to the right, and it can be said that, based on previous observations, the L/V for this wheel when leading at this crib is expected to vary about an average of 0.13 with a maximum of 0.52 and a minimum of -0.26.

This prediction may not seem as useful as drawing lines through the data and determining deterioration rates, but it can be stated with a reasonable degree of confidence. Establishing the upper natural process limit also enables a strong statement to be made about predictive maintenance.

If in the future, the same wheel passes the crib in the lead position and exceeds the upper natural process limit of 0.52, something significant has occurred. The reason is the wheel has done something it has never done before, and it would not be the result of common causes of variation. It most likely was due to a special cause such as truck deterioration. In that case, the start of a deterioration trend has been found.

Another horizontal line could be drawn on Figure 10 at a L/V ratio of 1.0. This is commonly recognized as the single-wheel safety limit for a flange climbing derailment. If a wheel were found by a TPD to have an L/V greater than 1.0, then it would normally be set out and maintained or repaired. The control chart in Figure 10 shows us to start monitoring L/Vs greater than 0.52 (upper control limit) for this wheel when leading at this crib. If this is done and the deterioration in performance is steady, there should be ample opportunity to maintain or repair the wheel before it reaches the safety limit.

To be useful for predictive maintenance, truck performance data must have stability and capability. A stable process is one in which all the data points lie between the upper and lower natural process limits. The outer wheel of axle 2, when leading at Flagstaff crib 1, is such a process, as Figure 10 shows. Put another way, the process is in control. A capable process is one in which the variation is small and the average is well below a conventional intervention limit. The example in Figure 10 is capable. Its standard deviation (σ) is 0.13, and the distance from its average to the safety limit is $0.87 = 6.7\sigma$.

Data from Flagstaff for other cars was analyzed with the same method. Figures 11 and 12 show typical results. Car Y is another FCA flatcar. Car Z is an RP refrigerated car.

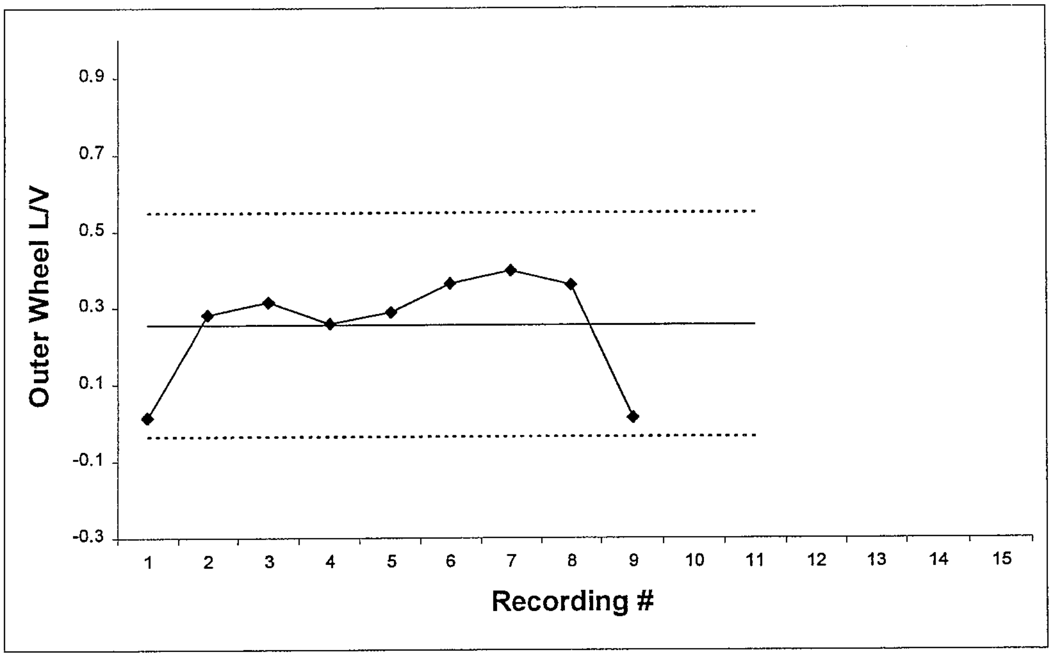

Figure 11. Car Y, Flagstaff Crib 2, Axle 1 Leading

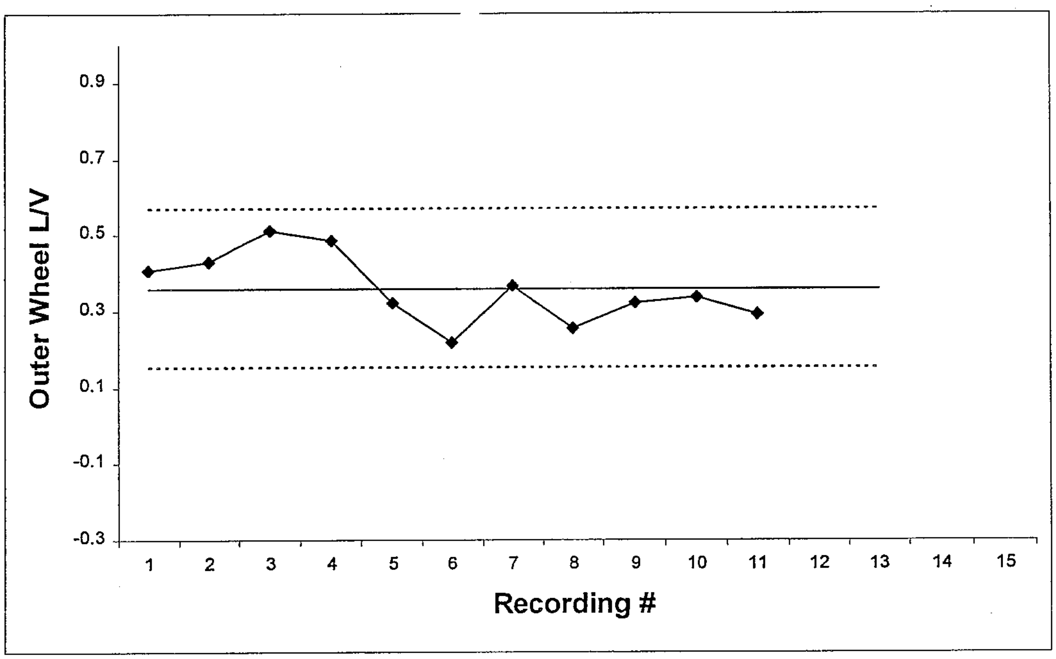

Figure 12. Car Z, Flagstaff Crib 2, Axle 4 Leading

In all cases, the performance was stable and capable. The summary statistics for each car are shown in Table 5. Although Car Z had a worse average performance than the other two cars, its variation was lower, so its performance is just as capable.

