

The work described in this document was performed by Transportation Technology Center, Inc.,  
a wholly owned subsidiary of the Association of American Railroads.

# An Algorithm for Predicting Wheel Impact Load Behavior

by Scott Cummings and Harry Tournay

## Summary

Choosing the appropriate time to repair a railway component can result in savings on many levels; e.g., minimized operating disruption, evenly distributed shop work load, component life cycle maximization, appropriate maintenance, and reduced track wear/degradation. Transportation Technology Center, Inc. (TTCI) has created an algorithm that estimates wheel degradation rate and predicts time to exceedence of a performance limit.\*

The algorithm assists in the application of predictive maintenance to impact generating wheels using data from Wheel Impact Load Detector (WILD) sites. TTCI is forming a partnership with two railroads to refine the algorithm and improve its utility using data from limited car series for which maintenance information is readily accessible.

A correlation is being established between wheels exhibiting large impact loads and corresponding roller bearing damage as well as other car component damage. Additionally, the worst performing components or railcars can be identified and repaired before failure thereby reducing the overall stress state of a railroad.

To remove a wheel from service before it exceeds the performance limit, maintenance planners should be interested in the *potential* impact load that a wheel with a particular defect and state of deterioration is capable of producing. With this line of thought, the factors causing variation in impact load can act only to reduce the measured impact load from its maximum potential impact load. By assuming that the higher impact loads represent the true potential impact load, it becomes possible to trend the data based on local maxima, or the largest impacts within a limited time window.

Impact load producing wheels are a significant cost to railroads. The Association of American Railroads' Stress State Task Force has estimated that the timely removal of such wheels could save the railroads over \$25 million annually in track and fuel costs.

\*Contact the authors for the availability of the trending algorithm.



## INTRODUCTION

Wheels that are out of round or contain flat spots create vertical impact loads as they roll down the track. These impact loads can cause losses to a railroad primarily in terms of degraded, damaged, or even broken track structure and vehicle components. To combat this and other stress state problems, several types of wayside detectors have been developed and deployed across North America, including Wheel Impact Load Detectors (WILD) which have the capability to measure both static and dynamic vertical loads produced by passing wheels. TTCI has created an algorithm to assist in the application of predictive maintenance to impact-generating wheels using data from WILD sites.

Data from wayside detectors can be used to assess railcar health in two different ways: alarming and trending. Alarming refers to near-real time data analysis used to issue urgent warnings to railroads or even locomotive engineers so that potential derailment situations can be avoided. Trending is a less time sensitive process by which general behavior patterns are monitored to produce estimates or predictions of the optimal opportunities for maintenance interventions. By choosing the appropriate time to repair a component, savings can be realized on many levels: minimized operating disruption, evenly distributed shop work load, component life cycle maximization, appropriate maintenance, and reduced track wear/degradation. Additionally, the worst performing components or railcars can be identified and repaired before failure thereby reducing the overall stress state of a railroad.

## Need for an Impact Load Detector

Wheels are never exactly round and the track is never exactly flat; hence, when in motion, all wheels should exhibit some form of dynamic behavior in addition to the static wheel load. Thus, the first objective of a predictive method should be to discern between wheels produced within manufacturing and maintenance tolerances and showing “normal” dynamic behavior and those showing signs of degraded behavior. Assuming a wheel is manufactured within tolerance, any sign of degraded behavior is assumed to be due to some form of damage that causes a local discontinuity in the radius of the wheel.

The degradation rate of impacting wheels differs greatly from wheel to wheel, which motivates the development of a predictive trending methodology.

Damage to the track structure is the primary cause for concern related to wheel impact loads. However, correlation is being established between wheels exhibiting large impact loads and corresponding roller bearing damage as well as other car related damage.

