Forecasting Vertical Acceleration of Railway Wagons - A comparative study

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***Abstract*— Advances in modern machine learning techniques has encouraged interest in the development of vehicle health monitoring (VHM) systems. These techniques are useful for the reduction of maintenance and inspection requirements of railway systems. The performance of rail vehicles running on a track is limited by the lateral instability and track irregularities of a railway wagon. In this study, a forecasting model has developed to investigate vertical acceleration behavior of railway wagons attached to a moving locomotive using different regression algorithms. Front and rear vertical acceleration conditions have predicted using ten popular learning algorithms. Different types of models can be built using a uniform platform to evaluate their performances. This study was conducted using ten different regression algorithms with five different datasets. Finally best suitable algorithm to predict vertical acceleration of railway wagons have suggested based on performance metrics of the algorithms that includes: correlation coefficient, root mean square (RMS) error and computational complexity.**

Keywords - Vehicle health monitoring; vertical acceleration; railway wagons; regression analysis

I. Introduction

Typical dynamic behaviors of railway wagons are responsible for safe, cost-effective and reliable operation of freight railways. The dynamic performance of such systems can be determined by the characteristics of the wagon and the irregularities in the track. The performance of rail vehicles running on a track is limited by the lateral instability inherent to the design of the wagons steering and the response of the railway wagon to individual or combined irregularities. Railway track irregularities need to be kept within safe operating margins by undertaking appropriate maintenance programs [1], [2], [3]. Predicting vehicle characteristics online from track measurement data has been addressed by various studies [4],[5],[6],[7],[8],[9],[10],[11]. Machine learning techniques have been introduced in different research projects to predict typical dynamic behavior of railway wagons running on the track [12],[13],[14],[15],[16].

Regression analysis is the most significant and popular learning areas for future decision making or forecasting of data. Researchers already have introduced different types of regression algorithms, including popular regression analysis for time series data forecasting, tree based algorithm, rule-based learning, lazy learning, multilayer perception, and statistical learning [17],[18],[19],[20],[21],[22],[23],[24],[25], [26],[27],[28]. Currently various statistical forecasting and regression approaches are used to monitor railway wagons to ensures safety and security.

Central Queensland University (CQU), in association with the Centre for Railway Engineering (CRE) [11], has been investigating a Health Card device for railways. This Health Card system is an autonomous device used for analysis of car body motion signals that can detect track condition and monitor derailment conditions. The Health Card is capable of resolving car body motions into six degrees of freedom. To do this the Health Card uses accelerometers and angular rate sensors with a coordinate transform. Two prototypes have been developed based on wired and wireless solutions. The Health Card system uses fast Fourier transforms to efficiently convert the signal into a time-frequency spectrograph so that events can be detected according to their short-term spectral content. From spectral analysis, it has been found that small residual responses exist in the pitch and yaw degrees of freedom and the wagon was not laterally constrained [4],[11].

Transportation Technology Center, Inc. (TTCI), USA conducted a performance-based track geometry study that involved extensive field tests as well as modeling efforts [12]. The modeling efforts have led to the successful development of neural networks that relate complex track geometry inputs to vehicle response. Through implementation of this performance-based system in the future, railroads can expect to reduce track geometry-caused train derailments and improve prioritization of track geometry maintenance.

Nefti et al. [13] used artificial neural networks (ANNs) architecture to predict railway systems malfunctioning due to track irregularities. Different neural network structures are created to find out the best structure for predicting railway safety. Experimental analysis showed that the model performed satisfactorily and can predict the desired output with a very low error factor. Cen et al. [14] investigated a machine learning approach to automate the identification process of railroad wheel using collected data from wheel inspection. Decision trees and SVM based classification schemes are used to analyze the railroad wheel inspection data. The experimental results indicate that the proposed approach is very efficient, producing a classifier ensemble that has high sensitivity and specificity during classification [14],[15].