Table 5. L/V Performance Statistics for Three Example Cars

L/V	Average	Standard Deviation (σ)	Upper Natural Process Limit (UNPL)	Distance from Average to Intervention Level
Car X	0.13	0.13	0.52	6.7σ
Car Y	0.26	0.10	0.55	7.7σ
Car Z	0.36	0.07	0.57	9.2σ

If the variation in truck performance data can be reduced then the data becomes more capable of being used for predictive maintenance. One way of reducing the variation is to take advantage of the fact that recordings are made at more than one crib at a TPD. Figure 13 shows the effect of averaging the L/V recorded at cribs 1 and 2 for Car X.

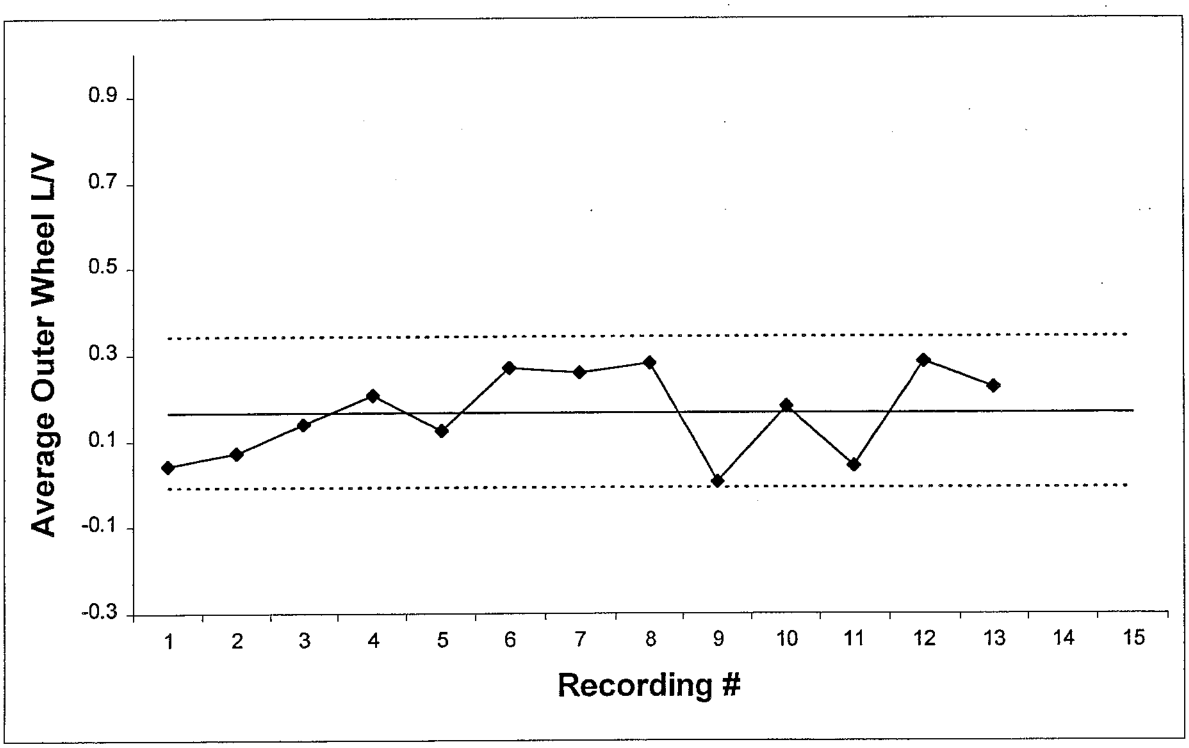

Figure 13. Car X, Flagstaff Average of Cribs 1 and 2, Axle 2 Leading

Comparing Figures 13 and 10 shows how the effect of averaging over cribs 1 and 2 has been to reduce the variation in the recordings and to make the process more capable. The new statistics are given in Table 6 for comparison with Table 5.

Table 6. L/V Performance Statistics for Car X Sub-Grouped on Cribs

AverageL/V Cribs 1 & 2	Average	Standard Deviation (σ)	Upper Natural Process Limit (UNPL)	Distance from Average to Intervention Level
Car X	0.16	0.06	0.34	14.3σ

In SPC terminology, averaging data like this is called "sub-grouping." Careful choice of sub-groups (such as cribs) can remove variation and make the data more useful for prediction. The variation within subgroups is also important. It should be small (i.e., the difference between cribs should be small) and stable. The variation within sub-groups can also be checked with a control chart. Figure 14 shows the range between cribs 1 and 2 for Car X axle 2 leading at Flagstaff.

