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Condition Monitoring and Trend Analysis of Railway Turnouts Based on In-Situ Accelerometer Measurements

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Abstract

High dynamic forces at railway switches and crossings (S&C) are the primary cause of frequent defect formation. Regular acquisition of onsite sensory data aids condition evaluation or maintenance planning, which subsequently mitigates problems of unexpected malfunction of S&C components. Accelerometer data collected by in-situ sensors in UK and Czech Republic were used in this research for defining important metrics and validating prediction models. A number of metrics can be calculated from collected signals to provide information about the condition of S&C and its components. Change of these parameters over time is revealed by trend analysis and may signalize increased material deterioration or formation of a defect. Trend analysis methods span from simple regression to more advanced machine learning models for time series prediction and are listed in this paper. Evaluation of proposed models is performed on collected data, and validation metrics are discussed. This paper provides a baseline for the development of a S&C condition monitoring system and overviews techniques for analysis of large amounts of data collected by automatic sensory systems.

Keywords: Railway Switches and Crossings, Accelerometer Sensors, Trend Analysis, Predictive Maintenance

1 Introduction

Discontinuities introduced by railway switches and crossings (S&C) result in increased dynamic forces and frequent defect formation. Condition monitoring system based on a regular onsite collection of sensory data from passing trains provides an opportunity to predict defect occurrence or plan maintenance which ultimately increases safety and reduces costs, especially for high-speed tracks [1]. Several metrics can be calculated from collected signals to provide information about the condition of S&C and its components [2]. Change of these parameters over time is revealed by trend analysis and may signalize increased material deterioration or formation of a defect.

Trend analysis methods span from simple regression to more advanced machine learning models for time series prediction. The machine learning approach benefits from a large amount of data collected by automatic onsite sensors. Support vector machines (SVM) are traditionally used as baseline model [3]. A more complex approach includes specialized types of neural including long-short term memory networks (LSTM) or auto-encoders (AE) [4]. Ensemble of multiple machine learning models provides a more robust solution, especially for diverse data [5]. The trend line can also be used to estimate remaining useful life (RUL) and maintenance planning [6].

Two datasets of in-situ measured accelerometer data were selected. Dataset I contained tri-axial acceleration signals measured near the common crossing of S&C by the Brno University of Technology. It consisted of 27 train passages from one location in the Czech Republic. Known locomotive types included classes 150, 151, 162, 163, 350, 362 and 363, which were selected due to their mutual similarity to reduce the data variability. Machine learning models can identify concrete locomotive types provided sufficient training data [7]. Dataset II was obtained at a location in the UK around swing nose and was supplied by the University of Birmingham. The schematic of the measurement configuration is shown in Figure 1. It contained records of vertical acceleration signals from 598 trains from class 395, 374, 373 highspeed trains and some freight vehicles.