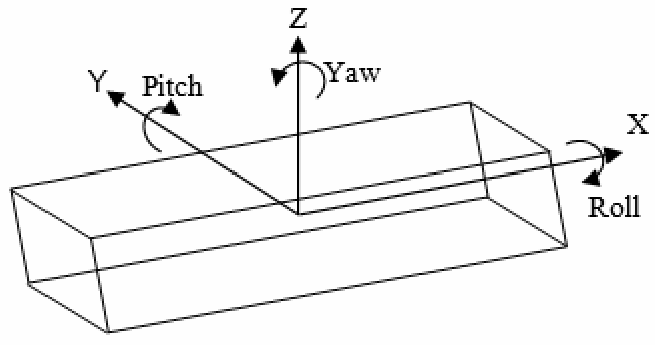

Fig. 1. Six degrees of freedom of wagon movement

Linear regression analysis was used to predict 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 percent error for all pads. Linear regression analysis was used to predict the deterioration rate with age of dynamic stiffness and damping coefficients. Results shows that the per-MGT rate of rail pad degradation in terms of dynamic stiffness is about 2.18MN/m and the rate for the damping is approximately 19.63Ns/m [16].

In this paper we have developed forecasting models to monitor vertical acceleration of railway wagons using popular regression algorithms. We have developed models with ten popular regression algorithms and applied them to a unified platform. We have assessed the performance of different models and proposed the most suitable algorithm for forecasting vertical displacement behavior of railway wagons. This paper is organized as follows. Section II discusses the background to the study. Section III presents classification algorithms overview. The development of the model with different algorithms is discussed in Section IV. Comparative analyses of the different algorithms are described in Section V. Section VI concludes the article with future directions.

II. BACKGROUND OF THE STUDY

To narrate typical dynamic behaviors of a railway wagons having six degree of freedom (DOF), three-dimensional coordinate system is normally used. Linear motion along the X, Y and Z axes are termed as longitudinal, lateral, and vertical translations respectively. Rotary motions about the X, Y and Z axes are termed as roll, pitch and yaw respectively as illustrated in Fig.1. The vertical displacements of wagon, i.e., the deflection in between up and down is called bounce mode. The rotation around the side-to-side axis of a train wagon or tilting up and down is called pitch mode. Vertical acceleration or displacements of railway wagons are determined from this bounce and pitch mode behavior. In our study, we have investigated vertical acceleration characteristics of railway wagons.

A set of four prototypes ”Health Cards” [11] has been developed by a team at Central Queensland University. Steven et al. [4],[11] placed dual-axis accelerometers on each corner of the body and each side frame. The aim of the sensing arrangement was to capture roll, pitch, yaw, vertical and lateral accelerations of the wagon body. ADXL202/10 dual axis acceleration sensors measured 16 channels of acceleration data in g units. Data was collected from a ballast wagon which was a conventional three piece bogie spaced lb = 10.97m apart. The accelerometers were spaced l = 14.4m apart. The test run was a normal ballast lying 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 [4],[29].

To inquire dynamic behaviors of railway wagons we have investigated vertical or bounce and pitch modes characteristics of railway wagons. Vertical acceleration for front and rear side of the wagons was investigated. Data used in this study is from the data collected by Centre for Railway Engineering, CQU [11], [29] of car body motion signals to detect track condition and provide derailment monitoring. For this experiment to calculate bounce and pitch modes of wagon body we have used 3 channels of data out of the 16 collected i.e.,' front left vertical, FLZ', 'rear left vertical, RLZ', 'front right vertical, FRZ'. AFLZ, ARLZ and AFRZ are respectively the averages of FLZ, RLZ, and FRZ.

To calculate vertical or bounce mode behavior of railway wagons we used the equation below as stated in [4]:

$$VERT = [FRZ - AFRZ + RLZ - ARLZ]/2 \quad (1)$$

We have considered l_b, the distance between bogies and l, the distance between transducer to calculate pitch mode acceleration. Calculated pitch mode acceleration is:

$$PITCHACC = [(FLZ - AFLZ - RLZ + ARLZ)/l] * l_b/2 \quad (2)$$

Front body vertical acceleration has been measured finally using:

$$RVertACC = VERT + PITCHACC \quad (3)$$

Rear body vertical acceleration has been measured finally using:

$$RVertACC = VERT - PITCHACC \quad (4)$$

According to the Australian ride performance standards peak to peak body vertical acceleration is 0.80g and average peak to peak body vertical acceleration is 0.50g [30]. All acceleration signals in the Australian railway standards are to be filtered to below 10Hz [30],[31]. For this study according to existing ride monitoring system we have used the Australian standard for RMS limits to monitor the signal condition. From several data sets collected in the study [4], in this paper we have highlighted five data sets in which major vertical displacement occurs. Data sets were filtered to 0.5-10Hz. The

