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COMMON CROSSING STRUCTURAL HEALTH ANALYSIS WITH TRACK-SIDE MONITORING

Track-side inertial measurements on common crossings are the object of the present study. The paper deals with the problem of measurement's interpretation for the estimation of the crossing structural health. The problem is manifested by the weak relation of measured acceleration components and impact lateral distribution to the lifecycle of common crossing rolling surface. The popular signal processing and machine learning methods are explored to solve the problem.

The Hilbert-Huang Transform (HHT) method is used to extract the time-frequency features of acceleration components. The method is based on Ensemble Empirical Mode Decomposition (EEMD) that is advantageous to the conventional spectral analysis methods with higher frequency resolution and managing nonstationary nonlinear signals. Linear regression and Gaussian Process Regression are used to fuse the extracted features in one structural health (SH) indicator and study its relation to the crossing lifetime. The results have shown the significant relation of the derived with GPR indicator to the lifetime.

Keywords: common crossing, structural health monitoring, track-side inertial measurements, rolling contact fatigue, Ensemble Empirical Mode Decomposition, Hilbert-Huang transform, Gaussian Process Regression

1. Introduction

The expectation of growth of the passenger and freight transportation in Europe demands the high efficiency, reliability and availability of operation of the European railway systems [1]. The railway infrastructure is characterized by the high costs of scheduled maintenance and, at the same time the significant impact of failures on the overall functioning of the railway system operation. The high maintenance costs are due to high share of maintenance to permanent way and switch and crossings (S&C) that according to [2], can reach up to 50 % of overall maintenance costs. The renewal and maintenance of S&C is one of the main cost divers and is estimated in [3] as almost 33 % of the total maintenance costs of railways. The high S&C costs are the result of frequent and cost-expensive, mainly low atomized manual inspections works.

On the other side, the S&C are a significant factor of the railway system availability and safety. According to study [4], the 6 % of unplanned turnout maintenance works cause up to 55 % of train delays. Therefore, railway turnouts have an indirect influence on operational costs due to delays and follow-up delays, rail replacement service, cancellation of train services, alternative routing. The impact on the safety is assessed to 31 % of the track related derailments caused by the S&C faults on the networks of Great Britain [5].

Therefore, the enhancement of the S&C inspection system, by applying the concept of prognostics and health management (PHM), is the key element to the improvement of reliability and availability. The projects and investments that are based on the S&C monitoring have significantly increased in the past years

in the railway networks [6-9]. German railways (DB AG) are developing and testing the system ESAH-M (Electronic Analysis System of Crossing - Portable), that is used for common crossing monitoring [9] (Figure 1, left). The system ESAH-M is based on measurement of the spatial accelerations in the frog nose, impact position and train velocities.

The measurement information that is collected over the lifetime of crossings is used to predict the failures of crossing elements: rails, fastenings sleepers and ballast. The most crucial element of common crossing, that usually first limits its lifecycle, is the rolling surface (Figure 1, right). The rolling contact fatigue (RCF) of crossings is a failure that occurs more suddenly than other failures and therefore is often a reason of unplanned maintenance works.

The fault detection and prediction that is based on monitoring of infrastructure objects is the subject of many recent studies. The generalisation of modern data mining approaches with application to the railway track infrastructure is presented in book [10]. A machine learning approach with image processing methods is proposed in [11] for early detection and prediction of the RCF failures in rails of common crossing. An overview of modern diagnostic methods for the common crossings and based on measurements study of the crossing improvement is presented in [12-13]. Monitoring and prediction of the track substructure quality development of ballasted and ballastless track in transition areas is studied in [14-15]. Theoretical and experimental studies of dynamic loading on the crossing frogs, with relation to the crossing geometry are considered in [16]. A comparative study of statistical and mechanical approaches for recovering the relation in inertial measurements to the crossing lifetime is shown in [17].

