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Quantification of rail transit wheel loads and development of improved dynamic and impact loading factors for design

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Abstract

An increase in the number of rail transit track construction and rehabilitation projects in North America has generated increased interest in optimizing the design of the track infrastructure and its components. Many rail transit track component design guidelines use historical wheel loads and loading factors that were derived from freight railroad design practices. These design factors may not be representative of the loading experienced on the rail transit networks today, leading to over-designed, sub-optimal infrastructure components. Therefore, researchers at the University of Illinois at Urbana–Champaign are conducting research to lay the groundwork for improved understanding of the loading environment entering the track structure using wheel loads data obtained from recently deployed field instrumentation and existing wheel impact load detectors. This paper evaluates the existing design impact factors and assesses their effectiveness when applied to the rail transit sector, using data from three representative rail transit agencies in the United States. New dynamic loading factors are also proposed to represent the rail transit loading environment more accurately. A quantitative approach to addressing design factors may provide economies in future designs and facilitate the use of probability of exceedance and other metrics that relate to factors of safety.

Keywords

Rail transit, wheel–rail interface, dynamic wheel load factor, impact factor, concrete sleeper, track components, mechanistic design

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Introduction

Understanding the loading environment at the wheel–rail interface is critical to the safe and efficient design of the track structure, its components, and their interaction with rolling stock. In the design of the track superstructure, knowledge of input loads also facilitates proper interpretation of other track structure responses (e.g., rail deflections, crosstie bending moments, thermal effects, etc.), and provides a baseline for determining how wheel loads are distributed and attenuated as they pass through the track structure. While it is well-understood that moving wheels produce a higher load than the same wheel at rest,[1] predicting the totality of the loading environment at the wheel–rail interface is non-trivial. This is because the total load is not always related to the vehicle's static load in a linear manner, and the degree of non-linearity and overall variability may change from mode to mode.

Developing accurate models for predicting dynamic and impact wheel load factors is critical to the efficient design of railway track structures and components given that load factors may be inconsistent across various types of track infrastructure and rolling stock. The current method of assessing a constant impact factor of three for concrete crosstie design as described by AREMA[2] and use of a wheel load dynamic factor of 1.33 to account for speed as described by Talbot and documented by Hay[3] is likely sub-optimal. In recent years, the collection of a large

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amount of rail transit field data has been undertaken, and these data on wheel–rail input loads facilitate generation of empirical relationships reflective of the current loading environment.

For the heavy axle load (HAL) freight railroad operating environment, research has been conducted to quantify the load at the wheel–rail interface.[4–7] To date, there has been comparatively little work conducted on rail transit systems, although commuter rail systems have been studied when their rolling stock operates on infrastructure owned by freight or intercity passenger rail operators.[8] It is hypothesized that the health of wheels found on rail transit rolling stock is quite good, due to more frequent wheel trueing and other forms of vehicle and track maintenance; thus, they likely generate lower dynamic and impact loads. Beyond static load and speed, which are widely considered to be the most critical variables, total wheel–rail interface loads have been shown to be influenced by wheel diameter, the portion of static load that represents the unsprung mass, presence of irregularities in track structure, track maintenance conditions, and a variety of other vehicle and track characteristics.[5,9,10] All of the aforementioned factors are expected to vary when comparing rail transit operations with HAL freight railroads, further emphasizing the need for research to quantify rail transit load factors.

Types of loads

The railway track loading environment includes the application of static, quasi-static, dynamic, and impact loads.[11] The static load is the load of the rail vehicle at rest and the quasi-static load is a low-frequency oscillation applied over the static weight,[12] which is the combined static load and effect of the static load at speed.[13,14] Dynamic loads are due to the high-frequency effects of wheel/rail interaction, considering track component response and involving inertia, damping, stiffness, and mass. Impact loads, which often create the highest loads in the track structure, are generated by track and/or wheel irregularities.

Prior literature discusses the distinctions among static, dynamic, and impact loads, their potential implications on the health of the track structure, and our ability to predict their magnitude.[9,11] After a brief discussion of rail transit static and dynamic loads, the remaining sections of this manuscript will discuss an approach used to quantify the totality of the track loading environment, as measured at the wheel–rail interface.

Static loads. Researchers at the University of Illinois at Urbana–Champaign (UIUC) conducted a data collection and processing effort to quantify static rail transit rolling stock wheel loads.[8] Graphical results from this study are shown in Figure 1 for the majority of rolling stock used on light, heavy, and commuter rail transit properties in the United States.[8] AW0 loads are the as-delivered, ready to operate static loads, and AW3 loads represent the AW0 load with an additional "live load" of six passengers/square meter. The AW3 load is typically referred to as the "crush" load of a vehicle, and is widely considered to be the most representative load to use for the design of the track superstructure and its components.[8] These data are useful for developing a baseline to compare the additional loads that are applied due to dynamic and impact