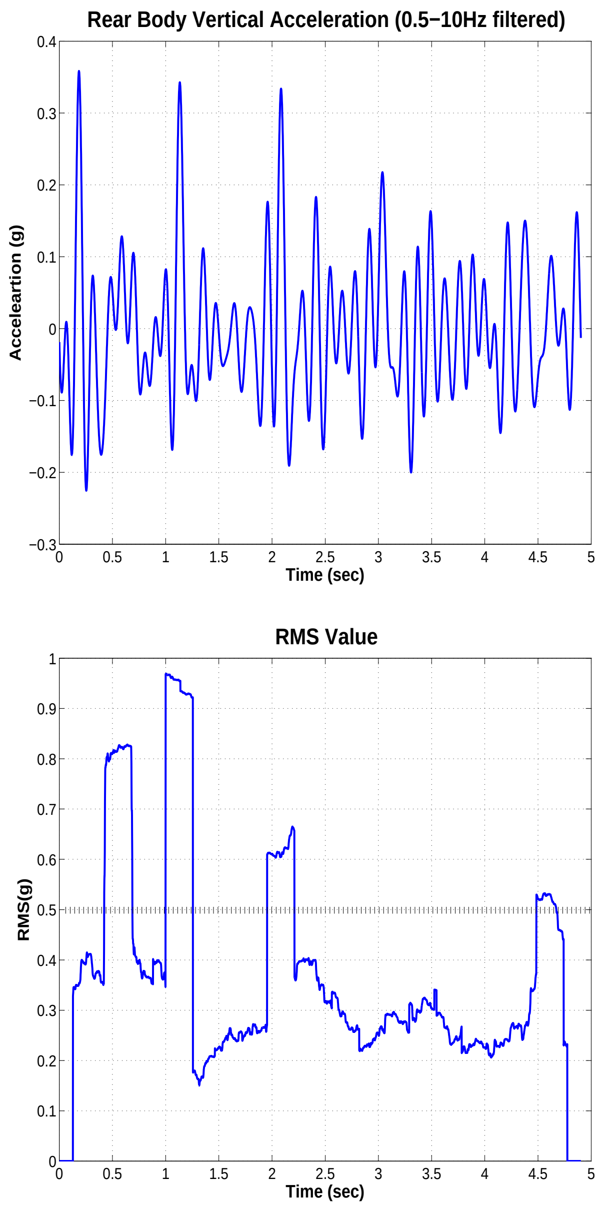

Fig. 2. Top fig.: Rear body vertical acceleration characteristics (0.5 -10 Hz filtered), Bottom fig.: Measured RMS value from filtered signal for data set 1. Major vertical deflection observed.

filtering has been done in the frequency domain by using the Fast Fourier Transform (FFT) with Hanning windows as used in [4]. Typical vertical displacement was observed for few data sets and hence RMS output was above the safety limit. This requires special attention and creation of warning signals for instances where RMS value is above the safety limit. A graphical representation of measured rear body vertical acceleration behavior is illustrated in Fig.2 for data set 1, in which we observed typical vertical accelerations behavior.

III. LEARNING ALGORITHMS

This section highlighted all the regression algorithms used in this paper to develop a forecasting model for railway. We have considered rule-based learning algorithm M5Rules and Decision table, Tree-based learning M5Prime and Decision Stump, Meta-based learning Random Sub Space, Lazy-based learning IBK, Regression-based learning simple linear regression, linear regression, Statistical learning based algorithm support vector machine (SVM) regression, and neural network based multilayer perception (MLP). We have considered all the above algorithms from WEKA [32] release 3.5.7 with default parameter settings. WEKA is a very popular Java based machine learning tools [32].

M5Rules: M5 rules create rule sets on continuous data and produces propositional regression rules in 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 class value [17].

Decision Table: Decision tables contain the same number of attributes as the original dataset, and a new data item is assigned a category by finding the line in the decision table that matches the non-class values of the data item. Wrapper method [18] is used to find a good subset of attributes to include in the table [19].