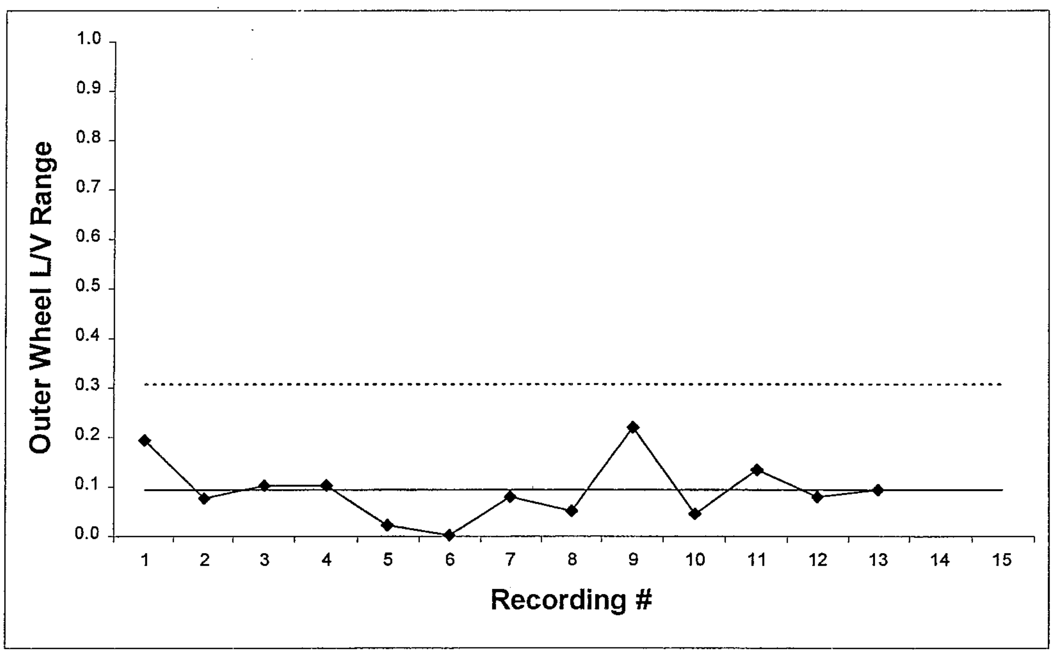

Figure 14. Car X, Flagstaff Range between Cribs 1 and 2, Axle 2 Leading

The average range (difference) between cribs 1 and 2 is 0.1. The maximum expected range is 0.3. All recordings had ranges that were within the expected region. Thus, the crib-to-crib variation is in control.

4.3.3.4 Analysis of Single Cars at Multiple Sites

The analysis presented so far has used only data from the Flagstaff site. Although enough data was obtained from Flagstaff to perform the analysis described above, more data should make it easier to discover trends. If data from other TPDs could be combined, then the datasets would be bigger. However, data from different sites should only be combined if the variation between sites is small.

To study site-to-site variation, data was extracted from *Inte*RRIS® for all the sites that Car W passed in the first 10 months of 2002. Car W is a FCA flatcar. The outer wheel of axle 1 was studied, and the L/V was averaged over the first two cribs at each site.

Three of the available sites had sufficient data for analysis of Car W. Figure 15 shows the results for these three sites. Table 7 gives the statistics for Car W, outer wheel axle 1 leading at the three sites.

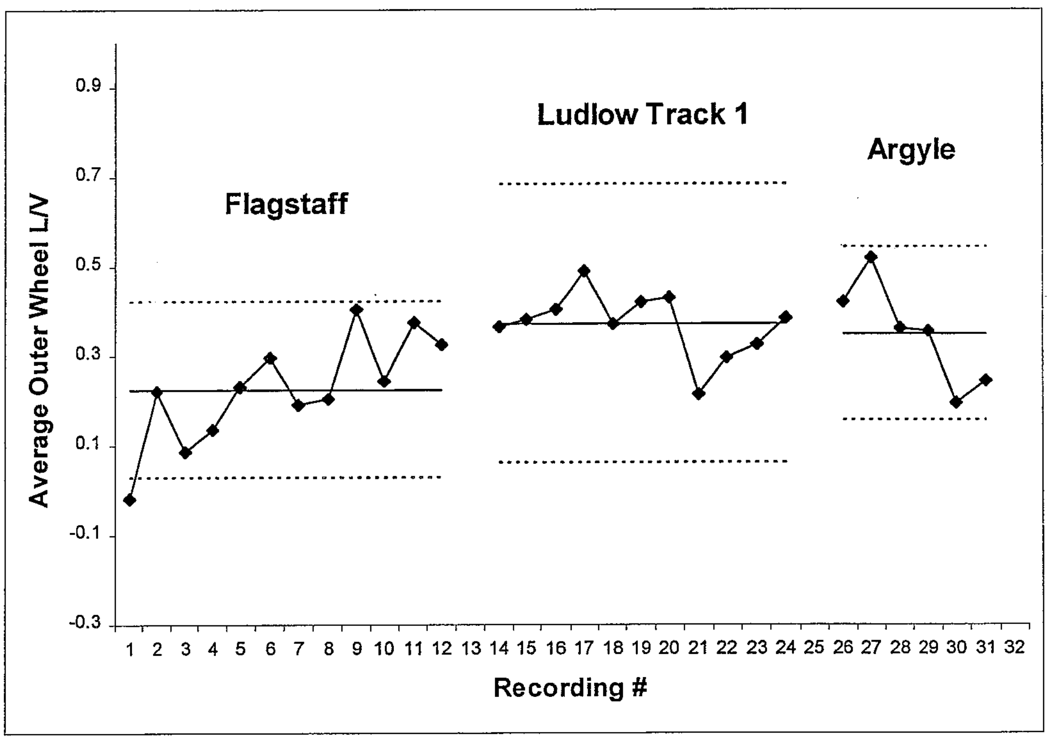

Figure 15. Car W, Crib 1 and 2 Average L/V, Axle 1 Leading at Three Sites

Table 7. L/V Performance Statistics for Car W Sub-grouped on Cribs

Average L/V Cribs 1 and 2	Average	Standard Deviation (σ)	Upper Natural Process Limit (UNPL)	Distance from Average to Intervention Level
Flagstaff	0.22	0.07	0.42	11.8σ
Ludlow 1	0.37	0.10	0.68	6.1σ
Argyle	0.35	0.06	0.54	10.1σ

The results from each of the three sites are different. The average L/V is lowest at Flagstaff and the standard deviation at Ludlow Track 1 is more than the other two sites. This suggests that in order to use TPD data from a national database some normalization of variations in site parameters may be required.

The high-standard deviation at Ludlow Track 1 is due to the large range in L/Vs measured at cribs 1 and 2 at this site. It may indicate that an adjustment is required to the instrumentation or that the track conditions at the two cribs are not the same.

The variation in curvature between the sites illustrates the need to be able to normalize the data before sites are combined. A normalization formula may need to be derived that adjusts for differences in curvature. Once this formula is applied to the data in Figure 15, the averages at each site will be similar and the data can be combined.

Then, over the 10-month monitoring period, there would have been 29 recordings of Car W. This would be sufficient data to establish an average and an upper natural limit for performance. It should also be possible to find deterioration trends in the data, if they exist.

4.3.3.5 Analysis of Single Cars Receiving Maintenance

The preceding analysis has established that truck performance (measured by single wheel L/V) is, in general, a stable and capable process. If the truck does not change, then its performance continues to vary between natural limits that are well below typical intervention levels. The converse of this statement is that if something does change on the truck that affects its performance, then the change should be apparent in the data. To test this hypothesis, several trucks that had received maintenance during the monitoring period were studied.

