Predicting Vertical Acceleration of Railway Wagons Using Regression Algorithms

G. M. Shafiullah, A. B. M. Shawkat Ali, Adam Thompson, and Peter J. Wolfs

***Abstract*—The performance of rail vehicles running on railway tracks is governed by the dynamic behaviors of railway bogies, particularly in cases of lateral instability and track irregularities. To ensure reliable, safe, and secure operation of railway systems, it is desirable to adopt intelligent monitoring systems for railway wagons. In this paper, a forecasting model is developed to investigate the vertical-acceleration behavior of railway wagons that are attached to a moving locomotive using modern machine-learning techniques. Both front- and rear-body vertical-acceleration conditions are predicted using popular regression algorithms. Different types of models can be built using a uniform platform to evaluate their performance. The estimation techniques' performance has been measured using a set of attributes' correlation coefficient (CC), root mean square error (RMSE), mean absolute error (MAE), root relative squared error (RRSE), relative absolute error (RAE), and computational complexity for each of the algorithms. Statistical hypothesis analysis is applied to determine the most suitable regression algorithm for this application. Finally, spectral analysis of the front- and rear-body vertical condition is produced from the predicted data using the fast Fourier transform (FFT) and is used to generate precautionary signals and system status that can be used by a locomotive driver for necessary actions.**

***Index Terms*—Fast Fourier transform (FFT), railway wagons, regression algorithm, vertical acceleration.**

I. Introduction

Advances in information and communication technology have enabled the adoption of machine-learning techniques in all sectors to solve real-world problems in business, engineering, and science. With the increased demand for railway services, railway condition-monitoring systems continue to advance at a remarkable pace to maintain reliable, safe, and secure operations. A system that is designed for railways to limit the risk of injury to persons or damage to property and to ensure safe and reliable operations is called a "rail-safety-management system." If a security-related incident has occurred, this system may support the operator in taking the appropriate action, communicating to the right authorities, checking the availability of rescue teams, and providing all necessary information [1]–[3].

To monitor lateral instability and track irregularities in this paper, train-wagon body-acceleration signals, i.e., six degrees of freedom (DOF) or six modes of vehicle body motion, i.e., *roll*, *pitch*, *yaw*, *lateral*, *vertical*, and *longitudinal*, are investigated using machine-learning techniques. In an earlier work [4], vertical acceleration at the front and rear location of the wagon body has been predicted using modern machine-learning techniques. In this paper, ten popular regression algorithms are used to predict vehicle vertical-acceleration motion of the wagon body. The performance of different models was assessed, and the most suitable algorithm for forecasting the vertical displacement behavior of railway wagons has been proposed based on statistical hypothesis analysis. Finally, instead of sending predicted data, only necessary events that cross the safety limits are transmitted to the driver in advance for necessary actions such as train-speed reductions.

II. Problem Description

Typical dynamic behaviors of railway wagons are responsible for the safe and reliable operation of freight railways. The dynamic performance is determined by the characteristics of the wagon and the irregularities in the track. Wagon characteristics involve wheels, bogie suspensions, load, etc. However, as an initial study, we only focus on railway track irregularities in this article. Railway track irregularities need to be kept within safe operating margins by undertaking appropriate maintenance programs [3], [5]. Examples of these include dips in track, battered joints, and kinks in alignment.

It is identified that the performance of rail vehicles running on a track is limited by 1) the lateral instability that is inherent to the design of the steering of a railway wagon and 2) the response of the railway wagon to individual or combined irregularities. The current ride monitoring systems detect incidents using peak-to-peak (PK-PK) or root mean squared (RMS) vibration magnitude levels. Monitoring of vertical accelerations to measure track irregularities and lateral instability is a current research topic. Collection of acceleration signals from the track and sending meaningful signals to the locomotive is a challenging research area. Time–frequency analysis has been used to

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efficiently transmit the signals to the locomotive. There is only limited research in terms of data throughput, data-collection procedure, and data-storing capacity. However, these systems clearly have some drawbacks in terms of energy consumption and computational cost.

III. Literature Review

The railway industry is working on developing advanced condition-monitoring systems in a progressive manner that ensures safe and appropriate operation of the railway systems. Currently, a variety of condition-monitoring systems are used to monitor track irregularities and lateral instability [6]. Generally, specialized track geometry measurement vehicles are used to determine track conditions. However, this alone is not a good predictor of railway vehicle response [3], [5]. Track geometry inspection and maintenance provide train-operating safety and reduced vehicle and track dynamic interaction. Predicting vehicle characteristics in real time from track measurement data has been addressed by various research organizations [7]–[13]. Freight wagon instrumentation studies have shown that severe dynamic forces occur when irregular defects' wavelengths and train speeds combine to excite a resonant mode in the vehicle [8].

Bonaventura *et al.* [9] introduced the ZETA-TECH Lumped Mass Model system for predicting the response of rail vehicles to measure track geometry in real time. Car-body vertical displacement (bounce), car-body roll and pitch angles, vertical wheel/rail forces, and vertical car-body accelerations are predicted with this system. These characteristics are used to assess the safe behavior of the vehicle [9]. An autonomous ride monitoring system (ARMS) developed by Amtrak [10] monitors peak and RMS acceleration on the 10-Hz low-pass filtered signal in accordance with standard requirements outlined by the Federal Railroad Association (FRA) [14]. This system measures wagon body and bogie motions, detects various acceleration events, and tags them with GPS time and location information. This information is then delivered to central processing stations via a wireless communication system. To ensure reliability and availability, there are multiple levels of protection and redundancy in this system [10]. However, the established wireless communication techniques for the ARMS are not energy efficient, and the features of its GPS have made the application difficult. There are great possibilities of malfunctioning due to the absence of satellite signals.