M5Prime: M5Prime 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. M5Prime extended decision trees by adding numeric prediction by modifying the leaf nodes of the tree [19], [20].

Decision Stump: This learning algorithm builds simple binary decision "stumps" (1-level decision trees) for numeric and nominal classification problems. It deals with missing values by treating "missing" as a separate attribute value [19].

Random Sub Space: Random sub space is a method 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 classifier is trained using each subset [21].

IBK: Instance-base 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. WEKA's default setting is k = 1 [17],[22].

Linear Regression: Regression analysis [23],[24],[25] 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 upon the values of an independent variable. The regression model is used to predict the value of Y from the known value of X and find the line that best predicts Y from X. Regression algorithm does this by finding the line that minimizes the sum of the squares of the vertical distances of the points from the line. The goodness of fit and the statistical significance of the estimated parameters are a matrix of regression analysis. A simple linear regression is a linear regression in which there is only one covariate and is used to evaluate the linear relationship between two variables.

SVM Regression: SVM is a statistical based learning, which has been used for binary classification for the first time. SVM model can usually be expressed in terms of a support vectors and can be applied to nonlinear problems using different kernel function. Based on the support vectors information, SVM regression produces the final output function. WEKA by default considers sequential minimal optimization (SMO) for SVM and polynomial kernel with degree 1 [17],[26].

Multilayer Perception: MLP algorithm consists of three layers: input, hidden and output. After receiving an input pattern, the Neural Network (NN) based architecture passes the signal through the network to predict the output in the output layer. Output compares with actual value and calculated error to modify the weights. WEKA uses the back propagation (BP) algorithm to train the model, though it is slower than few other learning techniques [26],[27],[28].

TABLE I

FORECASTING RESULTS FOR FRONT BODY VERTICAL ACCELERATION DATA FOR DATA SET 1

Algorithm	Correlation Coefficient	RMS Error	Model building time	Total Execution Time (sec)
M5 Rules	1.0	0.0	26.74	48.36
Decision Table	0.5518	0.03520	241.32	414.32
M5 Prime	1.0	0.0	24.96	44.05
Decision Stump	0.5038	0.0365	0.22	3.30
Random Sub Space	0.7293	0.0295	4.76	12.00
IBK	0.935	0.0156	0.05	22.15
Linear Regression	1.0	0.0	0.273	2.1
Simple Linear Regression	0.8753	0.0204	0.03	2.59
SVM Regression	1.0	0.0002	1.92	5.31
Multilayer Perception	0.9975	0.0034	81.18	138.0

IV. EXPERIMENTAL SETUP

To monitor typical dynamic behavior of railway wagons due to track irregularities and lateral instability in this study we have investigated vertical acceleration phenomenon. In our experiments we have used five data sets from the collected data [4]. We have examined both front and rear side of the railway wagons with ten popular learning algorithms. We have measured correlation coefficient, RMS error and computation complexity as a measure of performance metrics. Percentage split test options method were considered to evaluate the datasets as the datasets have more than 1000 records. We have used 70 percent data for training and remaining 30 percent for testing. The computational complexity includes both the model train period and the test set evaluation time. Few of the algorithms need more time to classify the test set than training the model. For our experiments we have used a unified platform. The configuration of the PC used in the experiments was Pentium IV, 3.0GHz Processor, 1GB RAM. We have used WEKA release 3.5.7 for all of the experiments. Stop watch has been used to count computational time. At first we have developed model with the stated ten learning algorithm to forecast front vertical acceleration behavior. We have evaluated performance of each model with five data sets and measure performance metrics. Later we have developed models to forecast rear vertical acceleration phenomenon. From the performance matrices we have proposed the best suitable algorithm to forecast front and rear body vertical acceleration characteristics of railway wagons. After necessary pre-processing and formatting we have passed the data into the learning algorithms to predict front and rear vertical acceleration of railway wagons. For initial data pre-processing, and formatting we have used MATLAB [33] and WEKA [32] learning tools. WEKA includes a comprehensive set of data pre-processing tools, learning algorithms and evaluation methods, graphical user interfaces and environment for comparing learning algorithms [34]. With the help of WEKA learning tools we have developed ten models using above stated learning techniques to predict vertical acceleration both in front and rear side of the wagon. Experiments have demonstrated that different algorithms predict vertical acceleration characteristics with minor to negligible errors. Computation complexity also differs with the learning techniques. From detailed analysis of the results we have proposed best suitable learning techniques to forecast vertical acceleration of railway wagons. Finally, we have generated precautionary signals with the proposed technique, if the data is beyond safety limit. From the predicted data we have measured RMS value using FFT and Hanning Window. Based on measured RMS signal, a precautionary signal has been generated to send to train drivers. For our experiment we have used the Australian ride performance standard which is 0.50g average peak-to-peak for body vertical acceleration. Signals can be sent to driver via wireless communications system to generate informed forward-looking decisions.