## Detector Description

A WILD site consists of multiple instrumented cribs on each rail in close proximity. Each instrumented crib is outfitted with strain gages located and oriented to measure

vertical load. The cribs are strategically chosen to maximize the portion of the wheel circumference measured. There are currently more than 60 WILD sites installed on tangent, concrete tie track across North American railroads. Each WILD site is accompanied by an Automatic Equipment Identification (AEI) reader in order to match car number and relative wheel location with wheel load. Although WILD systems make vertical load measurements at multiple wheel circumference locations, the data provided to system users is restricted to the following:

- Wheel static load (average force measured around circumference of wheel, outliers removed)
- Wheel impact load (maximum force measured around circumference of wheel)
- Wheel dynamic load (impact load – static load)
- Wheel dynamic ratio (impact load / static load)
- Train speed
- Date
- Unique wheel identification  
(e.g., car XXXX000001 axle 2, right side)

## Length of Degradation Period

For a predictive method to be of use in scheduling maintenance, a sufficient period must exist between the detection of non-normal behavior and exceedence of a performance limit. To investigate the expected degradation period of impact load producing wheels, a sample of nearly 7,000 wheels from a variety of car types including tank, hopper, gondola, and intermodal was examined over a service period of 2 1/2 years. The degradation period was analyzed for this data set as Figure 1 shows.

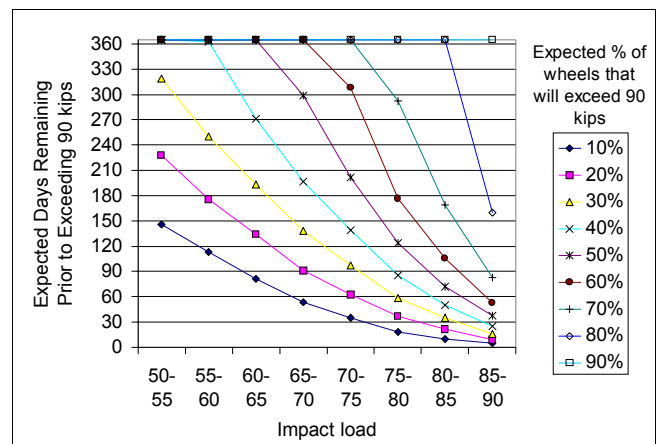


Figure 1: Expected Length of Degradation Period

Each wheel in the data set recorded a dynamic wheel load of at least 30 kips. Of these wheels, 39 percent eventually exceeded 90-kip impact load, 42 percent were repaired or replaced prior to exceeding 90-kip impact load, and 19 percent remained below 90-kip impact load with the data showing no obvious repair. Figure 1 shows the expected

percent of wheels, based on this data set, which will exceed 90-kip impact load if not repaired within a specific number of days after the first occurrence of a specific impact load range. This figure shows that a reasonable amount of time exists in which to schedule maintenance for most impact load producing wheels.

**Application of a Generic Predictive Model**

An ideal generic predictive model consists of five basic steps, as Figure 2 shows graphically:

1. Define normal behavior
2. Detect exceedence of normal behavior
3. Define performance limit
4. Determine degradation rate
5. Predict time/distance to performance limit

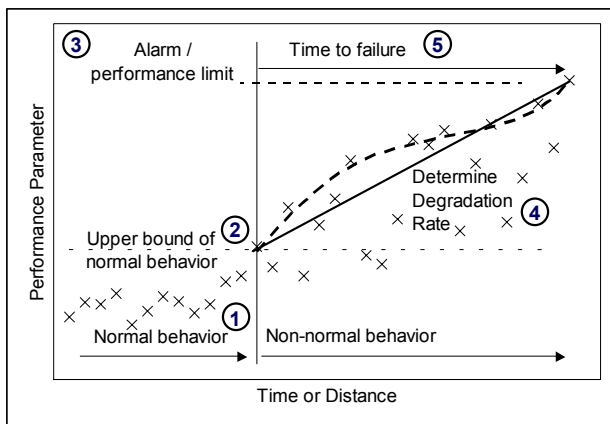


Figure 2: Generic Predictive Model

In the case of WILD data, the first step of the generic predictive model, defining normal behavior, can be established by either setting a dynamic load threshold or calculating Statistical Process Control (SPC) limits for the dynamic loads.