Rete Ferroviaria Italiana (RFI) [15] plays a key role in developing a modern, safe, reliable, and interoperable rail network for Italy. RFI is undergoing a technological evolution for the building of tracks and for train circulation. The Integraph Italia developed a technology to support RFI and is working to develop a real-time video system, record the impact of natural phenomena, and manage railway line faults. They have used forecast indicators to identify the characteristics of rail overheating due to high temperature, train-operating difficulties due to snow and intense wind, and landslide alert because of great rainfall. By using modern machine-learning techniques, it is possible to identify the above characteristics more efficiently with less cost than the existing system.

Popular machine-learning techniques are a new research area for railway monitoring. Some work has already been done using machine-learning techniques to monitor railway wagons. Nefti and Oussalah [16] used artificial neural network (NN) architecture to predict malfunctioning of railway systems due to track irregularities. Different NN structures are created to find out the best structure for predicting railway safety. Experimental analysis showed that the model satisfactorily performed and can predict the desired output with a very low error factor.

Li *et al.* [17] investigated a machine-learning approach to automate the identification process of railroad wheel defects using collected data from wheel inspections. A decision tree and a support-vector-machine (SVM)-based classification scheme were used to analyze the railroad wheel inspection data. The experimental results indicate that the classifiers learned are able to identify failing wheels with an accuracy of 76% [18]. However, typical applications like railroad wheel inspection demanded higher prediction accuracy.

Linear regression (LR) analysis was used to predict the dynamic characteristics of worn rail pads. The curve fitting approach showed the maximum correlation of dynamic stiffness and damping of worn rail pads under preloads while achieving less than 4% error for all pads. LR analysis was used to predict the deterioration rate with the age of dynamic stiffness and damping coefficients [19].

The Centre for Railway Engineering (CRE), Central Queensland University (CQU), has been investigating a health-card system [13] to monitor the dynamic behavior of a fleet of wagons throughout their service life. This is an autonomous device mounted on the body of each wagon for onboard analysis of car-body motion signals to monitor track conditions and prevent derailment. The health card is capable of resolving car body motions into six DOF. To do this, the health card uses accelerometers and angular rate sensors with a coordinate transform. The health-card system uses fast Fourier transform (FFT) to efficiently convert the signal into a time–frequency spectrograph so that events can be detected according to their short-term spectral content. An algorithm was developed to analyze signals from accelerometers that are mounted on the wagon body to identify the dynamic interaction of the track and the rail vehicle. From spectral analysis, it has been found that small residual responses exist in the pitch and yaw DOF and that the wagon was not laterally constrained [5], [13]. However, absence of energy-efficient features for data collection and communication between wagons to the locomotive make this system inefficient.

This paper is an extension of the existing health card system, which improves its drawbacks and makes an energy-efficient railway health-condition-monitoring system. Based on the problem description and literature review, an energy-efficient condition-monitoring system to monitor the vertical acceleration behavior of railway wagons has been investigated using machine-learning techniques. This paper is organized as follows: Section IV presents the regression algorithms that are considered in this paper; experimental setup is discussed in Section V; experimental outcomes are presented in Section VI; results and analysis are discussed in Section VII; Section VIII discusses statistical analysis; test results are discussed in

Section IX; spectral analysis takes place in Section X; and Section XI concludes this paper with future directions.

IV. Regression Algorithms

Regression analysis is the most significant and popular machine-learning area for future decision-making or forecasting of data or any incidents. Currently, various statistical forecasting and regression approaches are used to monitor railway wagons to ensure safety and security. Here, the popular regression algorithms that are used to develop a condition-monitoring system to predict front- and rear-body vertical acceleration of railway wagons are described. Rule-based learning algorithm M5Rules [20], Tree-based learning M5Prime (M5P) [21], [22], RepTree [20] and decision stump [21], metabased learning random subspace (RSS) [23], lazy-based learning instance-based *k* classifier (IBK) [20], [24], regression-based learning simple LR (SLR) and LR [25], [26], statistical-based learning algorithm SVM regression [20], [27], and NN-based multilayer perception (MLP) [27]–[29] are considered in this paper to develop the model to forecast the vertical acceleration behavior of railway wagons.

M5Rules: M5Rules create rule sets on continuous data and produce propositional regression rules in an if–then rule format. It dictates that an attribute is considered as a class and then looks at the attributes and begins to construct rules that will produce the specific continuous class value [20].

M5P: M5P is useful for numeric prediction. It is a rational reconstruction of Quinlan's M5 model tree inducer. Decision trees were designed for assigning nominal categories. M5P extended the decision trees by adding numeric prediction by modifying the leaf nodes of the tree [21], [22].

RepTree: RepTree is a fast regression tree that uses information gain/variance reduction and prunes it using reduced-error pruning. RepTree deals with missing values by splitting instances into pieces. Optimized for speed, it only sorts values for numeric attributes once [20].

Decision stump: This learning algorithm builds simple binary decision "stumps" (one-level decision trees) for numeric and nominal classification problems. It deals with missing values by treating "missing" as a separate attribute value [21].

RSS: RSS is a method used to construct tree-based classifiers whose capacity can be arbitrarily expanded for increases in accuracy for both training and unseen data. Random subsets are selected from the training set, and a model is built up using each subset [23].

IBK: Instance-based learning algorithms are derived from the nearest neighbor machine-learning philosophy. IBK is an implementation of the k-nearest neighbor's algorithm. The number of nearest neighbors k can be set manually or determined automatically. Each unseen instance is always compared with existing ones using a distance metric. The default setting of the Waikato Environment for Knowledge Analysis (WEKA) [30] is $k = 1$ [20], [24].

LR: Regression analysis [25], [26] is a statistical forecasting model that addresses and evaluates the relationship between a given variable (dependent) and one or more independent variables. The major goal in regression analysis is to create a mathematical model that can be used to predict the values of a dependent variable based on the values of any independent variable.