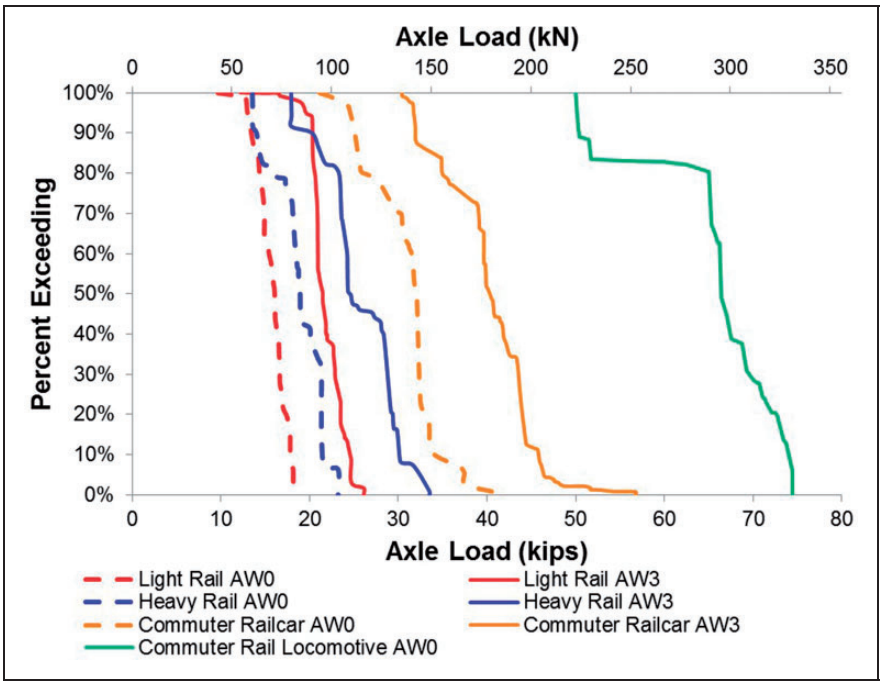

Figure 1. Light rail, heavy rail, and commuter rail static axle load percent exceeding distribution.[8]

forces. Additionally, they illustrate the wide variety in the three most common rail transit mode's axle loads, and the error that would likely result from an attempt to design components and systems that are globally optimal to all three rail transit modes.

Dynamic and impact loads. Many methods have been developed to predict dynamic loads, which have been summarized in prior research by Doyle[9] and Van Dyk,[4] and a subset of these methods were empirically generated using field data from their respective modes of rail transport. These predictive methods include a variety of track loading, health, and rolling stock design factors, as was documented by Van Dyk (2017). Much of the prior research has focused on the evaluation of dynamic impact load factors for HAL freight trains,[4,11,15] partially due to the widespread deployment of wheel impact load detectors (WILDs) on HAL freight railroad corridors in North America.

Despite the large number of methods and equations generated to predict dynamic loading conditions, researchers have noted that many methods significantly overestimate the magnitude of loads imparted into the track structure for HAL freight applications.[4,15] Additionally, it has been noted that many of the prediction tools also overestimate the loads in the rail transit loading environment, leaving room for further refinement given sufficiently large and accurate data sets.[10,16]

The prediction of impact loads, and its incorporation into design, is comparatively simpler. According to AREMA,[17] impact loads are incorporated into recommended design practices for concrete crossties as a 200% increase over the static load, or three times static load.

Revised dynamic and impact load factors. Use of the vast majority of the aforementioned dynamic factors is limited to a specific operating environment, limiting the breadth of their application and depth of their usefulness. As these factors have been developed over many years in different regions of the world, they may not accurately reflect the operating conditions found in North America, especially for rail transit applications. Additionally, prior research has shown that the impact factor of three may overestimate the flexural demands that are required under revenue service train operation.[18]

To improve the prediction of input loads at the wheel–rail interface and address a key step in the process of executing mechanistic design for track components as outlined by Van Dyk et al.,[19] the authors are developing revised predictive equations from field data. Given the design of the rail infrastructure requires knowledge of the total loading (total increase over static) that is expected, the loading factors in this paper include account for static, dynamic, and impact loads on rail transit systems. Additional mention will be made of dynamic loads and the need to relate wheel–rail load to speed.

To generate revised formulae inclusive of both dynamic and impact loads, focused field instrumentation was deployed and WILD data were used to compare actual loading data to predicted dynamic loads and impact factors. These data were collected or obtained for light, heavy, and commuter rail transit systems.

Data collection methodologies

Wheel impact load detector data

A WILD consists of rail-mounted strain gauges installed over a series of ballast cribs that are oriented in a manner that captures vertical rail strain which can be related to wheel loads[4,7] (Figure 2). A typical WILD site is over 15 meters (50 feet) in length, with cribs instrumented at various intervals to capture a single wheel's rotation five times, recording peak impact and average forces at a data collection rate of up to 25,000 hertz (Hz).[6,20] Using an algorithm that analyzes variability along the site, these average, or nominal, forces are filtered from the peak loads to obtain an estimate of static wheel load.[4] The peak wheel load is simply the highest recorded

Figure 2. Wheel impact load detector (WILD) field site on Amtrak's Northeast Corridor at Edgewood, MD, used to capture the MARC commuter rail train loads described in this paper.

measurement from the strain gauges along the length of the WILD. While the WILD has traditionally been used by infrastructure and rolling stock owners to identify poorly performing wheels, it has also proven to be a practical mechanism for producing reliable wheel load data that can serve rail infrastructure researchers and rail industry practitioners.[4,11,21,22]

WILD sites are constructed on tangent track with concrete crossties, typically with premium ballast, and well-compacted subgrade to reduce sources of load variation within the track structure due to track geometry and support condition irregularities.[4] Although loads experienced at other locations along the railway network may have higher magnitudes due to track geometry and support deviations, these data still provide relevant loading information and are useful in deriving equations for the expected loading environment.[19]

Focused loading environment instrumentation deployed by UIUC

Specifically designed, focused strain gauge instrumentation was deployed by UIUC to collect wheel–rail interface input loads on rail transit systems that did not have WILDs. Weldable 350 ohm half-bridge shear strain gauges (Figure 3) were applied to the web of the rail to create vertical load circuits using the same configuration used at a single crib of a WILD site (Figure 4).