A car owner selected a series of 600 double-stack cars to perform maintenance based on data from *Inte*RRIS®. The cars were chosen based on information provided to the car owner by a railroad owning several TPD sites. The car owner chose to use the performance index of truck side L/V (TSLV) for this evaluation. TSLV data for all of the cars from all TPD sites for the period January 1 to April 25, 2002, were plotted in terms of percent distribution as shown in Figure 16. The X-axis is the number of times each of the cars exceeded a TSLV value of 0.3 (a hit) per visit or pass by a TPD site. Eleven of the worst cars, based on the highest number of entries per visit were removed from service. The cars were inspected and each of them fitted with long travel side bearings. In addition, all of the column wear plates were tightened. The cars were placed back into service and the same distribution repeated for the period January 1 to March 5, 2004, to identify any changes as shown in Figure 17.

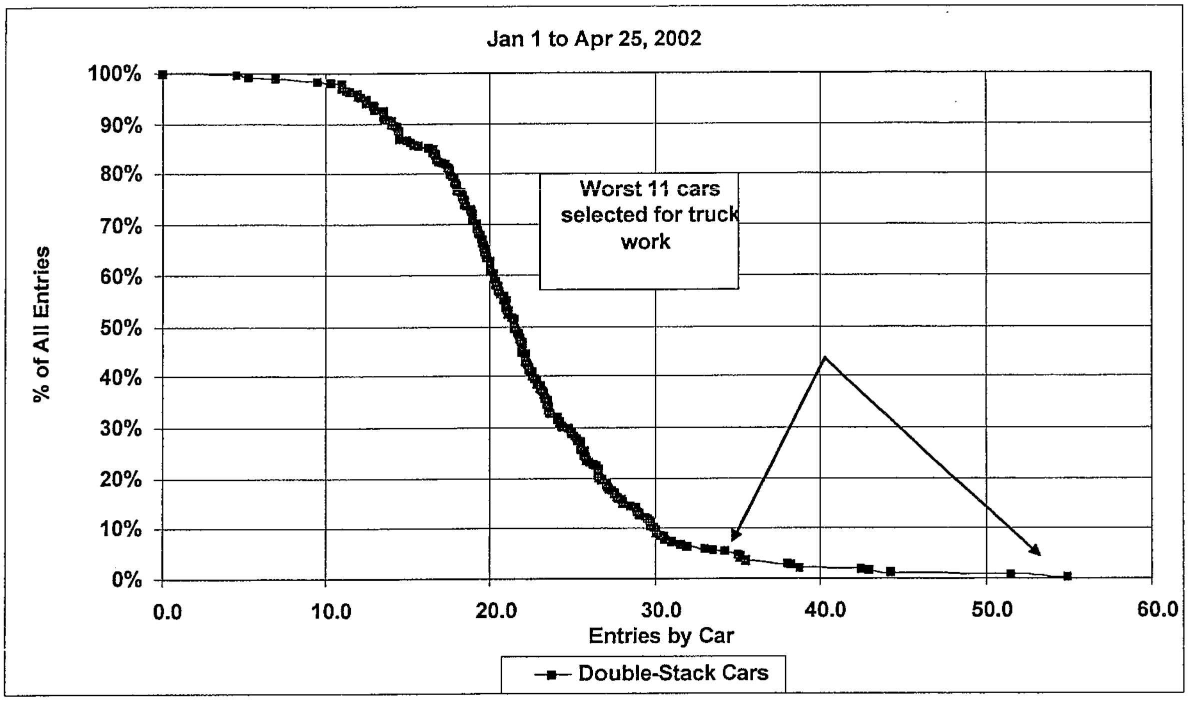

Figure 16. Distribution of TSLV Hits per Visit (using *Inte*RRIS® data)

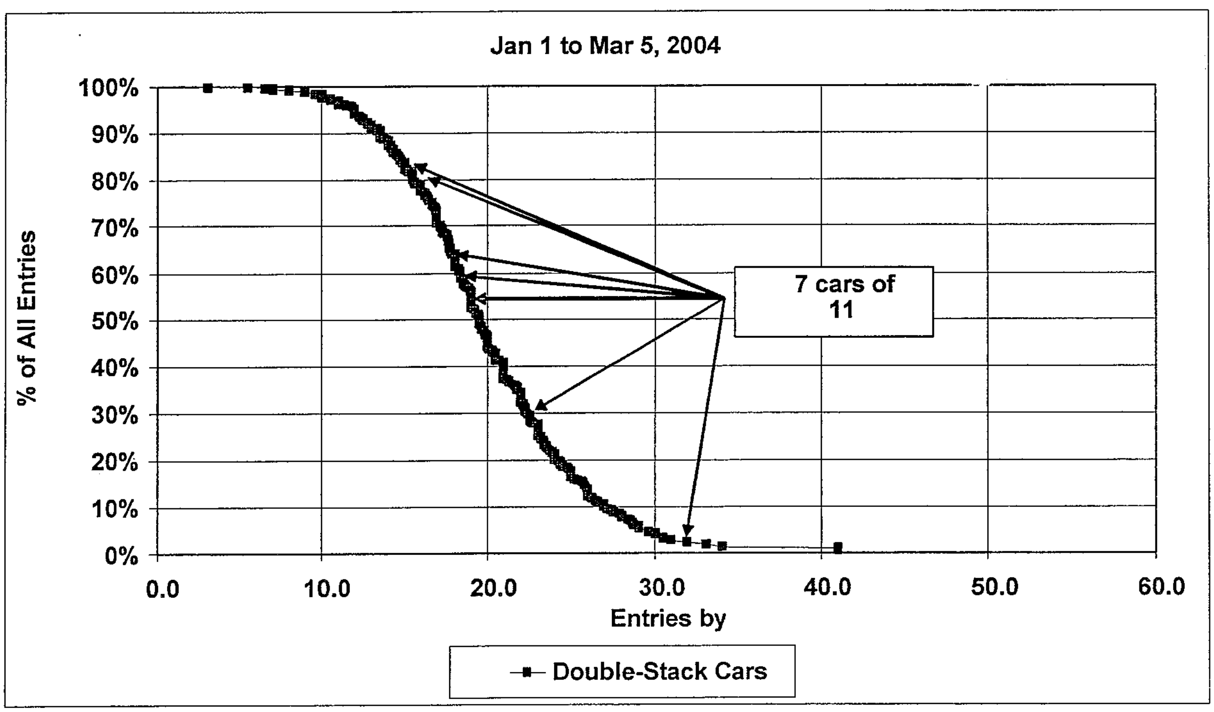

Figure 17. Distribution of TSLV Hits per Visit after Maintenance using *Inte*RRIS®

Several conclusions can be drawn from the distributions. The repairs made to the 11 cars (and subsequently to the entire 600 car series) did improve the performance based on the TSLV performance index. The hits per visit over 40 were eliminated for the entire population of the 600 cars. The 11 cars that were the worst performers still showed varying performance levels and that could be due to variation between TSLV readings from site to site. The variation could be reduced by plotting similar distributions for A-end and B-leading and selecting a few individual TPD sites.