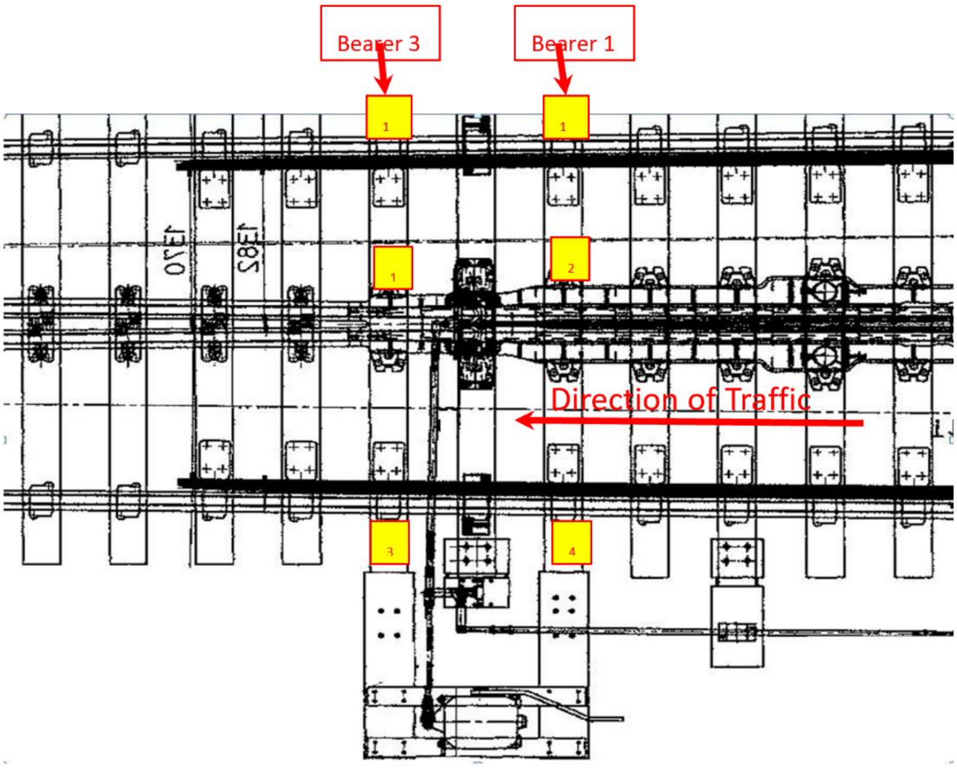

Figure 1: Schematic of sensor locations near swing nose used to collect dataset II

This paper evaluates different metrics with regard to their applicability to trend analysis and fault detection. Metrics are selected with respect to train dynamics within S&C to provide descriptive value. Fundamental trend analysis and regression models are introduced to serve as a baseline for further research and development of a S&C condition monitoring system.

2 Methods

Several metrics can be calculated from the measured accelerometer signal in order to evaluate changes in the S&C dynamic response over time. Measured data can be analyzed either in the time domain or in the frequency domain to reveal different types of issues. Some of the common signal analysis methods were adjusted for railway application to consider its specific phenomena. The following list summarizes the selected evaluation metrics:

i. U_{max}: Maximal absolute amplitude calculated according to equation $U_{max} = \max(|y|)$

ii. *RMS*: Root mean square, which is a square root of the mean square calculated according to the equation $RMS = \sqrt{\frac{\sum|y|^2}{n}}$

iii. *CF*: Crest factor is a ratio of maximal amplitude and root mean square according to equation $CF = U_{max}/RMS$

iv. PtP: Peak to peak value, which is a difference between maximal and minimal amplitude in the signal. $PtP = \max(y) - \min(y)$

v. $E_{a/b}$: A ratio of signal energy $E = \sum |y|^2$ between two directions $E_{a/b} = E_a/E_b$. It can be viewed as the angle of wheel impact on the crossing nose. A triaxial accelerometer must be used to enable this metric. Three combinations exist: X/Z, Y/Z, X/Y, where X is longitudinal, Y is transverse, and Z is a vertical direction.

vi. f_{mean}: Frequency mean weighted according to power at each frequency calculated in the whole frequency spectrum. Equation: $f_{mean} = \frac{\sum_i^n P_{f_i} f_i}{\sum_i^n P_{f_i}}$

vii. $f_{mean,P1}$: Frequency mean weighted according to power at each frequency calculated in the frequency range 200-1000 Hz, which corresponds to P1 force (hard impact) according to Jenkins, et al. [8]. Equation: $f_{mean,P1} = \frac{\sum_{i=200}^{i=1000} P_{f_i} f_i}{\sum_{i=200}^{i=1000} P_{f_i}}$

viii. $f_{mean,P2}$: Frequency mean weighted according to power at each frequency calculated in the frequency range 50-200Hz, which corresponds to P2 force (soft impact) according to Jenkins, et al. [8]. Equation: $f_{mean,P2} = \frac{\sum_{i=50}^{i=200} P_{f_i} f_i}{\sum_{i=50}^{i=200} P_{f_i}}$

ix. f_{std}: Frequency standard deviation weighted according to power at each frequency calculated in the whole frequency spectrum. It can also be calculated in the P1 and P2 frequency ranges. Equation: $f_{std} = \sqrt{\frac{\sum_i^n P_{f_i} |f_i - f_{mean}|^2}{\sum_i^n P_{f_i}}}$