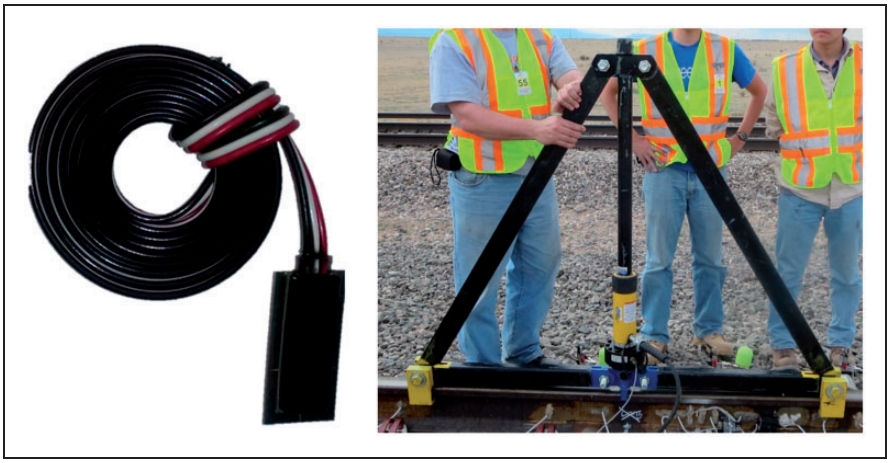

Figure 3. Weldable half-bridge shear strain gauge (left) and loading frame used to calibrate gauges by relating strain to known system input load (right).

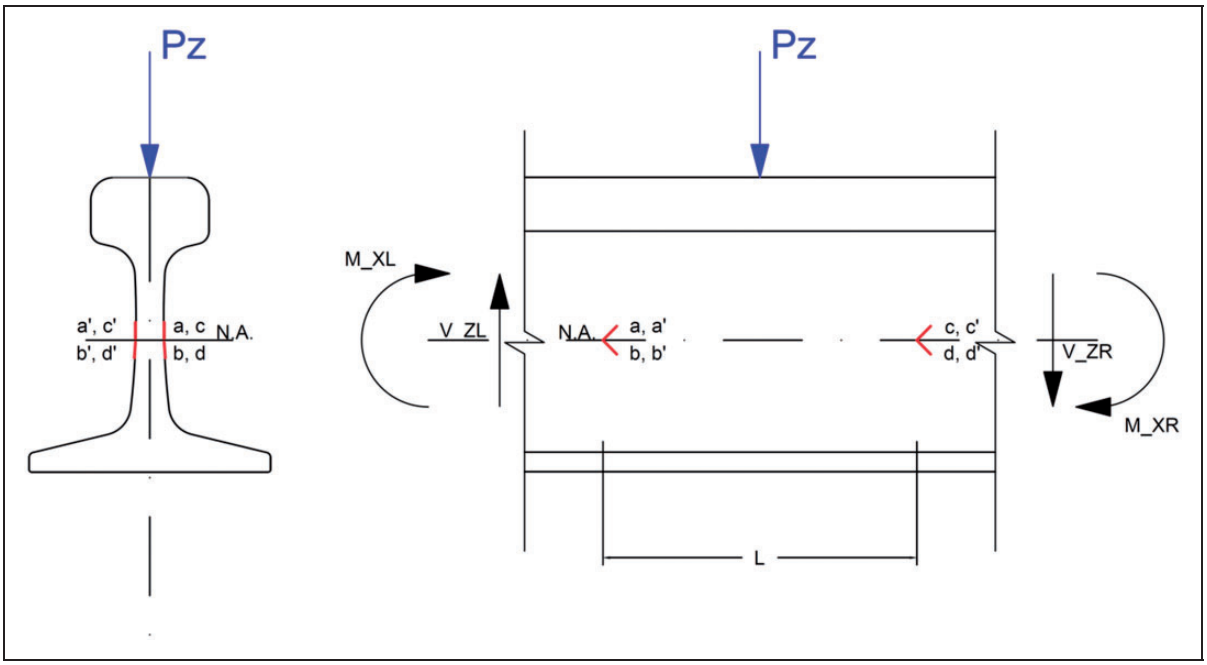

Figure 4. Vertical strain gauge orientation for field testing (strain gauges for quantifying lateral load were also deployed, but are not shown due to the scope of this article).

Installation of strain gauges on the rail required welding gauges to the rail using a portable strain gauge welding unit. This process involved first grinding the web and base of the rail to remove rust and expose pure metal, then clamping a ground wire to the base of the rail, and lastly placing the strain gauge and using the welding electrode to send current through the material, welding the strain gauge to the rail.