A major North American railroad has decided to use a 20 kip dynamic load threshold to define non-normal behavior. Although this may not be sufficient for a root cause analysis, the authors have accepted this threshold as adequate for the purposes of predictive maintenance. The detection of non-normal behavior then is simply identifying wheels with dynamic loads greater than 20 kips. AAR Interchange Rule 41 prescribes wheels to be removed from service at the car owner’s expense if the wheel exhibits impact loads greater than 90 kips. This satisfies the third step of the generic predictive model, defining a performance limit. The focus of the authors’ work related to WILD data has been the development of the final two steps, determining a degradation rate and predicting time to exceedence of the performance limit.

**Factors Causing Variation in Impact Loads**

Several independent experiments have been conducted in which a series of known impact causing wheels were placed

in a “hospital train” and pulled across a WILD site.<sup>1,2</sup> From these tests, it has been determined that the impact load a WILD measures can be influenced by the following factors:

- Wheel static load (sprung and unsprung mass)
- Train speed
- Track stiffness
- Wheel radial runout geometry
- Sub-optimal defect contact

The static load has been observed to influence the magnitude of both the static and dynamic portion of the impact load. An increase of a certain magnitude in static load usually corresponds to a larger increase in impact load.

Generally, wheels under a heavier static load exhibit a larger increase in impact load with increasing speed than wheels under a lighter static load. Some wheel defects exhibit a fairly linear increase of impact load with respect to increasing speed, up to a worst-case speed usually between 50 and 70 mph, while other wheel defects show almost no relationship between speed and impact load.

Although the track stiffness will increase during the winter in cold climates, the fact that WILD sites are all located on tangent main lines in sections with concrete ties lends some consistency to this influencing factor.

The defect geometry, as quantified by measuring the radial runout, has an enormous effect on the measured impact load. In one sense, this phenomenon is necessary to perform predictive maintenance since it allows the defect severity to be monitored over time as the defect enlarges. However, the defect geometry also interacts with the static load and train speed creating problems to be discussed in the next section.

Finally, the WILD measurement is subject to some repeatability errors due to a sub-optimal contact of the defect and the rail. There is a small percentage of wheel circumference that is not exposed to an instrumented crib at a WILD site, and thus, the measured impact load can be significantly less than the actual impact load produced by the wheel. Also, the wheel defect may not encompass the entire lateral dimension of the wheel tread, and thus it is possible for only the edge of the defect or a non-defective portion of the tread to contact the rail at the WILD site.

**Estimation of Degradation Rate and Predicted Time to Performance Limit**

With so many factors influencing the impact load, the variance of an individual wheel’s impact loads can be quite large. Most wheels pass many WILD sites during the time between defect formation and exceedence of the performance limit. In order to remove a wheel from service prior to exceeding the performance limit, a maintenance planner should be interested in the *potential* impact load that a wheel with a particular defect and state of deterioration is capable of producing. With this line of thought, the factors causing variation in impact load can act only to reduce the measured impact load from its maximum potential impact load. It is

possible to trend the data based on local maxima, or the largest impacts within a limited time window.

An algorithm was created to automatically determine a window size for selecting maxima and fit a least squares regression line to the selected points. The algorithm was designed to quickly decrease the predicted time to reaching the performance limit in the presence of sharp increases in impact load, which might be caused by a flat spot or sudden deterioration. Conversely, the algorithm was designed to slowly increase the predicted time to reaching the performance limit in the presence of non-increasing impact loads, which might be caused by one or more influencing factors causing less than maximum potential measured impact loads.

Figures 3 through 6 show example results of the local maxima algorithm applied to historical impact data from a single wheel. The line drawn to represent the predicted course of events generally becomes more accurate as the wheel impact loads increase.

Although many of the observed impact loads are less than the maximum potential impact for the wheel, the algorithm maintains an accurate prediction. This is especially evident in the final example (Figure 6) in which the predicted day for exceedence of the performance limit is correct, in spite of the relatively benign impact load at the time of the prediction.