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Figure 1 The track-side inertial measurement systems (left - ESAH-M, right - RCF initiation on the frog nose)

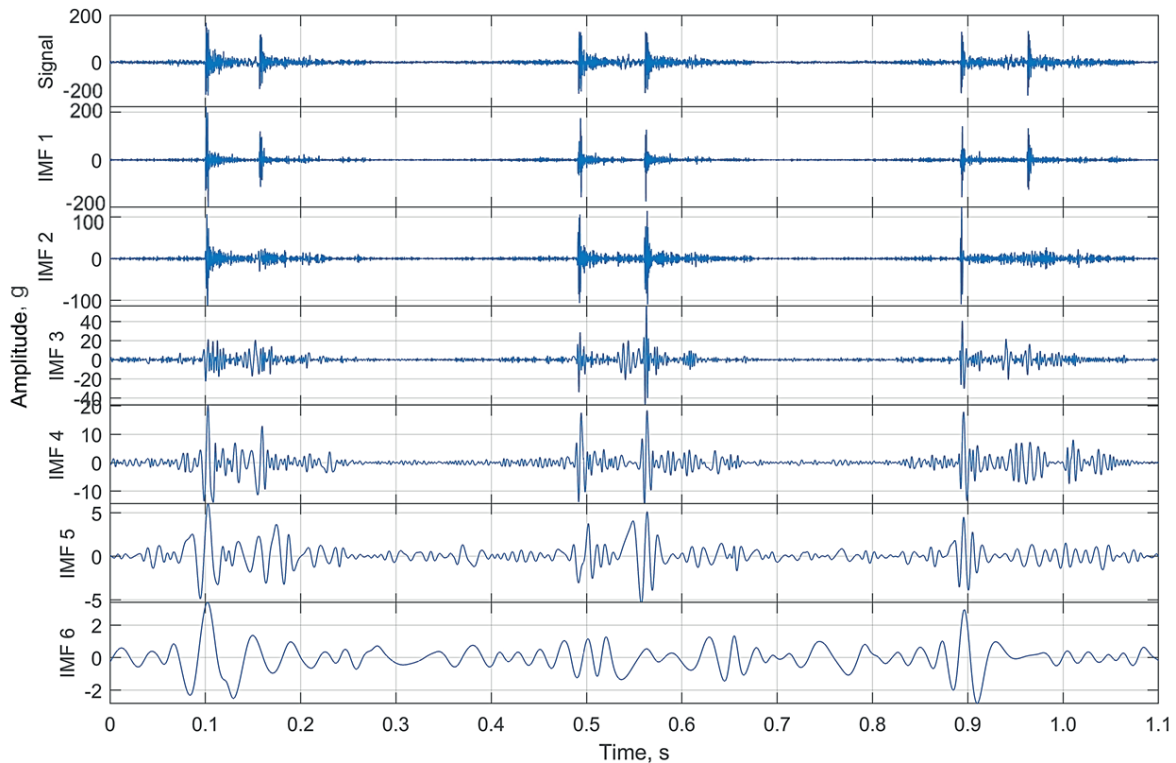


Figure 2 Vertical acceleration signal and its IMF components at the beginning of the crossing lifecycle

Scale modelling of an on-board inertial measurement system for detection of the track geometry failures is performed in [18]. The problem of early fault detection on common crossings with on-board inertial measurements with application of the machine learning methods is considered in study [19]. The application of the machine learning methods for evaluation of the railway ballast compaction is shown in [20]. Use of reinforcement learning for adjustment of the disturbance parameters in the railway operational simulation is offered in [21]. The model-based prediction of the crossing geometry deterioration is presented in [22]. An analysis of the critical failures on the railway turnouts and failure prediction using expert approach is proposed in [23]. Numerical predictions of the long-term accumulation of plastic deformation and wear are shown in [24]. Development of indicators for structural health monitoring of common crossing, with track-side inertial measurements, is presented in [25]. The time and spectral features were extracted from inertial measurements, principal component analysis was used to develop the indicator. Studies of the strain-stress distribution in the flange rail assemblies of railway switch is presented in [26]. The

optimized flange rail is proposed using mathematical modeling methods for the flange rail assemblies of various designs.