UIUC's Delta Frame (Figure 3, right) was used to calibrate the strain gauge instrumentation installed on the rail via application of vertical loads of up to 20,000 lbf (88.9 kN). The Delta Frame uses a hydraulic cylinder to apply loads. Vertical loads are applied using an upward facing steel triangular frame with loads applied in the center of the bottom side of the frame and reacting off the rail at the two bottom corners (Figure 3). Vertical load and strain are collected simultaneously throughout the calibration process, providing the opportunity to relate future strain readings obtained from the instrumentation to the vertical wheel load that generated them.

Interpretation of data and generation of results

As the data presented in this paper were acquired using related but distinct instrumentation methodologies, some clarification on the data collection differences is warranted. WILD sites collect data over many adjacent cribs to measure the full revolution of the wheel, whereas the UIUC-deployed instrumentation collects data at a single crib and does not capture the full rotation of a wheel. While the method deployed by UIUC has the limitation of not being able to know whether the peak load from a wheel is obtained during a given train pass, it captures every train pass on a captive rail transit system over long periods of time (c.a. one year). This volume of data helps to reduce variability and obtain readings from the entire circumference of a wheel.

Data analysis

Comparison of impact factor curves

The evaluation of rail transit wheel–rail interface input loading conditions was performed using data from three rail transit field sites in the United States:

- Light Rail Transit—St. Louis MetroLink at Fairview Heights, Illinois, hereafter referred to as "MetroLink,"
- Heavy Rail Transit—Metropolitan Transportation Authority (MTA) New York City Transit Authority (NYCTA) at Far Rockaway, New York, hereafter referred to as "NYCTA," and
- Commuter Rail Transit—Maryland Area Regional Commuter (MARC) at Edgewood, Maryland, hereafter referred to as "MARC."

These aforementioned rail transit properties are representative of current United States operations for each of the respective rail transit modes, in terms of operating speeds, axle loads, and materials used in the track structure. There are, however, limitations to the selection of discrete transit operators and field sites, given the intrinsic variability that occurs longitudinally along a railroad associated with the health of the track structure.

The former two sites (MetroLink and NYCTA) used UIUC-deployed instrumentation and the latter is a WILD site owned by Amtrak (Figure 2). For data collected from UIUC instrumentation on NYCTA, given there are not enough instrumented cribs to capture the nominal wheel load like a full WILD site, the AW0 weight (provided in the Federal Transit Administration (FTA) National Transit Database[23]) is used as the nominal load, and the measured loads were used for the "peak" load. The peak load is then divided by the nominal AW0 weight to obtain the impact load factor. As delivered wheel loads were supplied by MetroLink and were used for the nominal loads in lieu of AW0 loads at the MetroLink site, given the need to better account for wheel-to-wheel nominal load variability of the light rail vehicles (LRVs). These assumptions are conservative with respect to their estimation of impact load factors, given that actual weight of the railcar could be as high as its AW3 load, depending on passenger loading.

A histogram of peak wheel loads for each rail transit mode (Figure 5) reveals the variety in input loads as measured in the field and further emphasizes the disparity in loading as was shown in Figure 1 using only nominal loads. Additionally, when plotting the total (dynamic and impact) load factors for each rail transit mode (Figure 6), it is evident that that the three rail transit systems have distinct distributions of impact factors that are reflective of three unique relationships that capture the total loading environment that is applied above the static (AW0) loads.

Next, we use descriptive statistics to compare the three distributions of impact factors to determine if they were from the same sample distribution (Table 1).

In comparing the three distributions, the means were found to be similar between MARC (1.26) and NYCTA (1.23), but the variance and skewness is notably higher for the MARC data. Additionally, the standard deviations were quite different, as would be expected based on visual inspection of the data. These statistics lead us to the conclusion that the three distributions are unique and are not represented by a single distribution that would accurately represent a collective impact factor estimate.

Additional statistics were also employed in an attempt to reject the null hypothesis that the impact factor data are drawn from the same dataset (e.g., distribution function). Rejection demonstrates that the distributions are unique and the data are not drawn from the same distribution for all three rail