It is a regression method that models the relationship between a dependent variable Y, independent variables X_i, where $i = 1, \ldots, p$, and a random number ϵ. The model can be written as

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon. \quad (1)$$

This method is called *linear* because the relation of the dependent variable Y to the independent variables X_i is assumed to be a linear function of the parameters.

The regression model is used to predict the value of Y from the known value of X and to find the line that best predicts Y from X. LR does this by finding the line that minimizes the sum of the squares of the vertical distances of the points from the line. It assumes that all the data are linear and will find the slope and the intercept that make a straight line best fit for training data. The goodness of fit and the statistical significance of the estimated parameters are a matrix of regression analysis. Commonly used checks of goodness of fit include the r-squared value. The coefficient of determination r^2 is the proportion of variability in a data set, and the value of r^2 is a fraction between 0 and 1. If r^2 is equal to 1.0, all points lie exactly on a straight line with no scatter; this is called the best-fit situation.

An SLR is an LR in which there is only one covariate and is used to evaluate the linear relationship between two variables [25], [26].

SVM regression: SVM is a statistical-based learning algorithm, which has been widely used for binary classification. SVM models can usually be expressed in terms of support vectors and can be applied to nonlinear problems using different kernel functions. Based on the support vectors' information, SVM regression produces the final output function. WEKA [30], by default, considers sequential minimal optimization for SVM and a polynomial kernel with degree 1 [20], [27].

MLP: MLP algorithm consists of three layers: input, hidden, and output. After receiving an input pattern, the NN-based architecture passes the signal through the network to predict the output in the output layer. The output compares with the actual value and calculated error to modify the weights. WEKA [30] uses the back-propagation algorithm to train the model, although it is slower than other learning techniques [27]–[29].

In Section V, the prediction accuracy of the aforementioned algorithms has been evaluated using WEKA [30] learning tools with a classical data-splitting option. WEKA uses a very popular Java-based set of machine-learning tools. Prediction metrics that are considered in this paper are given in Table I with their mathematical notations [20].

V. Experimental Setup

To investigate the vertical acceleration behavior of railway wagons for railway operations, the necessary equations to estimate the bounce and pitch modes of this behavior are presented.

TABLE I
PERFORMANCE METRIC ATTRIBUTES WITH THEIR MATHEMATICAL NOTATIONS [20]

Correlation Coefficient (CC)	$CC = \frac{\frac{1}{n-1}\sum_i \left(Y_i - \overline{Y}_i\right)\left(Y^*_i - \overline{Y_i^*}\right)}{\sigma_{Y_i}\sigma_{Y_i^*}}$ where Y_i is the observation value and Y_i^* is the predicted value. σ_{Y_i} and $\sigma_{Y_i^*}$ are the standard deviation for Y_i and Y_i^*
Mean Absolute Error (MAE)	$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_i^*\right)$
Root Mean Squared Error (RMSE)	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - Y_i^*\right)^2}$
Relative Absolute Error (RAE) in %	$RAE = \frac{\left\|Y_i - Y_i^*\right\|}{\left\|Y_i^* - \overline{Y^*}\right\|} x100$
Root Relative Squared Error (RRSE) in %	$RMSE = \sqrt{\sum_{i=1}^{n}\left(\frac{Y_i - Y_i^*}{Y_i^* - \overline{Y^*}}\right)^2} x100$ where $\overline{Y^*} = \frac{1}{n}\sum_i Y^*$

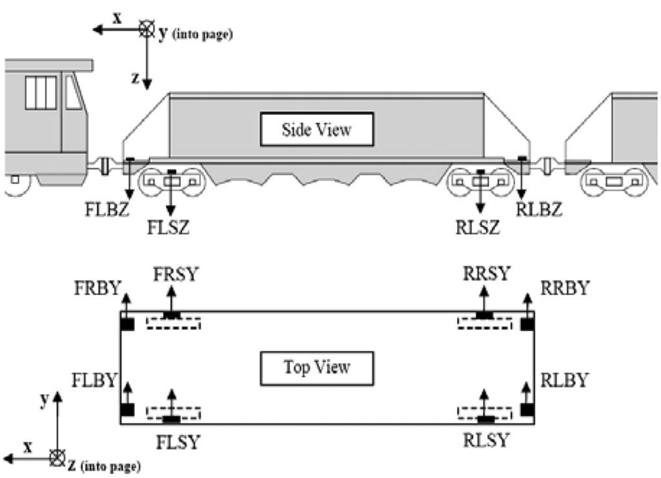

Fig. 1. Accelerometer locations and axis-naming convention [5].

A. Vertical Acceleration Measurements

The health-card system developed by a team of engineers at CQUniversity [13] aims to monitor every wagon in the fleet using low-cost intelligent devices. In the health card, solid-state transducers, including accelerometers and angular rate sensors with a coordinate transform, were used to resolve car body motions into six DOF. The algorithm was validated using collected field data, including accelerations that are measured at strategic points on the wagon body and the bogies.

Wolfs *et al.* [13] placed dual-axis accelerometers at each corner of the body and on each side frame to capture the roll, pitch, yaw, vertical, and lateral accelerations of the wagon body. Sensor locations and naming conventions are given in Fig. 1. ADXL202/10 dual-axis acceleration sensors measured 16-channel acceleration data in g units. Data were collected from a ballast wagon, which had conventional three-piece bogies that were spaced $l_b = 10.97$ m apart. The accelerometers were spaced $l = 14.4$ m apart. The test run was a normal ballast-laying operation, starting with a full load of ballast, traveling to the maintenance site, dropping the ballast on the track, and returning empty via the same route. A PC-based data-acquisition system was used to store data [5].