V. RESULTS AND ANALYSIS

Proposed algorithm with percentage split test options were used to predict vertical displacement behavior of a railway ballast wagon. We have used five sets of data in different instances i.e. different time and location. Initially we have developed models to predict front vertical acceleration for five data sets with the ten selected regression algorithms. We have measured correlation coefficient, RMS error and computational complexity for each algorithm. After that we have developed models for forecasting rear body vertical

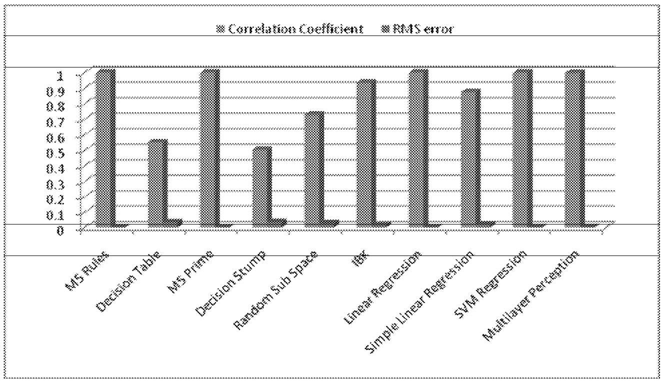

Fig. 3. Measured correlation coefficient and RMS error of different algorithm to predict front vertical acceleration data.

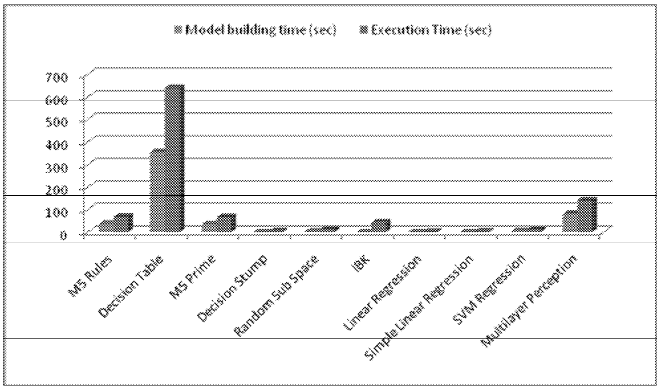

Fig. 4. Model building time and total execution time needed by different algorithm to forecast rear body vertical acceleration data

TABLE II

FORECASTING RESULTS FOR REAR BODY VERTICAL ACCELERATION DATA FOR DATA SET 1

Algorithm	Correlation Coefficient	RMS Error	Model building time	Total Execution Time (sec)
M5 Rules	1.0	0.0	38.23	69.00
Decision Table	0.7601	0.0171	355.35	640.14
M5 Prime	1.0	0.0	36.47	66.70
Decision Stump	0.5698	0.0217	0.19	4.64
Random Sub Space	0.8589	0.014	3.54	12.04
IBK	0.9151	0.0107	0.013	42.66
Linear Regression	1.0	0.0	0.28	2.49
Simple Linear Regression	0.849	0.0142	0.06	3.67
SVM Regression	1.0	0.0	4.87	9.12
Multilayer Perception	0.9856	0.0047	81.2	140.64

acceleration with the same data sets and learning algorithms. For rear body vertical acceleration we have also measured the same metrics as stated above. We have run our models with the ten learning algorithms using the WEKA learning tools and the five data sets. Trends of the measured matrices correlation coefficient, RMS error and execution time are almost same. Therefore as an example here we have highlighted data set 1 which has 5000 data records to draw comparative statements about the developed model.