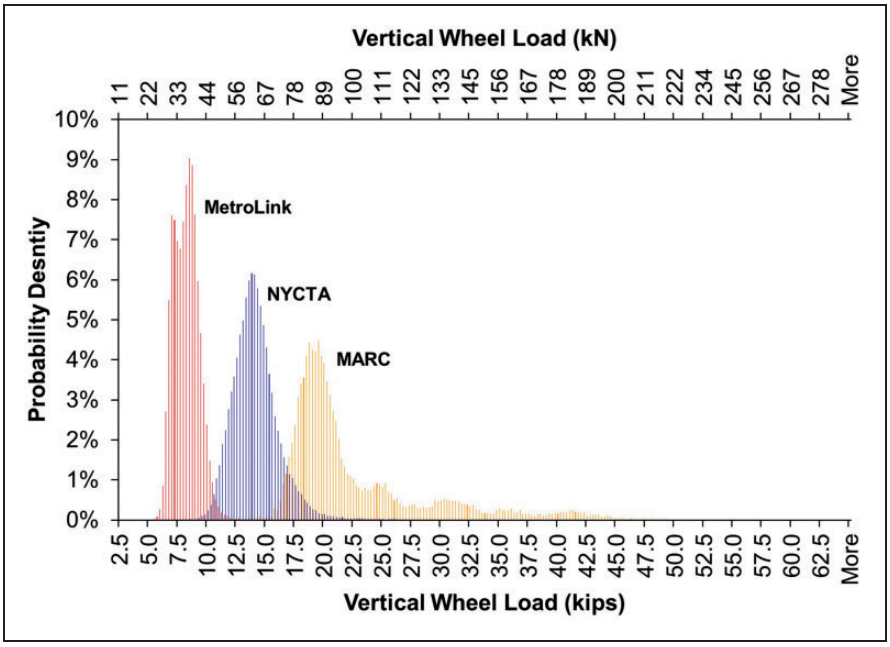

Figure 5. Histogram showing distribution of vertical wheel–rail loads from three rail transit systems (MetroLink, NYCTA, and MARC).

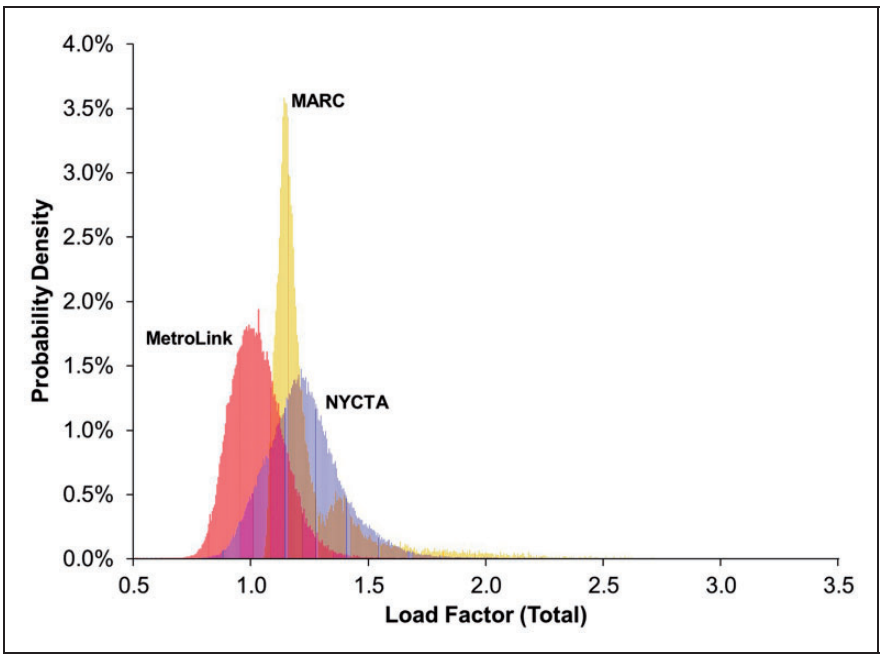

Figure 6. Histogram showing distribution of dynamic and impact load (total load) factors from three rail transit systems (MetroLink, NYCTA, and MARC).

transit modes.[24] To reject the null hypothesis, the Kolmogorov–Smirnov (K-S) test was completed given our impact factor data are continuous.[24] All of the K-S p values were found to be zero when comparing the three distributions to one another, indicating that we can reject the null hypothesis that the three distributions are from the same dataset. Therefore, with significant confidence, we can state that all three types of rail transit systems surveyed have unique distributions of impact factors. Confirmation of the three distributions being dissimilar has significant implications on track component design factor assumptions and demonstrates the need for unique design assumptions for each rail transit mode.

Distribution fitting and quantification of goodness of fit

Next, we aim to develop generalized relationships to fit the distributions of impact factors for the three rail

transit modes, to facilitate estimation of the percentage of loads that are included when selecting future impact factors. This evaluation was made using the distribution fitting feature in the commercially available software EasyFit (by MathWave Technologies), which is able to determine the most appropriate distribution(s) for a set of continuous data using approximately 65 typical distributions (e.g., log-logistic, Gamma, normal, Weibull, etc.) for comparison and fitting purposes.

In addition to application of the K-S test, the Anderson–Darling statistical procedure was used to compare the distribution of load factors for each transit system to the aforementioned common distributions. The Anderson–Darling method is particularly useful for this application given that it increases the power of the K-S statistic to investigate the tails of the distribution and produces a weighted statistic.[24,25]

Table 1. Descriptive statics comparing rail transit impact factor data from MARC, MetroLink, and NYCTA.

Statistic	MARC	MetroLink	NYCTA
Sample size	28,920	62,472	131,062
Range	2.9972	1.5372	4.6522
Mean	1.2583	1.0231	1.229
Variance	0.05745	0.01316	0.0368
Standard deviation	0.2397	0.11473	0.19184
Coefficient of variation	0.19049	0.11214	0.1561
Standard error	0.00141	0.00046	0.00053
Skewness	3.2837	0.61599	2.4371
Excess kurtosis	15.038	1.4685	17.537

This is important given our railway engineering application, and the criticality of the tail of the impact factor distribution to the design of future railway track infrastructure components.

The best-fit (optimal) distribution was then selected using the Anderson–Darling criteria and was plotted with each rail transit impact factor field data set (Figure 7). Of specific interest is how the tails are fitted, which is shown in greater detail in Figure 8 for the maximum 0.10% of impact factors. The extreme values for impact loads also show significant scatter for the MARC commuter rail-loading environment. It is likely that this greater variability is due to the capture of multiple cribs of data at the WILD location.