To examine the dynamic behaviors of railway wagons, vertical or bounce and pitch mode characteristics of railway wagons were investigated with both front and rear wagon body movements being considered for this analysis. A 3-D coordinate system is normally used to describe the dynamic behaviors of railway wagons having six DOF. Linear motions along the X-, Y-, and Z-axes are termed longitudinal, lateral, and vertical translations, respectively. Rotary motions about the X-, Y-, and Z-axes are termed roll, pitch, and yaw, respectively. The purely vertical displacements of a wagon, i.e., the deflections up and down, are called the bounce mode. The rotation around the side-to-side axis of the wagon or tilting up and down is called the pitch mode. Data used in this paper are from the data collected by the CRE, CQUniversity [13], of the wagon body motion signals to detect track conditions and provide derailment monitoring. For this experiment, to calculate the bounce and pitch modes of the wagon body, three channels of data out of the 16 collected have been used, i.e., "front left body vertical (FLBZ)," "rear left body vertical (RLBZ)," and "front right body vertical (FRBZ)." AFLBZ, ARLBZ, and AFRBZ are the averages of FLBZ, RLBZ, and FRBZ, respectively.

To calculate the vertical or bounce mode behavior (VERT) of railway wagons, the following equation has been used:

$$\mathrm{VERT} = [\mathrm{FRBZ} - \mathrm{AFRBZ} + \mathrm{RLBZ} - \mathrm{ARLBZ}]/2. \quad (2)$$

In addition to Bleakley's analysis [5], in this paper, l_b (the distance between bogies) and l (the distance between transducers) have been considered to calculate the pitch mode acceleration (PITCHACC). The calculated pitch mode acceleration is given by

$$\begin{aligned}\mathrm{PITCHACC} = [(&\mathrm{FLBZ} - \mathrm{AFLBZ}\\ &- \mathrm{RLBZ} + \mathrm{ARLBZ})/l] * l_b/2. \quad (3)\end{aligned}$$

Therefore, the front-body vertical acceleration (FVertACC) has been finally measured using

$$\mathrm{FVertACC} = \mathrm{VERT} + \mathrm{PITCHACC}. \quad (4)$$

The rear body vertical acceleration (RVertACC) has been finally measured using

$$\mathrm{RVertACC} = \mathrm{VERT} - \mathrm{PITCHACC}. \quad (5)$$

B. Prediction Model With Regression Algorithms

Models are developed both for the front and rear ends of the railway wagon body using ten popular regression algorithms. For initial data preprocessing and formatting, MATLAB [31] and WEKA [30] learning tools are used. After necessary preprocessing and formatting, by adopting the regression method, algorithms are developed to predict the front- and rear-body vertical displacement behavior of a railway ballast wagon with the help of WEKA learning tools.

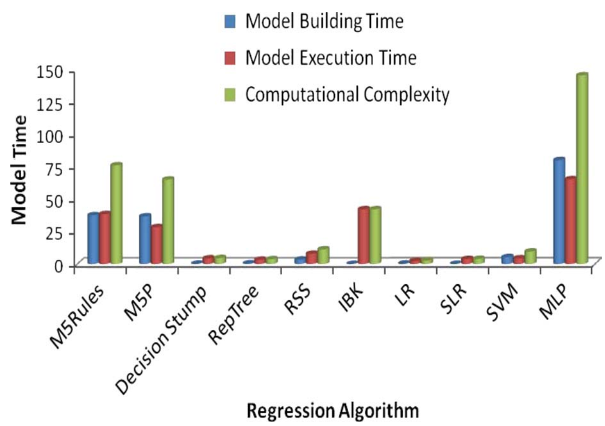

Fig. 2. Computational complexity of different algorithms for prediction of front-body vertical acceleration.

Initially, models are developed to predict front-body vertical acceleration for five data sets. After that, models for forecasting rear body vertical acceleration are developed with the same data sets and learning algorithms. Data sets were selected considering the track condition, the number of records, and the loaded and unloaded train conditions to provide a large experimental variety. Considering a raw data structure, regression algorithm analysis is chosen for this experiment, as it performs better than using other potential algorithms for estimation purposes.

A set of attributes to measure the estimation techniques' performance rather than a single attribute is considered, including correlation coefficient (CC), root mean square error (RMSE), mean absolute error (MAE), root relative squared error (RRSE), relative absolute error (RAE), and computational complexity. The classical data splitting option was considered to evaluate the data sets in which 70% of the data are used for training, and the remaining 30% are used for testing. The computational complexity includes both the model training period and the test set evaluation time. A unified platform with WEKA release 3.5.7 [30] is used for all the experiments. The configuration of the PC that was used in the experiments was a Pentium IV with a 3.0-GHz processor and 1-GB of RAM. This proposed method is very simple; initially, it prepares the input using (2)–(5) and then feeds the input into the regression model. From the results, the most suitable algorithm is proposed for this application.

VI. Experimental Outcomes

Experimental results for the various algorithms showed that the overall prediction accuracy is fairly similar; however, no algorithm performs the best for all of the estimated attributes. For the front-body vertical acceleration of railway wagons, the CC is the least for the model that is developed with the decision stump. M5Rules, M5P, and LR predictions were similar, and the performance of these algorithms was better than that of the remaining algorithms. However, they differ in terms of computational complexity, and LR requires the least computational time. The model training period and the test set evaluation time also differ based on algorithms and data sets. The computational complexity, which combines the model-training period and the model-evaluation period of different algorithms for the front body of wagons, is highlighted in Fig. 2.