Calculated metrics enable comparison between subsequent train passages and can be evaluated for short-term anomalies or long-term trend analysis to predict defect formation and plan maintenance. Besides the assumed probability distribution, the seasonal variation must be considered [9]. A regression line is fitted to the datapoints minimizing the distances defined by the least square error (MSE):

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - y)^2 \tag{1}$$

Coefficient of determination R^2 describes the amount of variability of the dependent variable explained by the variability of the independent variable and is another metric used for the evaluation of regression models:

$$R^2 = 1 - \frac{\sum (y_i - \frac{1}{n} \sum y_i)^2}{\sum (y_i - \hat{y}_i)^2} \tag{2}$$

3 Results

The conducted experiments considered two datasets. A locomotive part of the accelerometer signals was extracted and metrics were calculated. Correlation between some metrics is relatively high, so only the independent metrics should be selected for composition of the feature vector for trend analysis models.

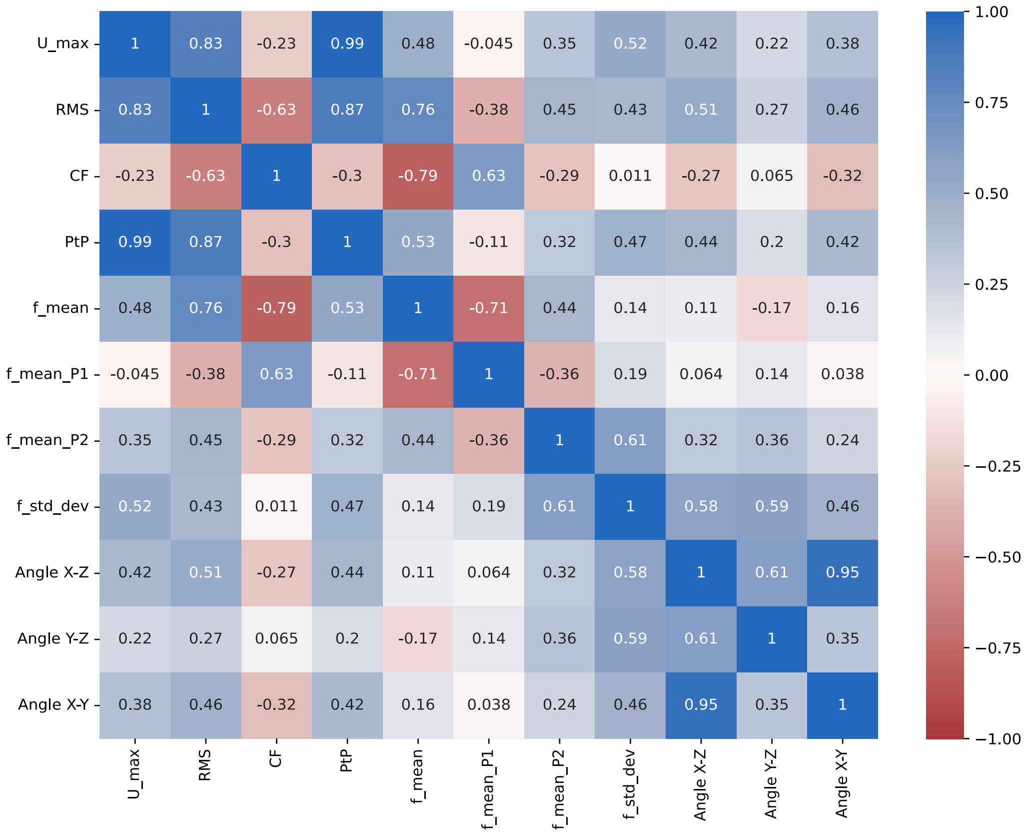

Figure 2. Correlation between selected evaluation metrics (dataset I)

Variation of calculated metrics is higher due to the unknown locomotive type in dataset II. Assuming that distribution of locomotive type is constant in time and the overall trend is not affected. A general trend can be identified despite a high variation of subsequent passages. A sudden shift in the metrics can be seen between 27.2.2018 and 4.3.2018. An increasing R^2 score can be observed for higher-order polynomials, but the extrapolation shape may not be ideal.