Goodness of fit rank order values for the K-S method and Anderson–Darling are shown for all three rail transit modes in Table 2. Based on the results from Table 2, it is evident that the three distributions' tails are best fit using a variety of different functions, with little overlap among the generalized distributions. This further accentuates the fact that the variables that impact the total load factor are unique for each location and rail transit modes that were examined.

The generalized distribution that provided the best fit as ranked by the Anderson–Darling criteria for each of the three modes was as follows: Log Pearson for MetroLink (equation (1)), Frechet for MARC (equation (2)), and Dagnum for NYCTA (equation (3)). All these distributions were shown in Figures 7 and 8 along with a histogram of the field data. Equations (4) to (6) provide the specific distributions that represent the data for MetroLink, MARC, and NYCTA, respectively, by inclusion of

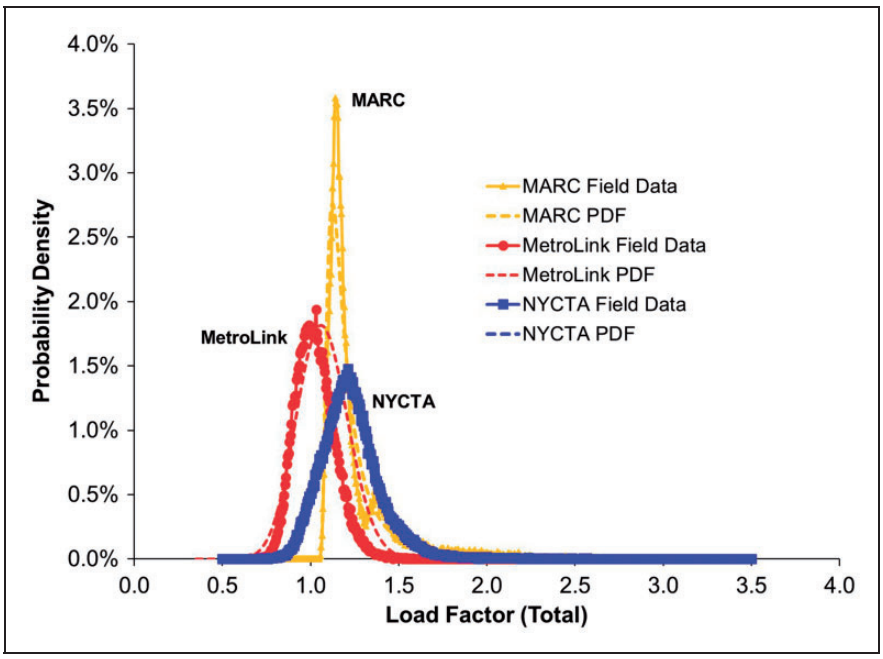

Figure 7. Total load factors for from three rail transit systems (MetroLink, NYCTA, and MARC) and overlay of best-fit distributions.

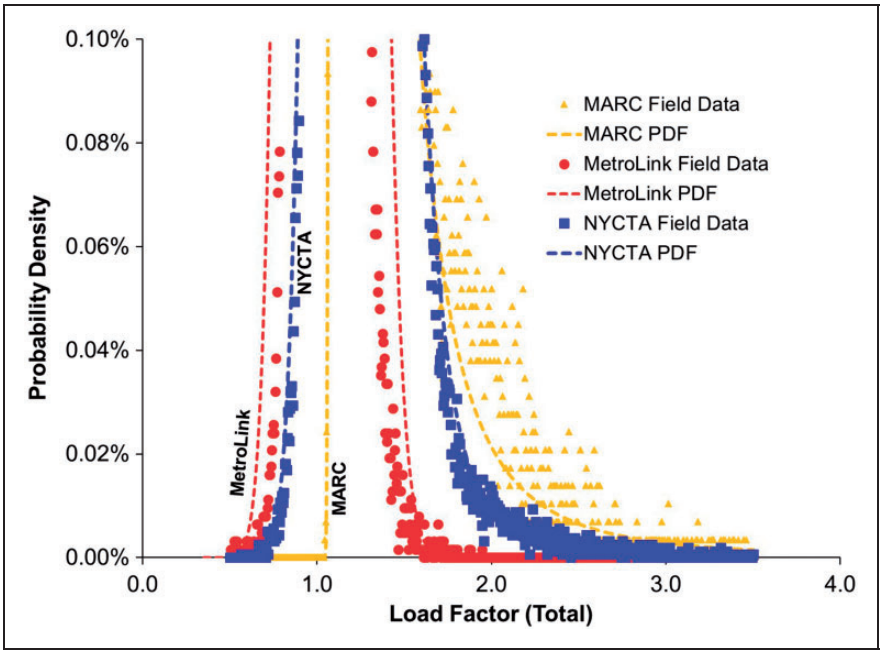

Figure 8. Extreme values (highest 0.10%) of Total Load Factors for from three rail transit systems (MetroLink, NYCTA, and MARC) and overlay of best-fit distributions.

Table 2. Ranking of goodness of fit comparisons of rail transit impact factor distributions using the K-S and Anderson–Darling methods to compare common distribution functions (sorted by Anderson–Darling rankings of MetroLink data).