4.3.3.6 Analysis of Car Series

While being able to predict when individual trucks will require maintenance is very important, there is also a requirement to predict when series of cars should be brought into the workshop for attention. Since railroad workshops have a limited capacity, it is also necessary to be able to select the car series that is in most urgent need of attention.

A list of car series was obtained from a Class 1 railroad. A car series is typically defined as all the cars built by one manufacturer at one time of one design. All cars in the series will have the same types of components and are often numbered sequentially.

One car series, Series Q, was selected from the list for analysis. This series contained cars that had been past the truck performance detector at Flagstaff several times in the 10-month monitoring period. The cars were steel coal hoppers.

Five cars in Series Q were found to be in the same train, and the train had been recorded eight times at Flagstaff. The configuration of the cars and recording dates are shown in Figure 18.

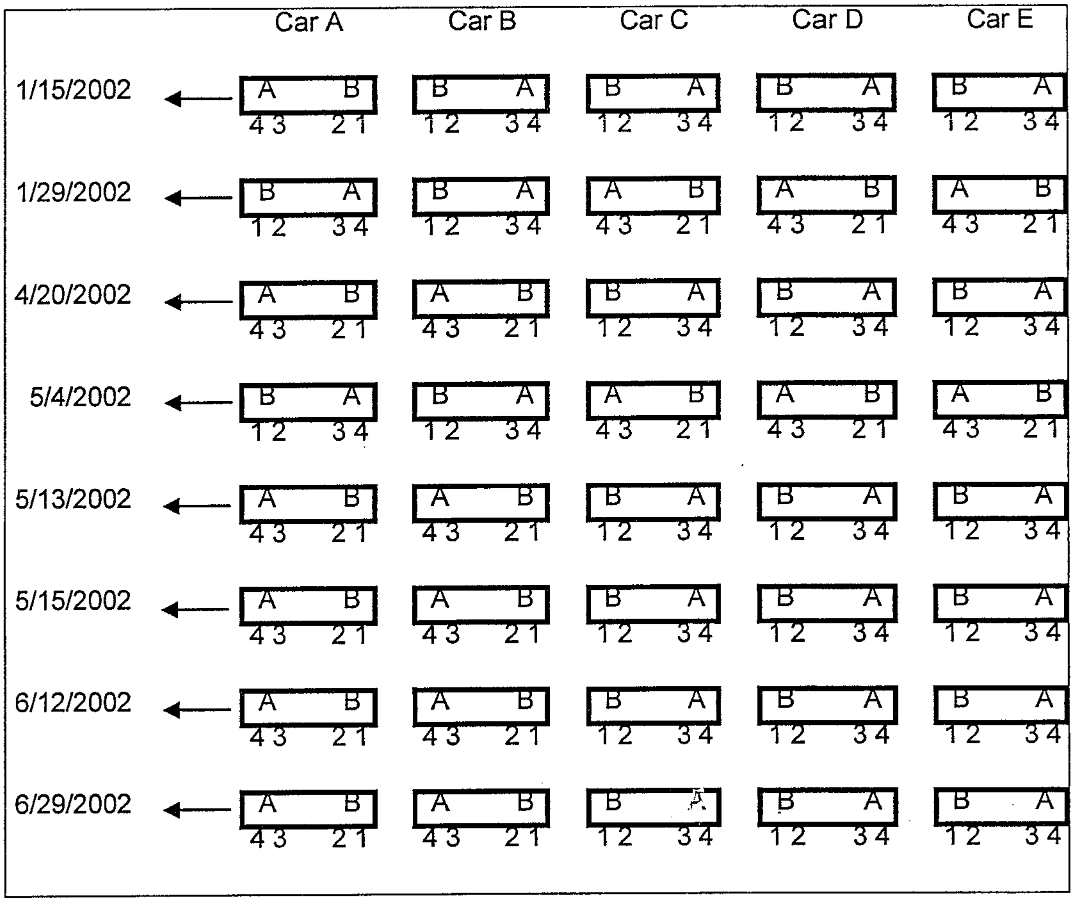

Figure 18. Series Q Recording Dates and Directions

The average L/V was calculated for the outer wheel of the leading axle of all five cars in the series. The average of this value was then calculated across cribs 1 and 2 on each date. The statistics are given in Table 8, and the results are shown in Figure 19.

Table 8. L/V Performance Statistics for Five Cars in Series Q

Average L/V Cribs 1 and 2 Series Q	Average	Standard Deviation (σ)	Upper Natural Process Limit (UNPL)	Distance from Average to Intervention Level
Flagstaff	0.24	0.04	0.36	18.8σ