The goal of this paper is an exploration of the modern signal processing machine learning methods according to their application for inertial measurement interpretation and recovering the relation to the crossing lifetime. The study is divided in two subsequent steps: degradation feature extraction and feature fusion with regression techniques. Two alternative approaches of crossing lifecycle prediction are studied.

2. The HHT based features extraction of crossing degradation

The measurements of accelerations were carried out on the switch EW 60-500-1:12 with stiff common crossing. The switch was constructed on a main line with mixed traffic and train velocities range 90-160 km/h. The common crossing of the switch is of the assembly type from steel R350HT. The switch was monitored over its overall lifecycle 29 Mt. The monitoring was performed with portable measurement system at 11 time

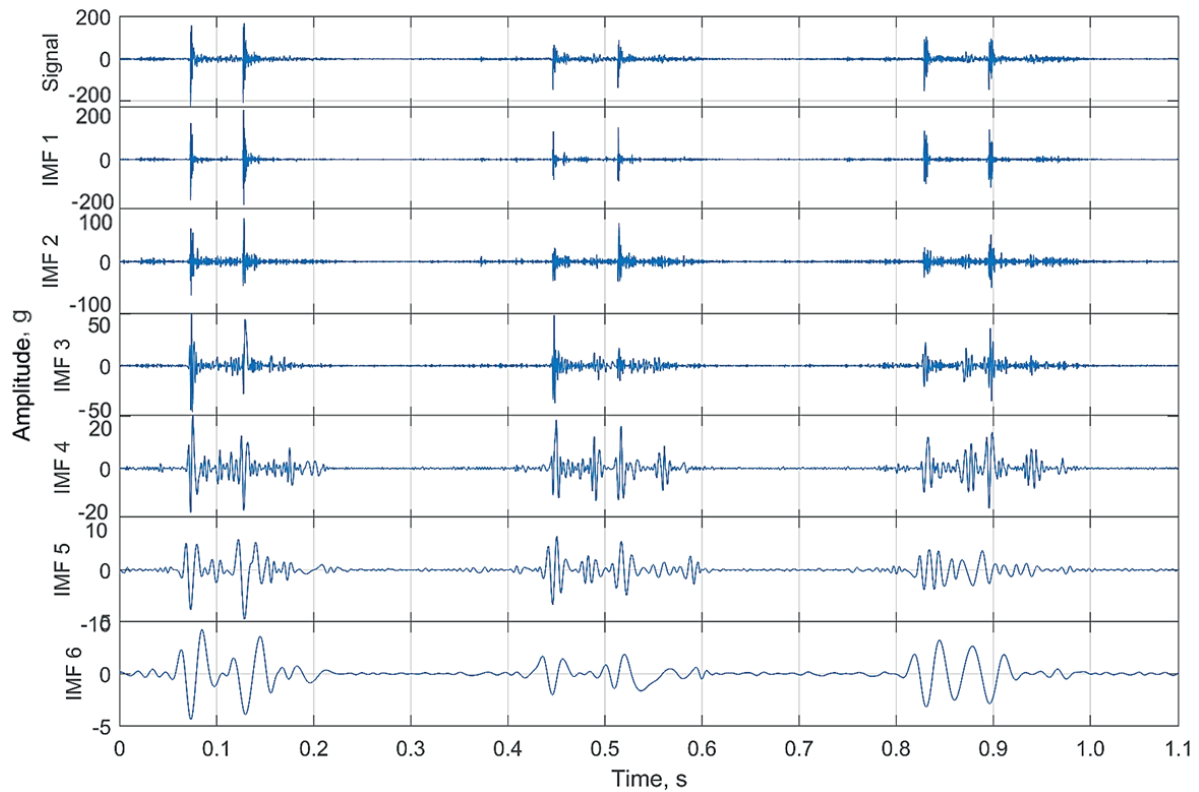


Figure 3 Vertical acceleration signal and its IMF components at the end of the crossing lifecycle

Table 1 Feature set for one observation

Abbr.	Description
V_i	wheel longitudinal velocity
$AufsPos$	impact longitudinal position on the frog nose
$xEn1 \dots xEn7$	energy features for the lateral acceleration IMFs
$yEn1 \dots yEn7$	energy features for the vertical acceleration IMFs
$zEn1 \dots zEn7$	energy features for the longitudinal acceleration IMFs

moments during the lifecycle. The measurement results consist of information for each wheel axle: 3 components of acceleration, wheel impact position, longitudinal wheel speed. The overall data set contains the information for 2701 wheel axles.