TABLE II
Average Prediction of Front-Body Vertical Acceleration With Ten Popular Regression Algorithms

Performance Metrics	CC	MAE	RMSE	RAE	RRSE	Time (s)
M5Rules	1.0	0.0	0.0	0.0	0.0	47.708
M5P	1.0	0.0	0.0	0.0	0.0	32.002
Decision Stump	0.5652	0.01222	0.01936	76.87486	81.92208	2.182
RepTree	0.88158	0.004	0.01048	24.48694	42.96972	2.116
RSS	0.9106	0.0048	0.01068	30.33382	45.0974	5.71
IBK	0.93432	0.00144	0.00708	9.2915	29.48776	15.898
LR	1.0	0.0	0.0	0.0	0.0	1.562
SLR	0.79074	0.00872	0.01216	55.07176	60.06034	1.716
SVM	1.0	0.00004	0.00004	0.24194	0.21656	3.692
MLP	0.98656	0.00018	0.0027	4.89084	8.0525	62.538

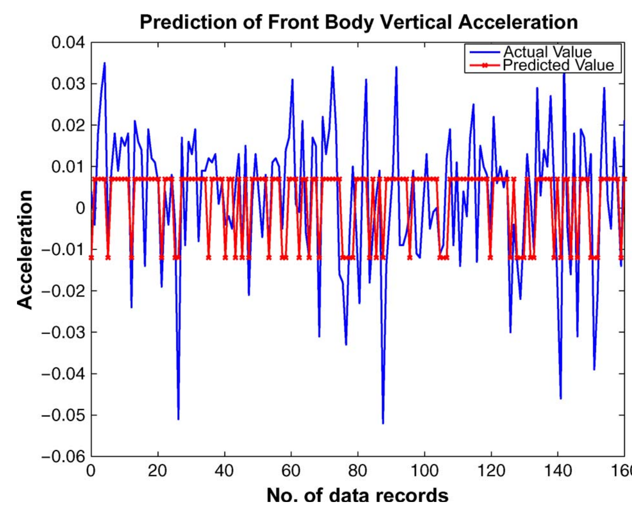

Fig. 3. Prediction of front-body vertical acceleration using the decision stump, which is the worst algorithm for this application.

The CCs of M5Rules, M5P, and LR were 1, i.e., the actual and predicted values were identical. The CC of SVM regression is 1, although it has higher RAE, RRSE, and computational time. Table II shows the output of performance attributes for different algorithms. Considering performance attributes, it is seen that the model that is developed with the decision stump is the worst model to forecast the front-body vertical acceleration of railway wagons, although it is a good performer in terms of computational complexity. Fig. 3 describes the prediction results for the model that is developed with the decision stump.

Compared with other algorithms, MLP needs the highest computational time, although it was predicted with a better CC of 0.9856 on average. Therefore, it is really difficult to select the most suitable algorithms from this stated analysis. However, considering the performance metrics and the execution time from this preliminary analysis, it appears that the model that is developed with the LR is the most suitable to forecast the front-body vertical acceleration.

Models are developed with the selected regression algorithms for rear-body vertical-acceleration data. Model results are summarized in Table III. It is shown that CC is the least for the decision stump. The CCs of SLR, IBK, and MLP are

TABLE III
AVERAGE PREDICTION OF REAR-BODY VERTICAL ACCELERATION WITH TEN POPULAR REGRESSION ALGORITHMS

Performance Metrics	CC	MAE	RMSE	RAE	RRSE	Time (s)
M5Rules	1.0	0.0	0.0	0.0	0.0	24.48
M5P	1.0	0.0	0.0	0.0	0.0	23.132
Decision Stump	0.49878	0.017	0.05686	77.5617	81.89062	1.776
RepTree	0.7079	0.00828	0.01684	38.5844	49.81472	1.714
RSS	0.71468	0.00882	0.01744	41.84734	53.06156	5.682
IBK	0.9453	0.00256	0.0095	12.02534	28.07964	15.84
LR	1.0	0.0	0.0	0.0	0.0	1.366
SLR	0.8245	0.01116	0.01788	50.34626	55.90768	2.404
SVM	1.0	0.00008	0.00012	0.37232	0.34306	2.554
MLP	0.99926	0.00016	0.00012	0.6549	3.31986	61.764

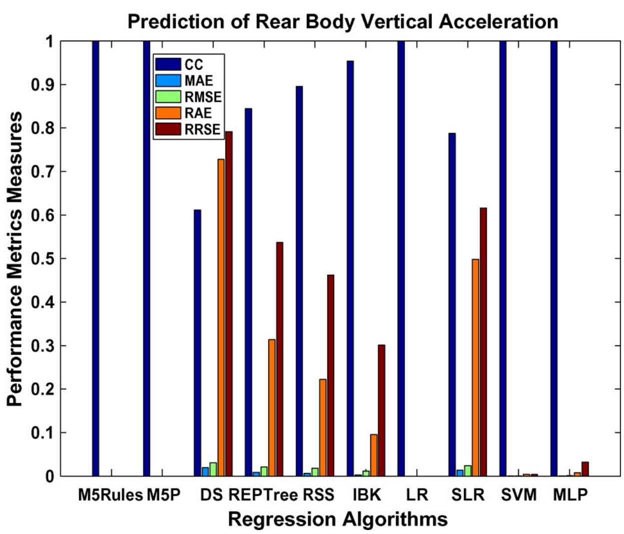

Fig. 4. Comparisons of performance metrics with different algorithms for prediction of rear-body vertical acceleration.

below 1.0 but above 0.8. Results show that, for M5Rules, M5P, and LR, the outputs of all performance metrics, except computational complexity, are the same. However, LR requires the least computational time. The CCs of M5Rules, M5P, LR, and SVM are 1.0, i.e., the actual and predicted values are the same. Fig. 4 represents the performance metrics of different algorithms. Therefore, considering the measured metrics from this preliminary analysis, it is concluded that the model that is developed with LR is the most suitable to forecast rear-body vertical-acceleration data. Fig. 5 describes the prediction accuracy of the model that is developed with LR.

In addition to experimental analysis, data analysis was conducted with the scatterplot method to investigate the possible relationship between two variables that both relate to the same event. From the data plot, it can be seen that the data are correlated and mostly line fitted. Among them, in the LR, approximately all points lie exactly on a straight line with no scatter; this is called the best-fit situation.