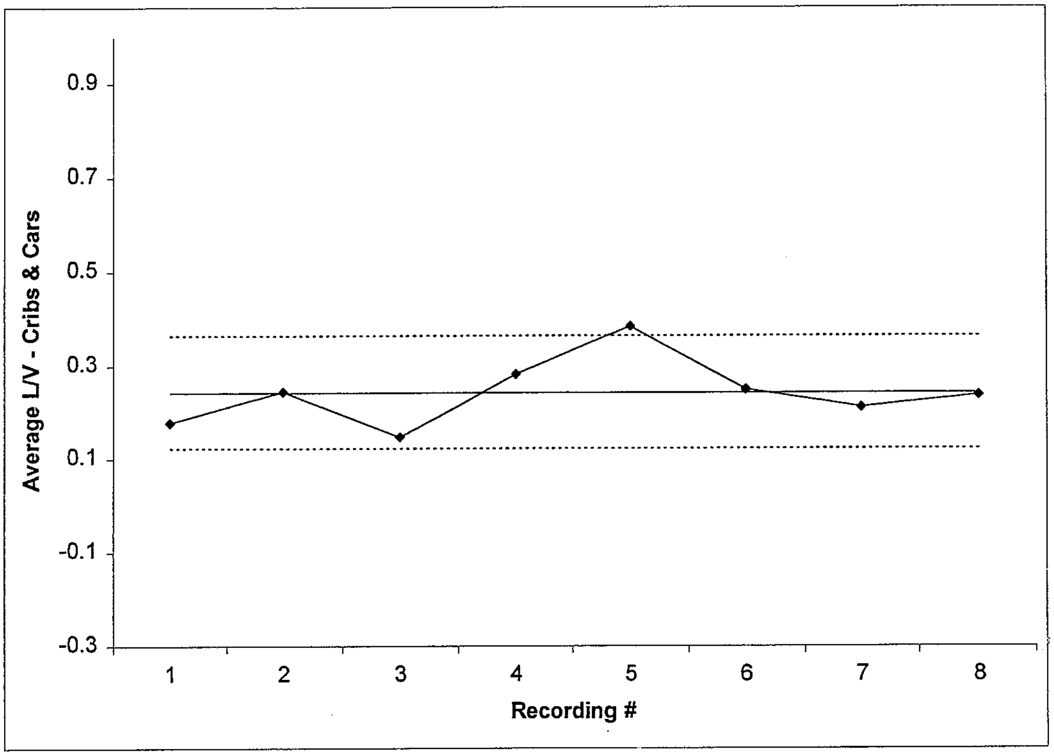

Figure 19. Five Cars in Series Q Average Leading Axle L/V

The performance data is the most capable that has been presented thus far. However, Figure 19 shows that there is one out-of-control point. For this data point — May 13, 2002 — the performance of the five cars in Series Q was significantly different to any of the other days. The simple explanation for this behavior is that all five cars were empty on that day; on all the other days, the cars had been fully loaded with coal.

In general, it will be easier to use performance data from hoppers and gondolas for predictive maintenance if the data is separated into loaded and empty conditions. This was not necessary for the other car types that were analyzed earlier since their loads will depend on the type and quantity of goods being transported.

Since the data presented in Figure 19 is an average of averages, it hides some details. Figure 20 shows the results before the averaging across cribs.

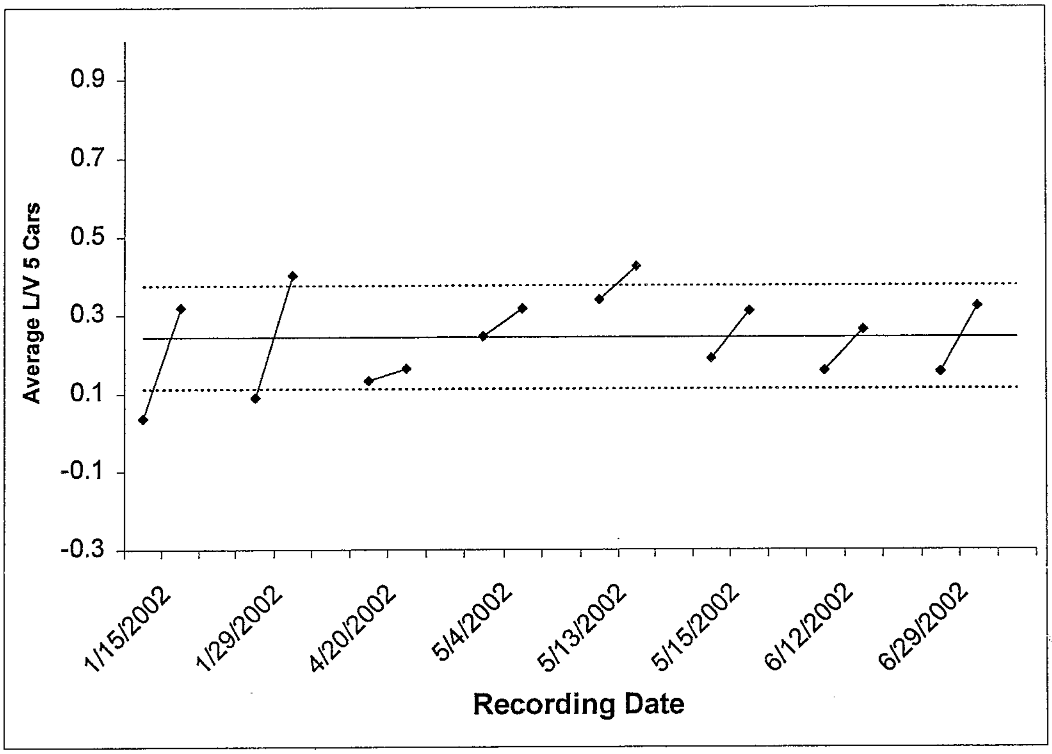

Figure 20. Five Cars in Series Q Average Leading Axle L/V Sub-grouped on Cars

For each date in Figure 20, two data points are shown — one for each crib. The results show that crib 2 measured consistently higher L/Vs than crib 1 for the five cars in Series Q. On the first two recording dates the differences between cribs 1 and 2 was higher than would be expected based on the normal variation between cars. This demonstrates that *Inte*RRIS® data lends itself to checking for variations from crib to crib and hence can allow data health checks to be implemented.

Selecting the same cars in a series is a controlled sampling technique. An alternative would be to take a sample of all the cars in a series recorded between chosen dates. Two further car series, Series R and Series S, were analyzed using this random sampling technique. Both these series are steel car hoppers. Series R was built in 1977 and last received programmed maintenance in 2000. Series S was built in 1978 and last received programmed maintenance in 1995.

Table 9 shows the number of cars in each series recorded at Flagstaff each month. Only loaded cars are included in this dataset. Figure 21 shows the variation in average performance for Series R and S. For each month, the average across all the cars seen (in that month) was calculated. Then the average between cribs 1 and 2 was calculated. The natural process limits were calculated from the crib-to-crib variation. The months of March and August have been omitted since they contained no recordings from either car series.