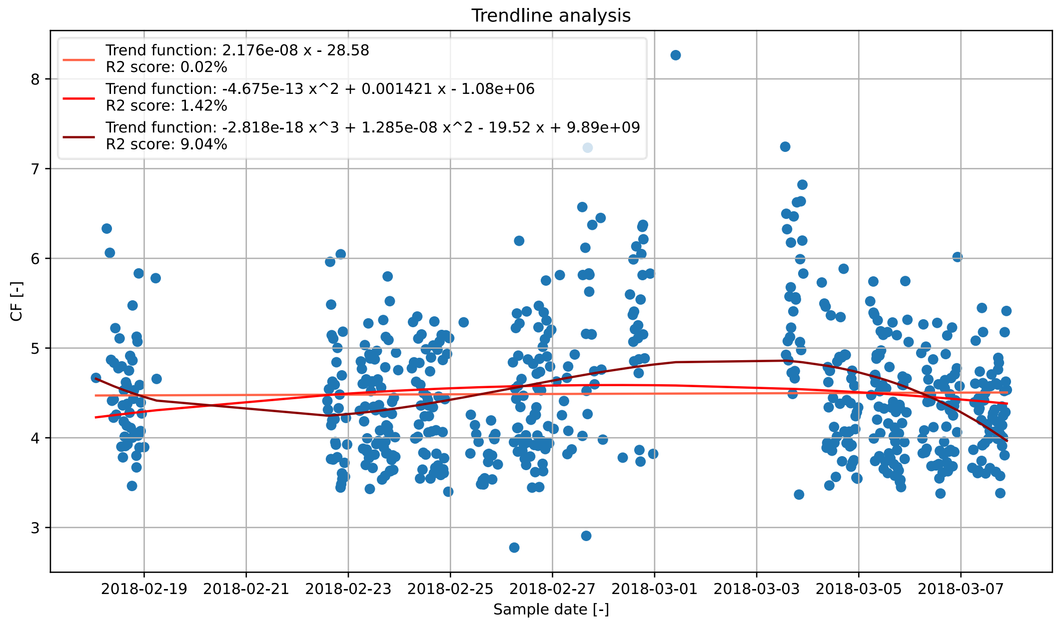

Figure 3. Trend analysis on crest factor (CF) using regression lines (dataset II)

The ratio of signal energy between different directions forms a descriptive parameter for trend evaluation. In the case of dataset I, with similar locomotive types, this parameter exhibits an increasing trend over time, especially for the ratio between X and Y directions. Variation due is rather low and monotonous trend occurs in all three ratios.