The feature extraction from acceleration signals is performed with HHT transform. The HHT consists of two steps: empirical mode decomposition (EMD) and Hilbert spectral analysis. The EMD decomposes signal to the intrinsic mode functions (IMFs) during the so-called “sifting process” where the mean signal envelopes are sequentially extracted [10]. The EMD provides many advantages compared to the short-time Fourier transform (STFT) and wavelet transform (WT): analysis of nonlinear and nonstationary signals, better time and frequency resolution. Numerous recent papers approve the successful application of the EMD in mechanical and civil engineering [27-28] for fault detection and prediction. In the present paper the Ensemble Empirical Mode Decomposition (EEMD) is used, that has no drawback of the mode mixing of EMD.

The results of the EMD decomposition in seven IMF for the two measured vertical accelerations, at the beginning and the end of the crossing lifecycle for the same and rolling stock and similar train velocity, are shown on the Figures 2 and 3.

Results of the decomposition show the significant differences in range of the intrinsic mode functions, especially for IMF4-6. In addition, there are evident differences in form and spectrum of the functions. The second step of the HHT is the Hilbert spectral analysis that is applied to each IMF and yields instantaneous frequency and amplitude. The Hilbert transform $H(\omega, t)$, for the data $X(t)$ is defined as follows:

$$H(\omega, t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{X(\tau)}{t - \tau} d\tau, \quad (1)$$

where: P - is the Cauchy principal value.

The instantaneous frequency is defined as:

$$\omega(t) = \frac{d\theta(t)}{dt}, \quad (2)$$

where: $\theta(t)$ - the instantaneous phase that is defined as $\theta(t) = \tan^{-1} \frac{H(\omega, t)}{X(t)}$.

The Hilbert energy spectrum is described as:

$$E(\omega) = \int_0^T H^2(\omega, t) dt. \quad (3)$$

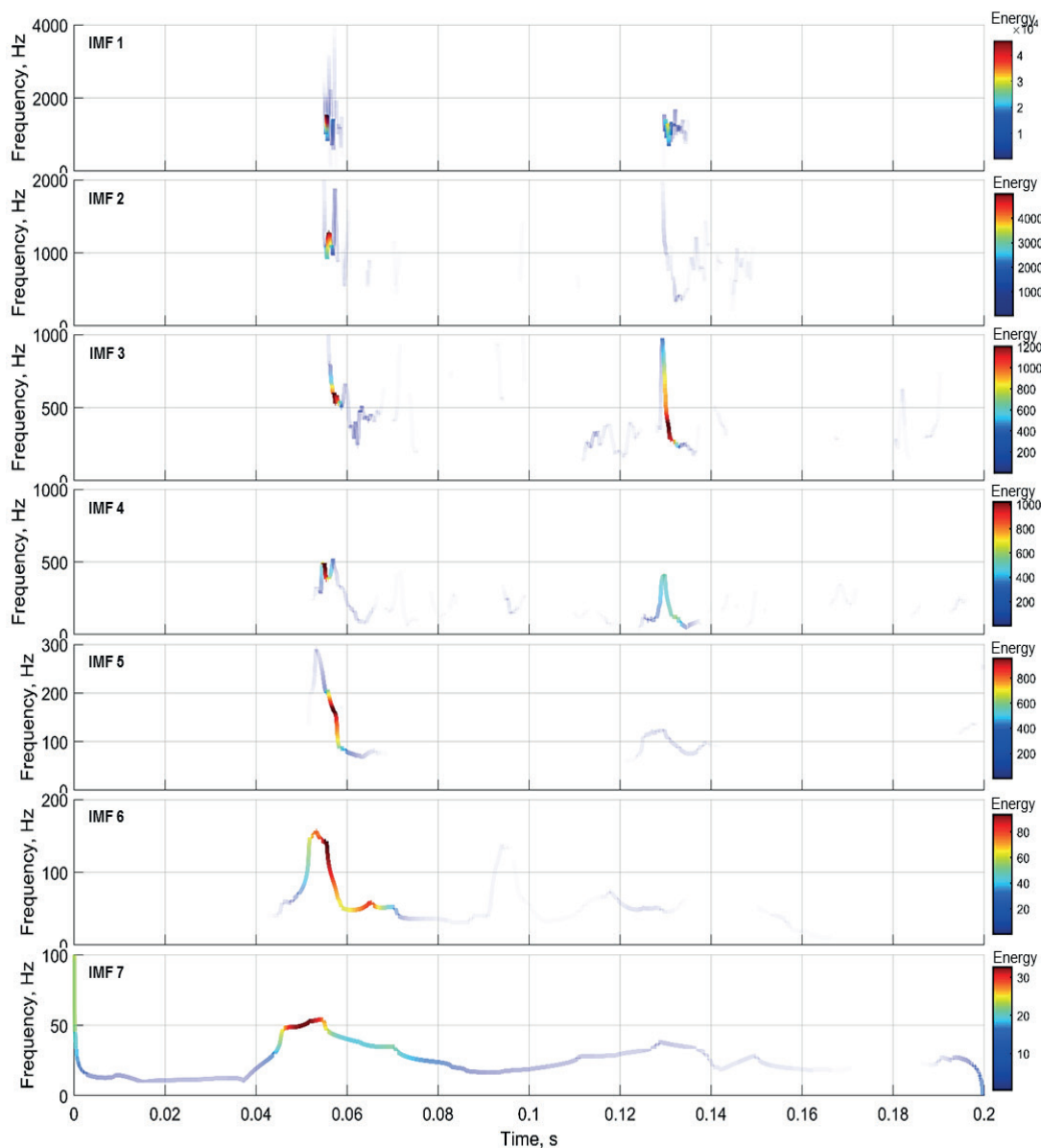


Figure 4 The HHT spectra for IMF components and their energies for 2 axles

The energy spectrum features are extracted from each IMF by the Hilbert transform. There are seven energy features for each of the three acceleration components. Additionally, two operation conditions are included to the data set: the wheel longitudinal velocity and the impact longitudinal position on the frog nose. Therefore, 23 features correspond to one measurement or one wheel passing. The acronyms and description of the features are shown in Table 1.

Results of the Hilbert transform in form of instantaneous frequency for each IMF and the energy spectrum highlighting are shown in Figure 4. The diagrams correspond to the first two axle passages to provide the simpler visualization. The energy spectrum distribution among the IMFs and along the time axis is inhomogeneous. The highest energy spectrum is present in IMF1 and IMF2 for the frequency range 1000-1500 Hz that contain more than 90 % of the total energy spectrum. The IMF has the highest energy spectrum in range of about 50 Hz.

3. Assessment of the SH indicator relation to the crossing lifetime

All the extracted 23 features have some relation to the lifetime, but they are subjected to the high noise due to random or systematic factors, as well. Therefore, none of the single features is good enough to be used as the SH indicator. The best features should be selected and fused in one SH indicator. There are many approaches to fusing of the extracted features in one SH indicator. Often used are the linear methods Principal Components or Partial Least Square Regression [29]. Another group of methods is based on regularization techniques, like Ridge or Lasso regression that can provide the optimal features set selection and generalized linear regression. Advantage of the linear regression is a simple interpretation of the machine learning models due to analytical relation between the predictors and regressor. The nonlinear methods, like Support Vector Regression (SVR), Regression Trees, GPR provide much better prediction, however at the same time they are difficult for interpretation.