Table 9. Recordings of Series R and S by Month

2002	Number of Recordings	
	Series R	Series S
January	46	35
February	2	2
March	0	0
April	24	18
May	46	34
June	42	46
July	3	1
August	0	0
September	4	2
October	6	12

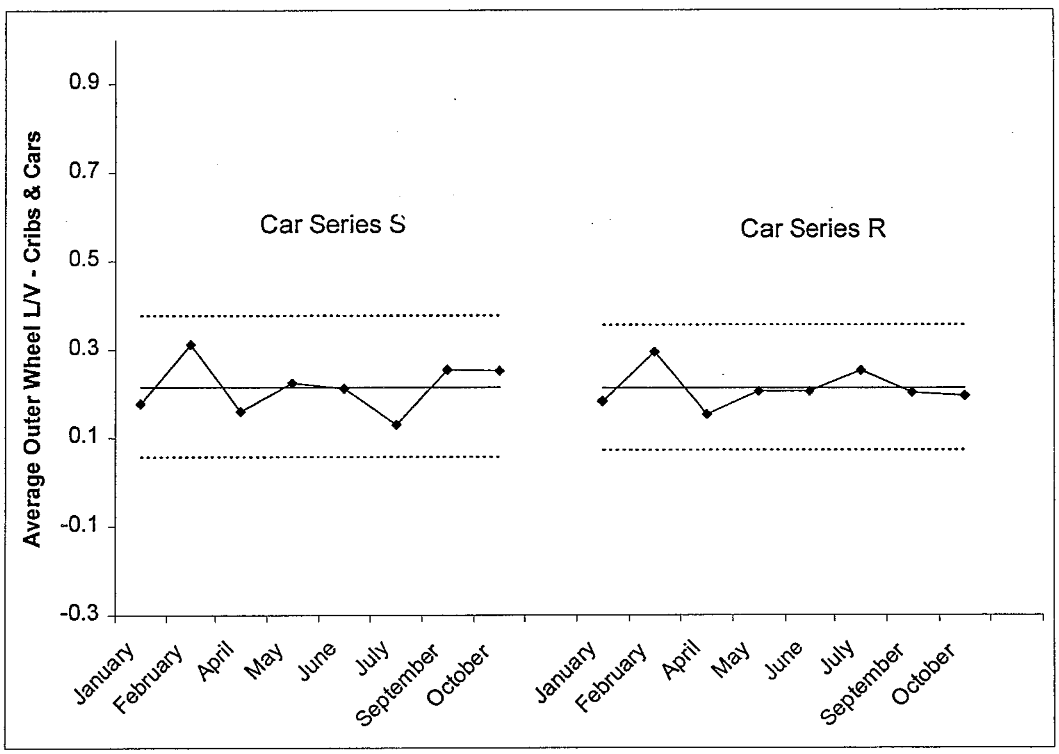

Figure 21. Outer Wheel Leading L/V Performance for Car Series R and S

The performance of both car series is very similar. The averages and natural process limits are almost identical for both. From this performance data, neither car series would be given priority over the other when planning the next programmed maintenance.

Table 10 shows the performance statistics for Car Series R and S. Since the capability of this data is so high (as indicated by the distance from the average to the intervention level), it should be possible to distinguish between car series and give priority for programmed maintenance to those that have the worst average performance. In the example given here, no difference was found between two car series sampled at random. Further analysis would be required to find a car series that was significantly different to those already analyzed.

Table 10. L/V Performance Statistics Car Series R and S

Average L/V Cribs 1 & 2 Flagstaff	Average	Standard Deviation (σ)	Upper Natural Process Limit (UNPL)	Distance from Average to Intervention Level
Series R	0.22	0.08	0.37	9.2σ
Series S	0.21	0.08	0.35	10.5σ

4.3.3.7 Analysis of Hybrid Performance Indicators

The single wheel L/V that this analysis has concentrated on is a good performance measure because it is related directly to flange climbing derailment potential. The same analysis could be repeated for other performance indicators. Hybrid performance indicators attempt to combine several performance measures into one number. An example is TTCI's "Axlescore," which is a weighted combination of lateral loads and single wheel, axle sum, and truck side L/V ratios.

The maximum possible value of Axlescore is 100. A normal intervention level would be 85. Figure 22 shows the Axlescore for Car X, axle 2 leading at Flagstaff crib 1. This axle is the one for which the outer wheel L/V was shown in Figure 9. The Axlescore performance statistics for this axle are given in Table 9.

Figure 22 shows that Axlescore is a stable performance measure. From Table 11, the distance from the average to the intervention level is 8.9σ; thus, Axlescore is also capable of being used for predictive maintenance.

Hybrid indicators such as Axlescore tend to be more capable than their component indicators. This is because they are averaging across several measures of performance, and averaging tends to reduce variation. Further analysis is necessary to determine if deterioration trends and maintenance improvements are readily found in Axlescore performance data.

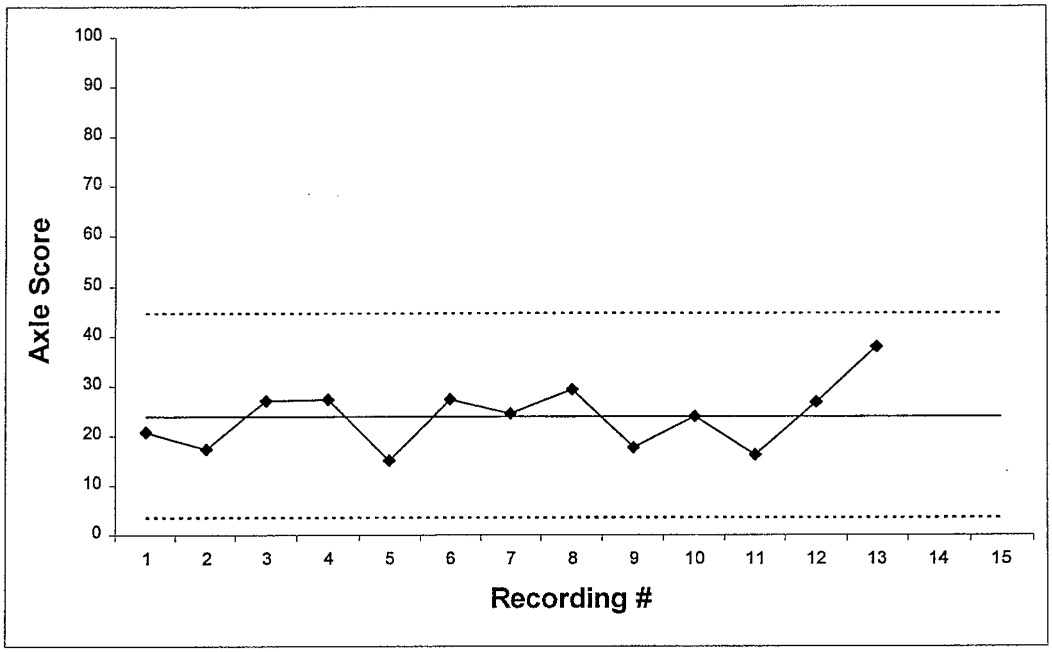

Figure 22. Axlescore Car X, Flagstaff Crib1, Axle 2 Leading

Table 11. Axlescore Statistics Car X, Flagstaff Crib 1, Axle 2 Leading

Axlescore Crib1 Flagstaff	Average	Standard Deviation (σ)	Upper Natural Process Limit (UNPL)	Distance from Average to Intervention Level
Car X	24.0	6.8	44.5	8.9σ