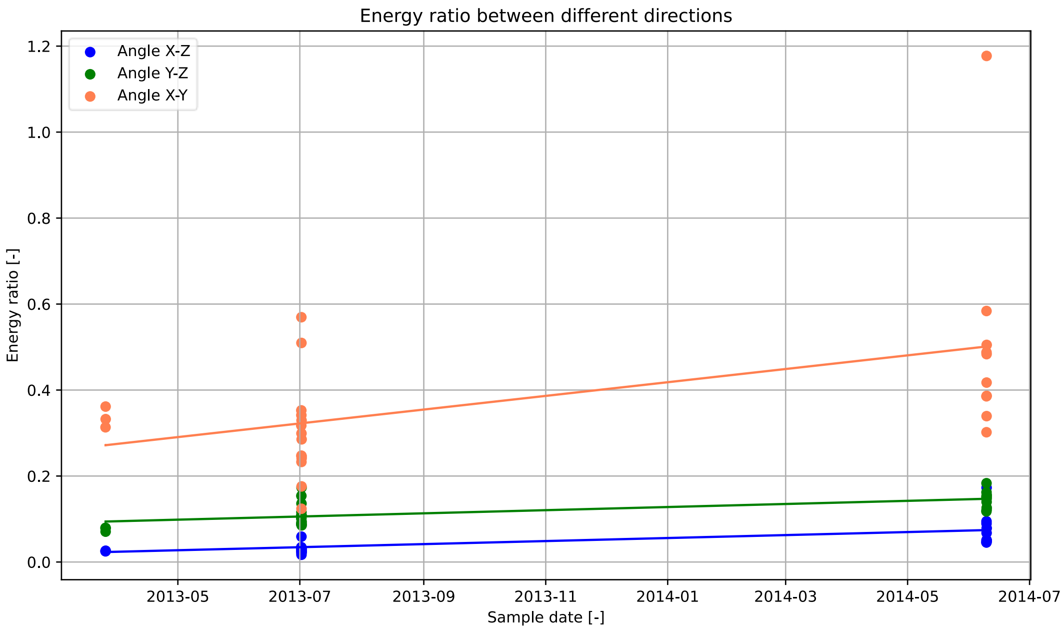

Figure 4. Trend analysis based on energy ratios between different acceleration directions (dataset I)

A long-term trend was also analyzed for dataset II. A linear regression model was fitted to the training datapoints spanning from 18. to 26.2.2018. The MSE was minimized to the value of 0.3729. Validation data 27.2. to 4.3.2018. MSE of the regression model increased to 1.8292, which is almost five times larger compared to the training dataset.

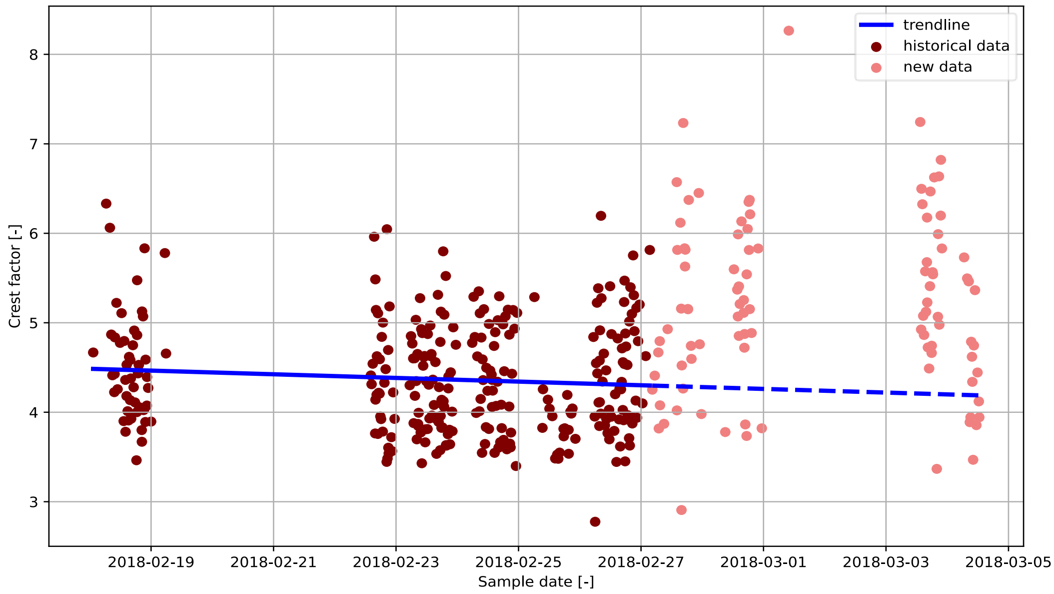

Figure 5. Example of long-term trend analysis using linear regression on dataset II. A trend change can be seen between historical and new data.

Training and testing intervals were selected intentionally to demonstrate MSE or similar metrics as a decision method. Newly measured datapoints can either recalibrate the trend analyzing model or notify the infrastructure operator. Placing a limit to moving standard deviation can detect the same anomaly. In the case of a sudden change of observed values, the moving standard deviation increases. The damage highlighted by Figure 6 was found to be the weakening support stiffness of the bearer.