	Kolmogorov–Smirnov			Anderson–Darling		
Distribution	MARC	MetroLink	NYCTA	MARC	MetroLink	NYCTA
Log-Pearson 3	14	2	25	44	1	37
Pearson 6 (4P)	7	5	11	4	2	9
Lognormal (3P)	11	6	12	8	3	11
Pearson 6	26	7	16	23	4	14
Pearson 5	28	3	15	24	5	12
Dagum (4P)	24	13	1	22	7	1
Pearson 5 (3P)	2	4	10	2	8	10
Gamma (3P)	22	12	20	14	13	17
Dagum	35	15	6	54	14	5
Burr (4P)	10	17	4	12	15	3
Log-logistic (3P)	6	19	3	5	17	2
Beta	31	18	14	13	18	13
Burr	12	21	2	13	19	4
Gen. extreme value	3	1	9	3	20	8
Frechet (3P)	1	38	38	1	37	34

distribution parameters that best fit the data. Despite the large number of common distributions checked, the p values for all data except MetroLink do not allow for rejection of the null hypothesis using an alpha value of 0.05. The Anderson–Darling rejection criteria were not met for any of the three distributions shown; thus, the distributions are all considered to be different than the sample data.

In spite of these results, the equations that were generated provide value given the level of accuracy that is needed for this particular design application. Specifically, the equations allow for future calculations of impact loads considering different percentile loading conditions (e.g., designing to the 99th percentile load). This type of calculation is an integral part of a probabilistic or mechanistic design process.

Log Pearson Distribution

$$F(x) = \frac{\Gamma_{(\ln(x)-\gamma)/\beta}(\alpha)}{\Gamma(\alpha)} \tag{1}$$

Frechet Distribution

$$F(x) = \exp\left(-\left(\frac{\beta}{(x-\gamma)}\right)^{\alpha}\right) \tag{2}$$

Dagum Distribution

$$F(x) = \left(1 + \left(\frac{x-\gamma}{\beta}\right)^{-\alpha}\right)^{-k} \tag{3}$$

MetroLink Best Fit

$$F(x) = \frac{\Gamma_{(\ln(x)+1.593)/0.0076}(211.83)}{\Gamma(211.83)} \tag{4}$$

MARC Best Fit

$$F(x) = \exp\left(-\left(\frac{0.14201}{(x-1.0094)}\right)^{1.9514}\right) \tag{5}$$

NYCTA Best Fit

$$F(x) = \left(1 + \left(\frac{x-0.55114}{0.6611}\right)^{-7.2334}\right)^{-0.95689} \tag{6}$$

In addition to the previous analysis of load factors, we have also summarized the aforementioned rail transit datasets by their percentile vertical loads in Table 3 and their dynamic or impact load factors in Table 4. It is interesting to note that MetroLink has both a lighter load *and* lower impact factor than either NYCTA or MARC. While the lower load is expected due to the static wheel loads, the lower impact or dynamic load factor is not necessarily expected to be lower. These values could also be used to estimate the percentage of loads that would be covered by a given design factor.

While further study is warranted as to why the impacts are lower for St. Louis MetroLink's light rail vehicles, the authors surmise that the differences in the suspension system of the trucks, wheel health, resilient (i.e., sandwich composite) wheel construction, and track health and degradation rates play a role in reducing these impacts compared to the other two systems. These factors are also noted in many of the aforementioned dynamic load factor equations summarized by Doyle[9] and Van Dyk.[4]

Development of improved dynamic/speed factor

To determine the influence of speed on the vertical loads imparted into the track structure, an accurate measurement of speed was needed for each vertical load reading. Speeds from train passes at the UIUC's instrumented locations were calculated using the time between measured loads and known axle spacing, and speed is provided as a direct output of WILD systems. Using the speed and wheel load data, loads were categorized into bins of speeds including no more than 8 kilometers per hour (5 miles per hour) for UIUC-installed instrumentation and 16 kilometers per hour (10 miles per hour) for the WILD data. For bins with more than 20,000 data points, data were subdivided until the bin contained fewer than 20,000 data points. Each speed bin was

Table 4. Distribution of dynamic/impact load factors from three rail transit systems (MetroLink, NYCTA, and MARC).

Mode	Mean	10%	50%	75%	90%	95%	97.5%	99.5%	100%
MetroLink	1.02	0.89	1.01	1.09	1.17	1.22	1.27	1.39	1.94
NYCTA	1.23	1.03	1.21	1.32	1.44	1.54	1.64	2.11	5.21
MARC	1.26	1.10	1.17	1.28	1.50	1.76	1.99	2.47	4.04

Table 3. Distribution of vertical loads from three rail transit systems (MetroLink, NYCTA, and MARC).

Mode	Mean	10%	50%	75%	90%	95%	97.5%	99.5%	100%
Measured load (in kilopounds)									
MetroLink	8.1	6.8	8.1	8.8	9.5	9.9	10.2	11.2	18.6
NYCTA	14.0	11.7	13.8	15.0	16.4	17.5	18.6	24.0	59.3
MARC (nominal)	18.1	15.1	16.7	17.7	26.8	30.7	35.2	38.0	41.1
MARC (peak)	22.7	17.5	20.1	24.4	32.2	37.8	41.5	46.7	64.6
Measured load (in kN)									
MetroLink	36.1	30.1	36.2	39.3	42.2	43.9	45.6	49.8	82.6
NYCTA	62.3	51.9	61.3	66.6	72.9	77.8	82.8	106.6	263.9
MARC (nominal)	80.7	67.1	74.2	78.7	119.1	136.6	156.5	168.9	182.9
MARC (peak)	100.8	78.1	89.3	108.5	143.1	168.1	184.4	207.9	287.4

Table 5. Summary of impact factor equations for prediction of light, heavy, and commuter rail transit wheel loads as a function of speed and wheel diameter.