4.4 Provide Support to FRA in preparing Report to Congress

The FRA appointed an independent entity to research and produce an interactive economic model to establish safety and maintenance related benefits from the use of WILD and TPD detector data in *Inte*RRIS® and VPD. TTCI provided support in terms of TPD and WILD data statistics from *Inte*RRIS® and attended several meetings and a workshop related to the economic model. TTCI has also solicited comments from various railroad personnel that attended a workshop training session on the economic model. TTCI, under the auspices of the AAR Stress State Task Force conducted a separate economic evaluation of the benefits of using WILD and TPD data on a national level. The results of the AAR economic analysis for TPD indicates a larger set of benefits than those produced by using the interactive model.

The major differences in the TTCI economic evaluation compared to that from the independent entity are:

- TTCI research indicated that the relationship between lateral load and rail/wheel wear is linear up to about 15 kips after which the slope becomes radically steeper as the wear regime changes from mild to severe wear. The interactive model assumes a linear relationship between lateral load and wear.

- The interactive models use of reach-time until truck would be repaired if no detectors existed is likely not relevant to TPDs. These trucks may run for a very long time before they reach a state that visual inspection would result in repair.

- The interactive model assumes 0.02 percent of the wheels would be removed (those above 20 kips). This information likely came from TTCI as the percent across all detectors. However, due to dramatic differences among detectors, curvature for one, it is difficult to compare the severity. For example, 20 kips from a detector on a 7-degree curve is far different from a 20 kip reading from a detector on a 3-degree curve. TTCI assumes 1 percent of the trucks at each detector will be removed. The load level varies from about 11 kips on a 3-degree curve to about 20 kips on a 6-degree curve.

A summary of TTCI's TPD economic analysis produced the following summary (Table 12).

Table 12. Summary of TPD benefits

Wheels	$173,748
Rail	$20,374,808*
Fuel	$32,627,267
Ties	$32,187,038
Derailments	$2,274,600
Total Benefit	$87,637,461
Cost to Correct	$13,049,184
Net Benefit	$74,588,277

*Includes new rail laid in replacement only

5.0 CONCLUSIONS

This pilot project has produced a set of tools that will enable the rail industry and the FRA to apply statistical analysis to performance data from defect detectors across the United States. The feasibility of applying statistical process control to performance data shows promise. Further research is recommended in applying the methodology for predictive maintenance techniques.

Performance-based data from *Inte*RRIS®has been used to produce the VPD. This database is comprised of specific vehicle-type data (e.g., hopper car, boxcar, coal gondola, tank car) and specific corridor-based data (all four corridors in which the new detectors are installed and any other that are chosen to include existing TPD and WILD detector units). This data enables statistical process control and other statistical analyses to be used for safety research by the FRA.

The VPD is a summary or reduced subset of the raw detector data. Detector data is processed monthly to reduce it to a statistical summary level. This data reduction will allow data aggregation to the corridor-level by all pertinent, independent variables.

To use truck performance data for predictive maintenance, the data must be stable and capable. Stable performance data varies between natural limits as long as nothing out of the ordinary happens. Capable data has an upper natural limit that is significantly below the conventional intervention level.

Truck performance data from the detectors currently installed in North America has been found to be stable and capable.

Averaging across cribs at each site makes the data even more suitable for predictive maintenance. However, crib-to-crib variation also yields useful information about detector behavior.

An algorithm for normalizing truck performance data to account for radius of curvature differences may be required before data from more than one detector site can be combined.

The performance of series of cars can be analyzed in a similar way to single cars. The variation of performance of cars within a series is small enough to allow different car series to be compared.

Examples have been found and presented where the effect of maintenance work is reflected in improved truck performance. It is anticipated that these trends and performance improvements will be found when more data is available for analysis and a site-to-site normalization algorithm has been developed.

TPD data, on a limited scale, has been examined for the capability to be used in a predictive sense. This has been supported by this FRA initiative in 2002. The SRI developments have been to extend the scale of examination of the data to the complete current *Inte*RRIS® dataset. In addition, current hybrid performance indicators / performance indices are being examined and alternatives, more directly based on vehicle condition, have been developed. In addition, site performance parameters are being investigated to evaluate site condition on an ongoing basis. Attention in the immediate future is on evaluating site condition for suitable data, applying performance parameters to "healthy" data, and determining measures of normal performance and limits thereon for available performance index data in *Inte*RRIS®.

The FRA is expected to finalize its report based on the deliverables of the pilot project to the U.S. Congress using the content of this final report. Depending on a favorable report, Congress may sanction future funding to further the statistical tools and enhance the capabilities of the VPD.

6.0 FUTURE WORK

As part of continuing work in this area of research, the AAR under a Strategic Research Initiative, is developing methods (algorithms) that will enable the prediction of appropriate maintenance interventions, based on measured vehicle or component performance, as recorded in data obtained from *Inte*RRIS®.

A generic model of the process has been developed. This is based on the assumption that "normal" behavior can be described statistically and that deviation from this condition can be detected by the deviation of measured data beyond statistically determined control limits. On detection of this deviation, appropriate regression models can be developed to assist in projecting the degradation of condition to predetermined maintenance limits.

The WILD initiative has led to the conclusion that:

- Normal behavior is relatively easy to determine and the deviation from this norm relatively easy to detect.
- Normalization of data with respect to vehicle load and speed describing degradation from the norm is very difficult to achieve. This is influenced by factors such as the lateral position of the wheel passing over the detector, the shape of the defective wheel (making results direction sensitive), etc.
- Degradation rates from first deviation from the norm to predetermined performance limits vary from a matter of days to years. This means that continuous, "dynamic" measures for degradation and updates on this information are necessary

A statistical, weighted, algorithm to predict WILD data trends has been developed and is being tested for effectiveness.