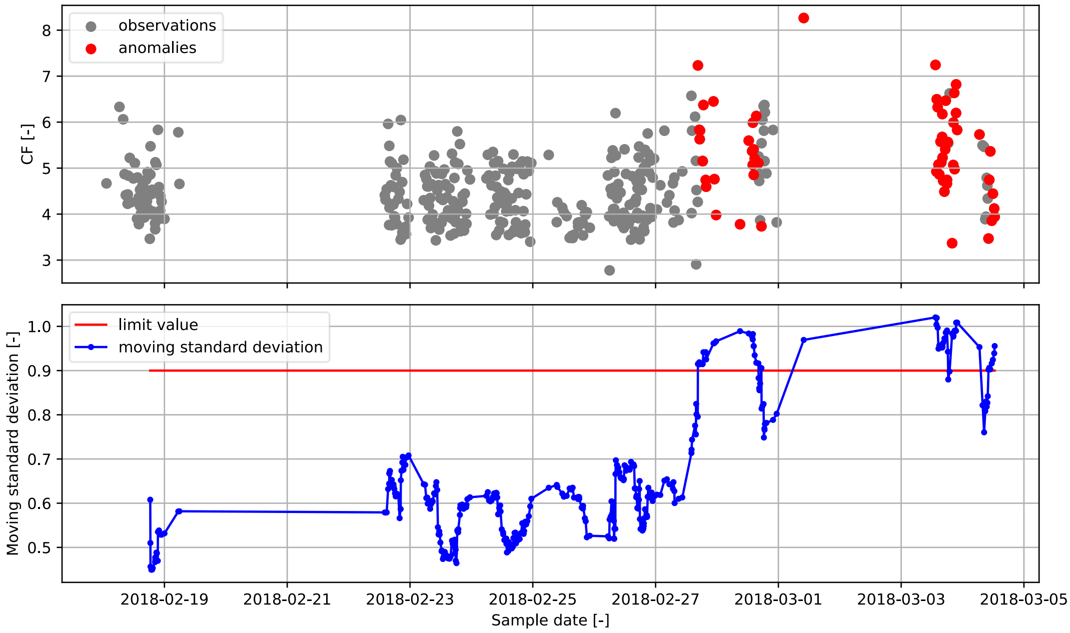

Figure 6. Example of short-term anomaly detection on dataset II using moving standard deviation with a window of size 30. A sudden change of this parameter detects outliers in the measured data.

4 Conclusions and Contributions

Preliminary results on the limited datasets demonstrated a technique of transforming measured accelerometers signals into a set of metrics that can be analyzed for both long-term trends and short-term anomalies. Possible options were discussed, including different prediction models and validation metrics for the detection of changes in the measured data.

Contrary to long-term analysis, a short-term evaluation of measured data can contribute to anomaly detection such as sensor malfunction or urgent problems in S&C. Anomalies may also be considered outliers; therefore, it is crucial to distinguish between short-term defects and noise to prevent false alerts. Seasonality in data must also be considered as a signal can be decomposed into its periodic and non-periodic parts. In the case of accelerometer measurements, the periodicity may be caused by temperature changes

It was also demonstrated that large variability of input data results in a problematic evaluation of proposed models. Identification of locomotive type can improve the outcomes by selecting only similar locomotives for the analysis. Currently available datasets demonstrated a slightly increasing trend over time for metrics such as crest factor, but it is yet to be validated with more data. The cause of the trend change observed in dataset II is unknown. It might be helpful to log all the events that can affect the accelerometer measurements.

More data combined with additional information about track operation, changes in track mode, maintenance or weather will allow the development of more detailed models. The data-driven approach in S&C condition evaluation benefits from large amounts of data collected by automatic systems. Models can be calibrated in real-time and used for the estimation of parameters such as RUL or maintenance planning.

This paper defined several metrics based on specifics of train passage dynamics through S&C and introduced their utilization for trend analysis and fault detection. The current effort focuses primarily on acquiring high-quality data that contain additional information such as train type, speed, structure condition, weather or maintenance. This database will allow to develop and validate specialized machine learning models and evaluate the suitability of different approaches for application within the S&C condition monitoring system.

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