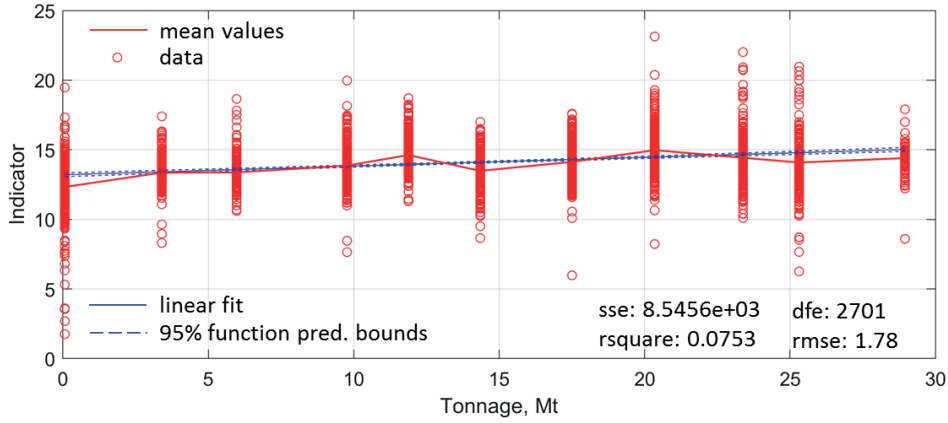


Figure 5 Linear regression of the structural health indicator

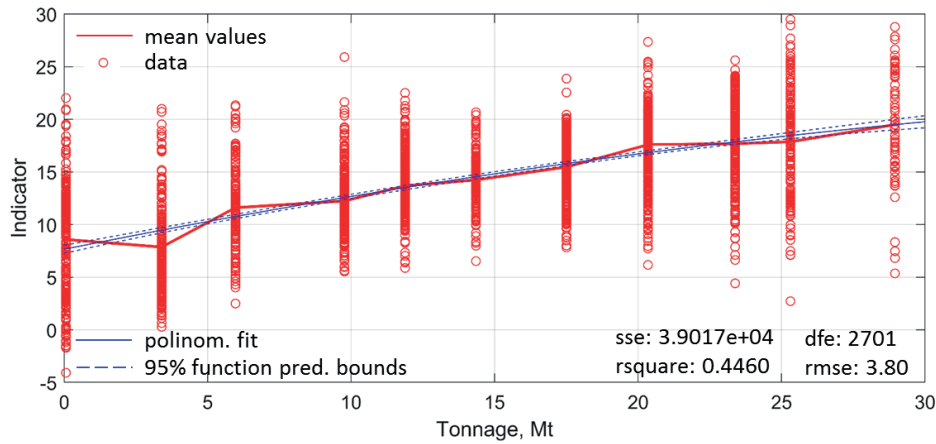


Figure 6 Gaussian process regression of the structural health indicator

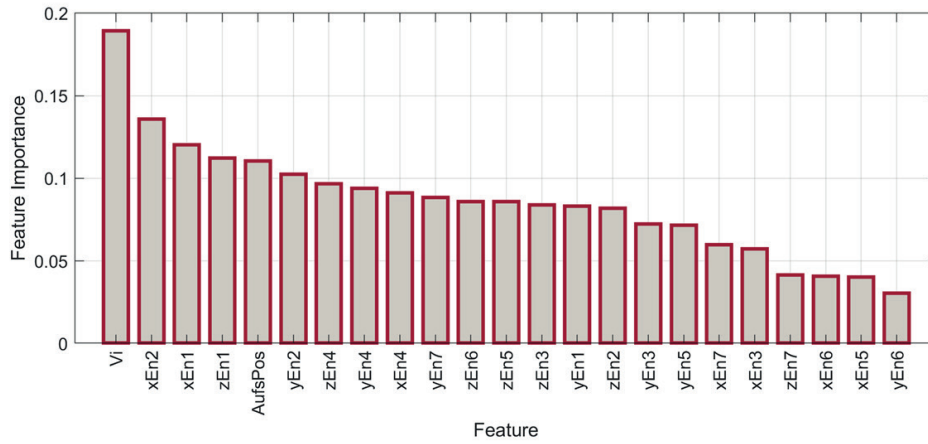


Figure 7 Feature importance ranking

3.1 Linear regression

The linear regression with the Lasso regularisation is used for the lifetime prediction of the common crossing. A multiple linear regression model is defined as follows:

$$\hat{y}_i = b_1 x_{i1} + b_2 x_{i2} + \dots + b_p x_{ip}, \quad (4)$$

where:

$\hat{y}_i$ - estimated response,

b_p - the fitted coefficients for p -predictor or feature,

x_i - the features of i -observation.