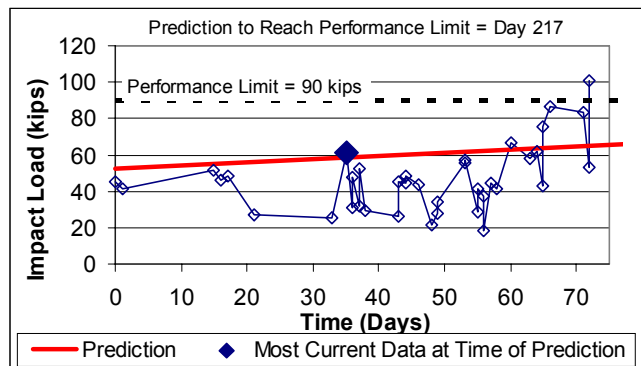


Figure 3: Local Maxima Trending Example

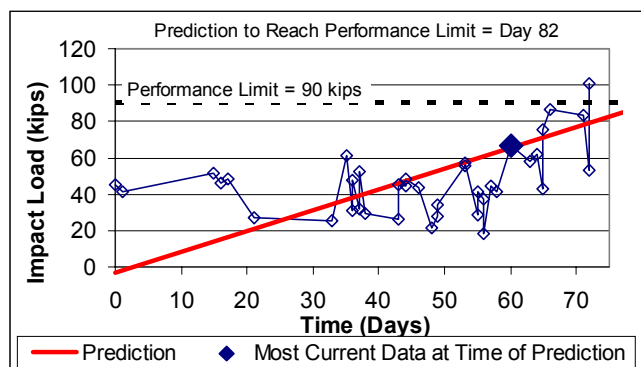


Figure 4: Local Maxima Trending Example

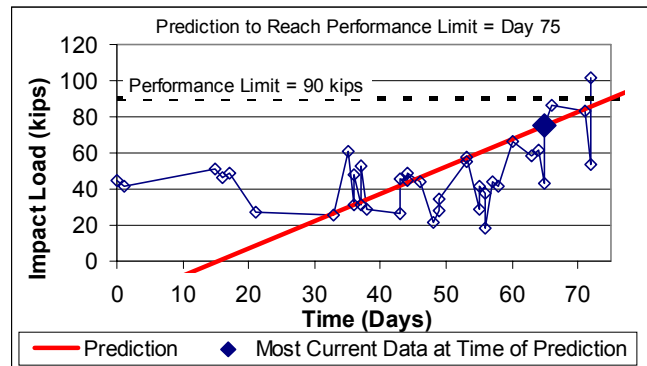


Figure 5: Local Maxima Trending Example

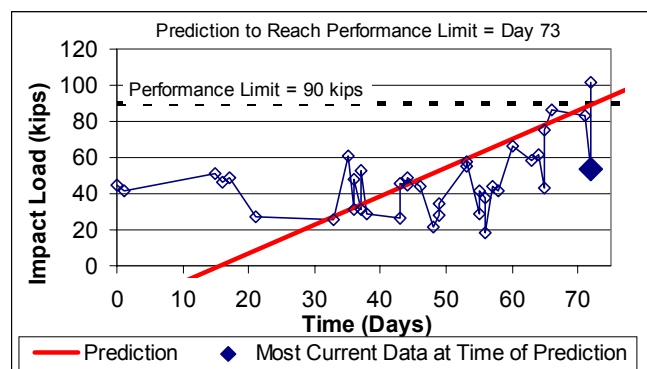


Figure 6: Local Maxima Trending Example

## CONCLUSIONS AND FUTURE WORK

A trending algorithm has been produced which estimates wheel degradation rate and predicts time to exceedence of a performance limit. The algorithm is time based and therefore more effective for wheels under cars in consistent service, such as coal cars in unit trains. A partnership is developing with two railroads to refine the algorithm and improve its utility using data from limited car series for which maintenance information is readily accessible.

Contact the authors for the availability of the trending algorithm.

## REFERENCES

1. Kalay, S., "Wheel Impact Load Detector Tests and Development of Wheel-Flat Specification," Association of American Railroads, Report R-829, May 1993.
2. de Jozef, B., Kendrik, A., and Pak, W., "Controlled tests and coal train monitoring with the Salient wheel impact detector," Report No. T-993-88, Research and Development, CP Rail System, November 1988.