VII. Results and Analysis

From the initial experiments, it was observed that the error rate of the measured performance metrics varies based on algorithms, data quality, and the number of records. No algorithm could predict the data sets with the highest performance for all the performance metrics. However, all the models closely performed and with negligible error. From the initial experiments, it was decided that the model that is developed with LR is the most suitable to predict both front and rear wagon body vertical-acceleration characteristics.

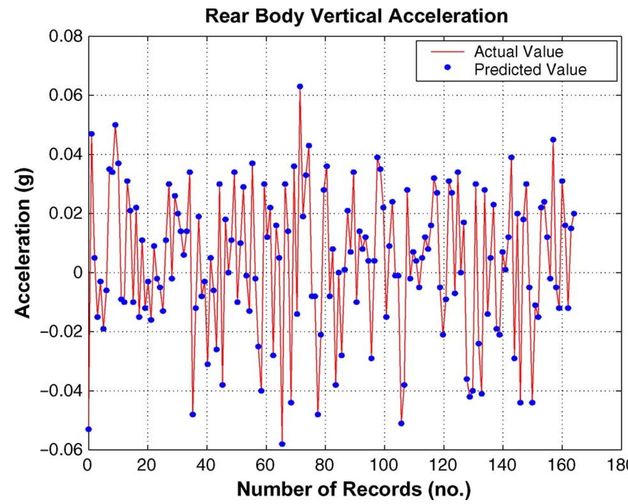

Fig. 5. Prediction results with the LR model for rear-body vertical acceleration.

However, it is really difficult to select the most suitable algorithm for this application. The most popular no free lunch theorem [32], which was introduced by Wolpert and Macready, describes this situation in a convenient way: "If algorithm A outperforms algorithm B on some cost functions, then loosely speaking there must exist exactly as many other functions where B outperforms A." A more useful strategy is to gain an understanding of the data set characteristics that enable different learning algorithms to perform well and to use this knowledge to assist the learning algorithm selection based on the characteristics of the data set [27], [32].

Therefore, to find the most suitable algorithm, statistical analysis involving hypothesis tests is applied to further evaluate the performance of different developed models and finally propose the most suitable algorithm to forecast the front- and rear-body vertical-acceleration characteristics of ballast wagons.

VIII. Statistical Analysis

From the preliminary experiments described above, it is not possible to identify the most suitable algorithm to predict the front- and rear-body vertical-acceleration behavior of railway ballast wagons. Therefore, in this stage, a model is developed using statistical hypothesis analysis to select the most suitable algorithms based on the selected attributes. The popular t-*test* hypothesis was used in this experiment, which is a statistical hypothesis test in which the test statistic has a Student's t-distribution if the null hypothesis is true. The t-test assesses whether the means of two groups are statistically different from each other and that it is the ratio of the difference between the two means and the measure of the variability or dispersion

TABLE IV
STATISTICAL HYPOTHESIS STATUS FOR FRONT-BODY VERTICAL ACCELERATION

Algorithms	Variance	Results	Hypothesis Status
LR vs M5Rules	1.0	H0	Accept
LR vs M5P	1.0	H0	Accept
LR vs Decision Stump	0.1417339	H1	Reject
LR vs RepTree	0.168577904	H1	Reject
LR vs RSS	0.156313834	H1	Reject
LR vs IBK	0.200209033	H1	Reject
LR vs SLR	0.141689165	H1	Reject
LR vs SVM	0.762652682	H1	Reject
LR vs MLP	0.277732594	H1	Reject

TABLE V
STATISTICAL HYPOTHESIS STATUS FOR REAR-BODY VERTICAL ACCELERATION

Algorithms	Variance	Results	Hypothesis Status
LR vs M5Rules	1.0	H0	Accept
LR vs M5P	1.0	H0	Accept
LR vs Decision Stump	0.141447618	H1	Reject
LR vs RepTree	0.144993325	H1	Reject
LR vs RSS	0.144364883	H1	Reject
LR vs IBK	0.180852956	H1	Reject
LR vs SLR	0.140593171	H1	Reject
LR vs SVM	0.611621285	H1	Reject
LR vs MLP	0.252275396	H1	Reject

of groups. The t-*value* is calculated [33] using the following formula:

$$t = \frac{\bar{X_T} - \bar{X_C}}{SE(\bar{X_T} - \bar{X_C})}. \tag{6}$$

In the above formula, the means of two data sets are $\bar{X_T}$ and $\bar{X_C}$. The top part of the formula is the difference between the means, and the bottom part is called the standard error of the difference.

To formulate an analysis plan from the calculated t-value, a level of significance needs to be considered, which is also called the alpha level (α). In most social research, the *rule of thumb* is to set the alpha level at 0.05, and the confidence level is 0.95. If the calculated value is below the threshold value for statistical significance, then the null hypothesis, which usually states that the two groups do not differ, is rejected in favor of an alternative hypothesis, which typically states that the groups do differ [33], [34].

For experiments, a t-test with 95% confidence level is selected. As LR was found to be the most suitable algorithm in the preliminary analysis, LR is selected as the standard algorithm for this analysis and is compared with other algorithms using the t-test hypothesis.

The hypothesis considered for the analysis is as follows.

- *null hypothesis H0 or accept*: When the t-value of $A1 =$ t-value of A2, in which A1 is the standard algorithm, in this case LR, A2 is any other algorithm. If the t-value of A2 is equal or 0.95 of the t-value of A1, then $\mathrm{A1} = \mathrm{A2}$. Otherwise
- *alternative hypothesis H1 or reject*: $A1 \neq A2$.

IX. TEST RESULTS

Initially, t-test analyses are conducted with the output results of different algorithms for the selected attributes stated in Table II. For t-test analysis, all performance metrics are considered except computational complexity. The results of the t-test analyses for front-body vertical acceleration are illustrated in Table IV.