The Lasso regularization technique is used to identify important prediction among the redundant ones and therefore to obtain the lower prediction errors. The optimal b_p coefficients are found by solving the following problem:

$$\min_{b_0, b} \left(\frac{1}{2N} \sum_{i=1}^N (y_i - b_0 - x_i b)^2 + \lambda \sum_{j=1}^p |b_j| \right) \quad (5)$$

where:

λ - a positive regularization parameter,

N - the number of observations.

Figure 5 demonstrates the results of the linear regression together with the SH indicator points for each measurement day

during the overall lifecycle of the common crossing. Results show some relation of the indicator to the lifetime but it is relatively weak one with the low coefficient of determination. One possible explanation of that fact could be the nonlinear behavior extracted from the EEMD features that could be explained by the nonlinear regression methods.

3.2 Gaussian Process Regression

In contrast to the linear regression, the Gaussian process regression is a non-parametric approach that finds a distribution over the possible functions that are consistent with the observed data. The Gaussian process is specified by its Kernel covariance function $K(x, x')$ and mean function $m(x)$. It can be defined as follows [30]:

$$f(x) \sim GP(m(x), K(x, x')), \quad (6)$$

where: $m(x) = E[f(x)]$,

$$K(x, x') = E[\{f(x) - m(x)\}\{f(x') - m(x')\}].$$

The Gaussian process based fault assessment and prediction are used in many studies [31-32]. The squared exponential Kernel covariance function is used in the present study for the model learning. The resulting SH indicator prediction, with the learned GPR model in 5 fold cross validation, is shown in Figure 6.

Figure 6 shows the clear ascending trend of the SH indicator data points with monotonous growth of the mean values. The results of the GP regression, different to those of the linear regression, demonstrate much better relation of the SH indicator to the crossing lifetime. The polynomial fit shows narrow function bounds that are relatively low, compared to the explained function variation. Figure 7 shows the feature importance ranking for the GP regression. The highest influence has the operation condition feature - the train velocity. The high influence of the energy spectrum features, corresponding to the interaction in the lateral

and longitudinal direction, is remarkable. The lowest influence have the features extracted from IMF6-7.

4. Discussion and conclusion

The study results have explored the possibilities of the HHT and EEMD application for monitoring and fault diagnostics of the common crossings. The methods allow to recover the deep relations to the crossing deterioration in the inertial measurement information. The undoubtable advantage of the applied feature extraction methods is the meaningful representation of the nonlinear and non-stationary processes. However, the extracted features show the nonlinear relations to the lifetime. That causes difficulties during the following feature fusion to the SH indicator by the linear regression methods. The linear regression with regularization provide the low prediction quality. The quality of prediction could be substantially enhanced by the nonlinear regression methods. The applied GP regression provides higher determination coefficient than the linear regression and therefore much better relation of SH indicator to the crossing lifetime. However, the better result of prediction brings also more difficult interpretation by the non-parametrical nonlinear GP regression with multiple predictor set.

Despite the relatively good results of the HHT and GPR techniques application for the common crossing deterioration estimation, the possible challenges of their application should be noted, as well as the future solution ways. The prediction is performed for one common crossing and the model trained could not be applicable for another one. One model for many crossings should be developed and tested. The wide scatter range of the developed SH indicator can cause the low prediction quality for low number of observations. The scatter range could be explained by the acceleration measurements from different train types. That factor can be potentially taken into account what in turn could improve the prediction.

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