For front body vertical analysis it was observed that correlation coefficient is least for decision stump and decision table classifier. Results showed that for M5Rules, M5 Prime, Linear regression, SVM regression correlation coefficient was one, i.e., actual value and predicted value is almost identical. However, root mean square (RMS) error was zero only for M5Rules, M5 Prime, and linear regression. Decision Table consumes highest execution time. Considering correlation coefficient, RMS error and execution time we may conclude that the model develop with the decision table is the worst model to forecast front body vertical acceleration of railway wagons. Linear regression needs the least execution time. Multilayer perception gives a better correlation coefficient of 0.9975 with a slightly higher execution time. Therefore, considering the performance metrics correlation coefficient, RMS error and execution time it is observed that the model developed with linear regression forecasts the front body vertical acceleration most efficiently. SVM regression is the second choice for this application as it is a bit lagging with linear regression in terms of execution time and RMS error. However, M5 Rules and M5P also suitable algorithms to predict front body acceleration behavior.

We have developed 10 models with the stated classifiers algorithm for rear body vertical acceleration data. Model

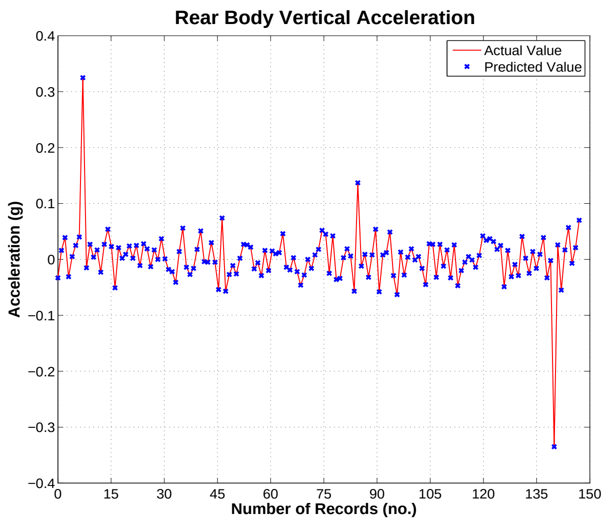

Fig. 5. Model developed with linear regression predicted data set 1 with a correleation coefficient to 1.0, i.e., actual and predicted data are identical

results are summarizes in Table 2. From the above results it was observed that decision table needs highest and linear regression needs least computational time. Correlation coefficient is the least for decision stump classifier. Correlation coefficients of simple linear regression, IBK, multilayer perception are below 1.0 but above 0.8. Results showed that for M5Rules, M5 Prime, Linear regression, SVM regression correlation coefficient was 1.0, i.e., actual value and predicted value was same. RMS error was zero for all of these four algorithms. SVM regression requires less execution time than the M5Rules, and M5 Prime. However, execution time of SVM regression is higher than linear regression. Therefore considering correlation coefficient, RMS error and execution time we may conclude that model developed with linear regression is the most suitable to forecast rear body vertical acceleration data. SVM regression may be the second choice for this application. Fig. 4 represents the actual and predicted value for data set 1 using the model developed with linear regression.

From the experimental results it is really difficult to select a best suitable algorithm. No algorithm is uniformly most accurate over the dataset studied, consistent with the basic idea of the No Free Lunch (NFL) theorem. However, from literature it is observed that linear regression model works better when model considered only few numbers of weights. Since our data has only three attributes, therefore, linear regression is able to extract efficiently the appropriate weight values to fit the regression line.

VI. Conclusion

Intelligent machine learning techniques play a key role in developing monitoring system for both freight and passenger railway systems. To find the most suitable algorithm to forecast vertical acceleration of railway wagons in this paper we have developed models using ten popular regression algorithms. We have compared the algorithms in terms of correlation coefficient, RMS error, and computational complexity. The experimental results showed that linear regression algorithm forecasted both front and rear vertical acceleration data more efficiently than any other algorithm tested. SVM regression is suitable for this application though it needs higher execution time than linear regression. This is first time modern machine learning techniques have been used in this context, which still requires verification in different areas. Therefore, it deserves further investigation that focuses on some specific areas which are:

- introduce weighted performance metrics with statistical analysis to select most suitable algorithm
- investigate lateral acceleration of rail wagons
- predict front end rail wagon behavior from rear wagon collected data
- integrate the model with SQL database to send warning signals to drivers.

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