	Revised dynamic/impact factor estimate equation	
Rail transit mode	SI units	Imperial units
Light	$1 + 0.0665 * \frac{\text{Speed (kph)}}{\text{Wheel Diameter (cm)}}$	$1 + 0.105 * \frac{\text{Speed (mph)}}{\text{Wheel Diameter (inches)}}$
Heavy	$1 + 0.323 * \frac{\text{Speed (kph)}}{\text{Wheel Diameter (cm)}}$	$1 + 0.510 * \frac{\text{Speed (mph)}}{\text{Wheel Diameter (inches)}}$
Commuter	$1 + 0.198 * \frac{\text{Speed (kph)}}{\text{Wheel Diameter (cm)}}$	$1 + 0.313 * \frac{\text{Speed (mph)}}{\text{Wheel Diameter (inches)}}$

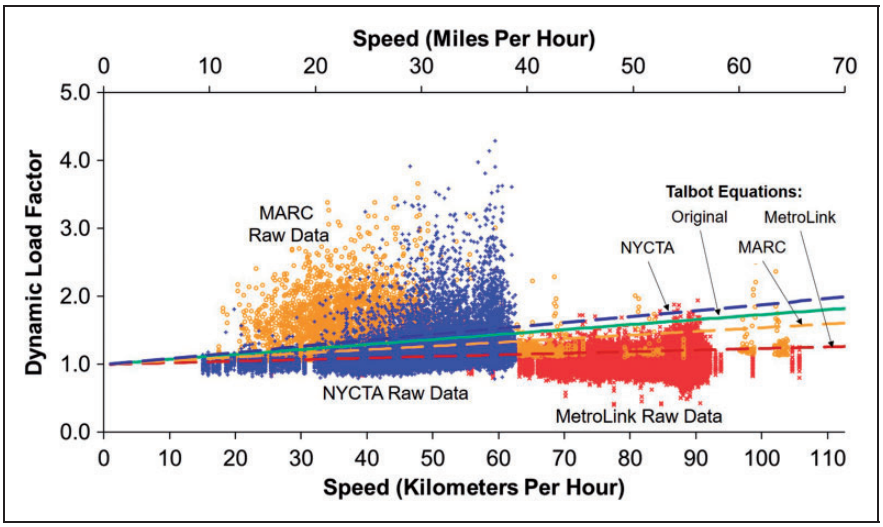

Figure 9. Raw data and predictive curves generated from field data from three rail transit modes.

analyzed to find a variety of relevant percentiles (e.g., 90th, 95th, 99th, and maximum) of wheel loads.

To better estimate the effect of speed, an estimate of wheel load data was developed using field load data, using an approach similar to that which was used by Van Dyk (2017). The Talbot equation's slope[3] was modified to minimize the sum of percent exceeding and root mean square deviation for each rail transit dataset. The change in the dynamic factor due to the aggregate of factors experienced in the field on three systems surveyed can be expressed in the three equations shown in Table 5.

Based on the slopes of these three lines, it is evident that the wheel health and track maintenance vary for each mode. Light rail transit data displayed the lowest slope (Figure 9), thus the least influence of speed on wheel–rail loads. This factor of 0.067, roughly 20% of the Talbot factor, may indicate that the dynamic factor for light rail can be reduced greatly from its current value of 0.33 (or 1.33 when added to the integer one in the equation). The heavy rail transit data, on the other hand, tend to indicate that a higher dynamic factor is required to adequately account for increased loads as a function of speed.

Conclusions

This paper presents results to quantify the aggregate effect of speed and other vehicle and track irregularities to generate accurate dynamic and impact load factors for rail transit systems. Specifically, the following conclusions can be drawn from this research:

- Total load factor distributions for the three rail transit systems were shown to be statistically different, demonstrating that unique, specific load factors are needed to adequately represent the existing wheel loads on rail transit infrastructure and improve design of the critical components that make up the track structure. All distributions would indicate that the current AREMA impact factor of three could be reduced, possibly by as much as half.

- Existing dynamic load factors were analyzed, and the Talbot approach to estimating dynamic loading due to speed and wheel diameter was found to be quite conservative, with the light rail transit loading environment being overestimated by a factor of three. Conversely, heavy rail transit factors were underestimated by approximately 50%. Finally, commuter rail transit factors matched the Talbot prediction quite well.
- For a given mode, in the absence of field data related to the track loading environment, the selection of an appropriate load factor should be based on knowledge of their track and rolling stock maintenance practices.
- Finally, this paper demonstrated that focused load-related field instrumentation could be deployed to answer system-specific loading questions within a given light rail transit mode. The modest effort required to install instrumentation and process data from such an installation could provide significant returns on investment (ROI) with respect to mechanistically designing track components.

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