For front-body vertical acceleration, only M5Rules and M5P are in the range of the required confidence level with LR. These two algorithms may be accepted with the standard LR algorithm. All other algorithms are rejected based on this hypothesis analysis. However, among these algorithms, LR requires the least computational time. Therefore, considering statistical analysis and computational complexity, it is concluded that LR is the most suitable algorithm for prediction of front-body vertical acceleration.

Next, the t-test hypothesis is applied on the average results of different performance metrics for rear-body vertical acceleration. The output of hypothesis testing is summarized in Table V. From the results, it is observed that M5Rules and M5P are identical with LR. Therefore, LR, M5rules, and M5P are acceptable for forecasting of rear-body vertical acceleration. All other algorithms are rejected in this hypothesis test. LR requires the least computational time. Considering t-test analysis and computational time, LR is the most suitable algorithm to predict rear-body vertical acceleration.

Therefore, from the experimental results, it is concluded that LR predicted with the greatest accuracy for both front and rear wagon body condition. From the predicted front- and rear-body vertical acceleration data, this algorithm has been devised to generate precautionary signals if the data are beyond the safety limit. From the predicted data, RMS values are measured and used to generate waveforms using an FFT approximation technique.

X. SPECTRAL ANALYSIS

Vehicle condition monitoring systems enable reduction of maintenance and inspection requirements of railway systems while maintaining safety and reliability. Monitoring the wagon body for instances of vertical acceleration and lateral instability has promising implications. The existing ride monitoring systems and associated standards apply PK-PK and RMS measures to detect an exception. The RMS value gives a positive-valued measure of the magnitude of cyclic variation in the signal, and PK-PK values give a positive-valued measure of the magnitude of the extremities of the signal [5], [35].

FRA specifies safety standards for vehicle track interaction in North America. FRA specifies two levels for ride acceleration limits: level 1 (safety limits) and level 2 (maintenance limits). For body vertical acceleration, 0.40–0.59 g PK-PK is the range for level 2 limits, and greater than 0.60 g PK-PK is the level 1 limit [10]. The European standards are more flexible than the North American and Australian standards considering the frequency content. Additional operational and safety limits are introduced in European standards, which give significant advantages over other standards. The operational limits are related to track fatigue and running behavior, whereas the safety limit is related to derailment risk. The safety limits are filtered at lower frequencies than the operational limits. For the body vertical acceleration, limits are 0.50 g PK-PK and 0.20 g RMS. Filtering for the operational limits is 0.4–10 Hz, and for the safety limit, it is 0.4–4 Hz [36].

The Australian Railway Standards specify lateral and vertical accelerations for new and modified rolling stock. In this standard, measurements were to be taken from the floor level of the rail wagon as close as possible to the bogie center. According to the Australian ride-performance standards, the PK-PK body vertical acceleration limit is 0.80 g, and the average PK-PK body vertical acceleration is 0.50 g. All acceleration signals in the Australian railway standards are to be filtered to below 10 Hz [37], [38].

For this paper, the Australian standard RMS limits have been used to monitor the signal condition. Waveform analysis is performed using the FFT to extract only necessary events of the acceleration properties of track conditions that cross the safety limits for transmission to the driver in advance for further actions. This feature reduces data storage and communication cost and, hence, reduces power consumption by sending less information to the driver or the base station.

The code has been developed in a MATLAB platform [31] to read predicted data, preprocess the data, perform the spectral analyses, and provide graphical representation to the locomotive. In this stage, data sets were used from the predicted results for the model building using LR since it was selected as the most suitable algorithm during the experiment. Filtering has been done in the frequency domain by using the FFT with Hanning windows as used by Bleakley [5]. Experimental results show that typical vertical displacement has been observed in some places, and RMS limits exceed the Australian safety standard due to train-track irregularities. In Fig. 6, the top figure represents the front-body vertical acceleration behavior of railway wagons. The signal has been bandpass-filtered to remove the low-frequency content below 0.5 Hz and the high-frequency content above 10 Hz. The bottom figure represents measured RMS values from the filtered signal. The RMS values are calculated over 2-s periods in steps of one sample, and it shows that the RMS value exceeds the Australian safety limit during one event. Fig. 7 represents the rear-body vertical acceleration condition, and it is observed that the RMS output goes beyond the Australian safety standard limits in several places. It is observed that the typical vertical displacement that is observed both for front- and rear-body vertical acceleration and the RMS output is beyond the relevant safety limit in some places.

Based on the measured RMS signal, a precautionary signal must be generated to send to train drivers in advance. Signals that are sent to the driver through wireless communications systems for informed forward-looking decisions and initiation of suitable actions would prevent disastrous accidents from happening.

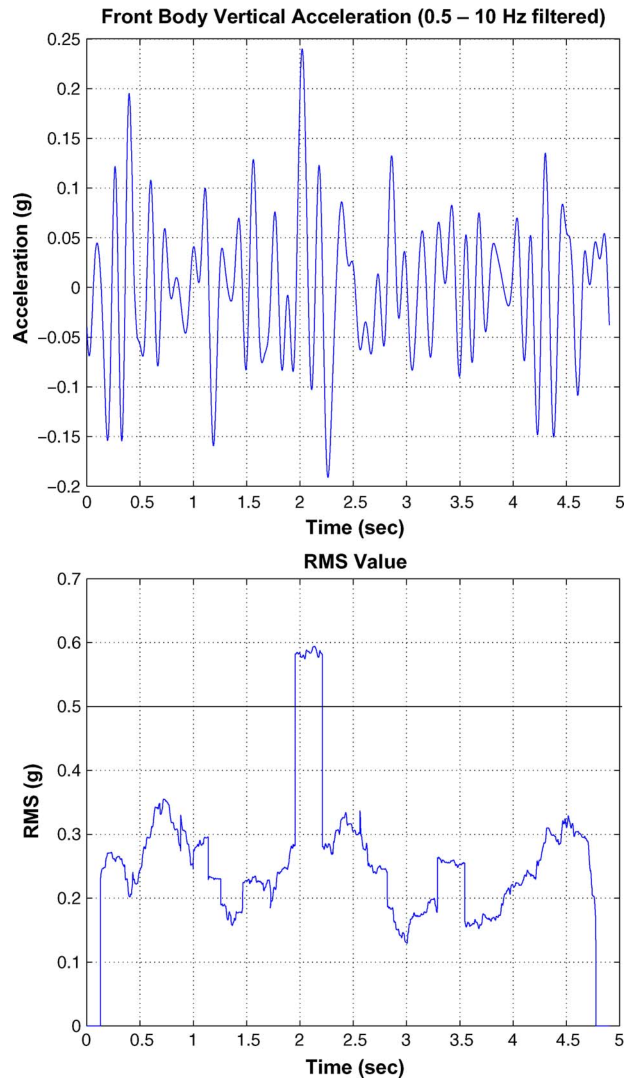

Fig. 6. (Top) Front-body vertical acceleration characteristics (0.5–10 Hz filtered). (Bottom) Measured RMS value from the filtered signal.

The track that was used to collect data collection in this paper [5] was particularly rough and under maintenance. The track was selected because it provided an interesting level of vehicle–track excitation. However, it is not the general scenario of the Australian Railway Network operating-line safety condition.

XI. Conclusion

Machine-learning techniques play a key role in developing monitoring systems for both freight and passenger railway systems to ensure safety and security both inside the wagon and on the rail track. Both front- and rear-body vertical acceleration phenomena have been predicted using ten popular regression algorithms. From experimental results, it has been shown that the approach is very effective and has predicted front- and rear-body vertical movement characteristics with negligible errors.

Initially, metrics comprising CC, RMSE, MAE, RRSE, RAE, and computational complexity have been measured from

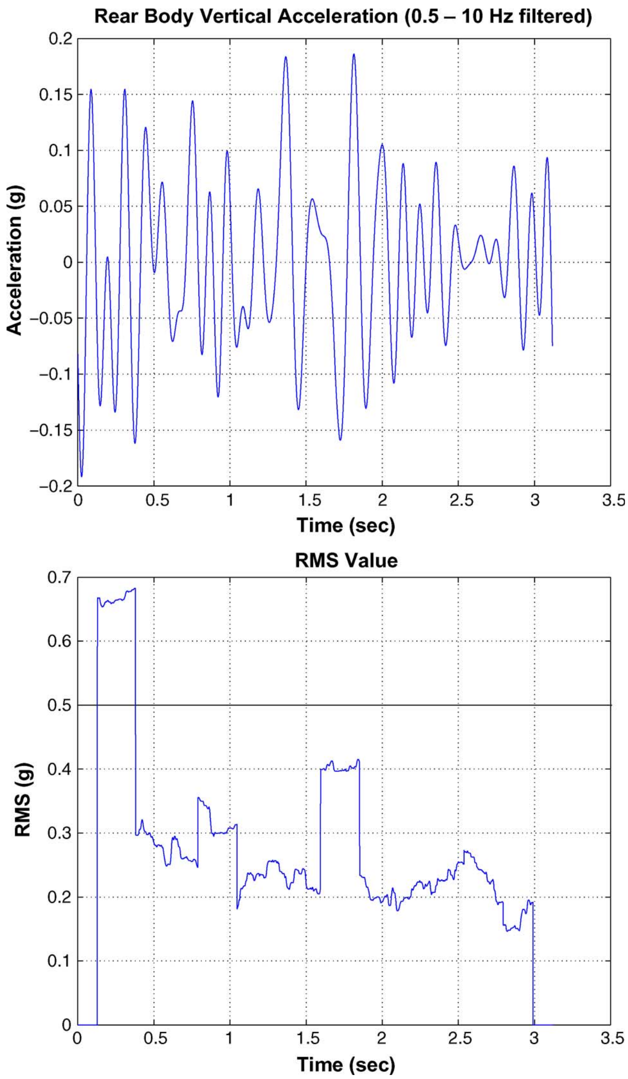

Fig. 7. (Top) Rear-body vertical acceleration characteristics (0.5–10 Hz filtered). (Bottom) Measured RMS value from the filtered signal.

the developed model. From the preliminary analyses, it has been observed that accuracy of the models varies based on performance metrics, the number of data records, and data quality. It has been observed that LR performs better overall than any other algorithms for all of the performance metrics considered. However, some other algorithms also performed similarly. Therefore, statistical hypothesis analysis has been applied to select the most suitable algorithm to predict front- and rear-body vertical acceleration characteristics. From the performance metrics and statistical analyses, it has been proven that LR performs more efficiently than any other algorithms for this problem. Finally, with the predicted front- and rear-body vertical acceleration data, waveforms have been developed for RMS values to monitor railway wagons using the FFT approximation technique.

This useful tool can be used to monitor railway systems, particularly railway track irregularities and derailment potential, with integrity and reliability, which reduces maintenance costs and inspection requirements of railway systems. It reduces computational cost and power consumption of the system, as the learning mechanism is used to forecast performance, and the FFT is used to send only alerts regarding meaningful events. However, in addition to track irregularities, wagon characteristics are also involved, including intrinsic characteristics of wheels, bogie, suspension, load, etc. More detailed analysis should be carried out taking into consideration these aspects to develop an energy-efficient health monitoring system for railway use. This paper also deserves further investigation that will focus on the following specific areas.

- Investigate lateral acceleration of rail wagons.
- Investigate the wireless communications system to communicate individual wagons to the locomotive or driver end.
- Integrate the model with the SQL database to send a warning signal to locomotives.

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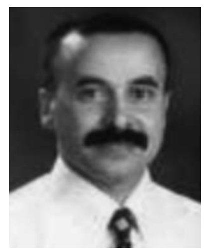

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