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Original Research

A New Method for Operational Monitoring of Railway Tracks to Reduce Environmental Noise

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Abstract

Noise is a serious environmental side effect of rail transport, freight transport in particular. Significant contributors to railway noise are the mechanical vibrations produced by vehicles due to rail roughness. Our paper presents an application of the loading force identification method, based on the inversion of regressive parametric models, in the reconstruction of rail roughness. Rail roughness is identified from the accelerations of vibration signals measured on the axle boxes of rail vehicles in motion. Our article shows an experimental verification of the proposed method.

Keywords: railway noise, rail roughness, inverse problem, parametric model, diagnostics

Introduction

The appearance and growth of rail irregularities has many negative consequences. First of all, a high level of rail irregularities threatens the safety of rail traffic through an increase in the probability of derailment, an increase in the level of impact forces, and a decrease in the durability of all the components of the track-vehicle system and their accelerated deterioration. Secondly, it decreases ride comfort and increases the negative influence on the environment by generating noise heard by passengers of the rail vehicles and which is also emitted to the environment.

Noise is the audible effect of structural and forced vibrations [1] resulting from rail roughness, and its reduction in vehicles is carried out as a product design and optimization activity. On the other hand, noise is a serious environmental side effect of rail transport, particularly freight transport [2-3]. Recently, the subject has increased in importance. This is due to the undeniable growth in quality demands in the railway transport sector toward requirements to significantly lower the level of emitted noise and produced vibrations. Railway noise stems from the interaction between rough wheels and tracks. A grinding process is therefore used to make rails smoother, while rail dampers are used to absorb rail vibrations. Rail dampers are mass-spring systems attached to rails that reduce railway noise at the source. They are applied in residential areas and lower noise by 3-7 dB(A) in the most important frequency range for human hearing (0.5-4.5 kHz) at the source [2]. On the other hand, wheels can be manufactured to be smoother using brake blocks made of composite materials, rather than standard cast-iron brake blocks that roughen the wheel surface. Composite brake blocks are found to reduce noise by 8-10 dB(A) [2].

It is necessary to monitor the development of rail roughness due to environmental regulations aimed at reducing noise levels [4-5]. Such monitoring is currently being carried out [6-9], but the applied techniques are costly and this further results in the low frequency of performed measurements. Rail roughness is nowadays measured using special vehicles equipped with optical or mechanical sensors. The second group of tools used for measuring rail roughness consists of hand-driven bogies that test roughness or rail profile. As already mentioned, these devices are expensive and, therefore, there are not many of them. Another factor that limits the frequency of rail roughness inspections is the

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requirement of traffic exclusion on the tested route, which, especially for tracks with heavy traffic, could be difficult.

In view of the importance of the issue and the difficulty of its solution, the authors propose to identify rail roughness as a kinematic excitation on the basis of the system response measured on the unsprung elements of rail vehicles (e.g. axle boxes). Such a response, in the form of vibration accelerations, is easy to measure, does not require special vehicles, and the measuring equipment is relatively inexpensive. It is possible that the measuring system for the vibration acceleration measurements could be installed in selected trains, and data from that system would be used to identify rail roughness. As stated, such a solution is much less expensive and easier from an organizational perspective (no necessity of traffic exclusion on the tested route). Because of these advantages, rail monitoring could be performed much more frequently.

Nevertheless, this idea is not a new one and has been investigated by many researchers [6-9]. The novelty of the approach considered in this work lies in a parametric inverse filter that uses a system identification approach. The filter allows the reconstruction of a time domain signal corresponding to rail roughness and, after conversion of the reconstructed signal into a frequency domain, the evaluation of its amplitude and frequency. According to railway regulations, both the amplitude and frequency content of the roughness are taken into account during assessment of a rail's technical condition.

Problem Formulation

The identification of rail roughness based on the vibration accelerations measured on the vehicle is an example of an inverse problem defined in the following way: the model of the system is known as well as the response of the system. Kinematic excitation in the form of the rail roughness is to be identified. The graphical presentation of the inverse problem type can be found in Fig. 1.

As mentioned above, this is a complex problem due to the fact that it is nonlinear and non-collocated. The problem has to be solved in the time domain. The method of quality function minimization was proposed as its solution [10]. This nonparametric method, however, is time consuming

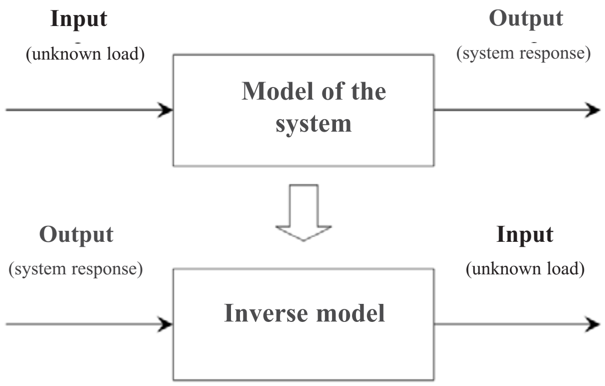

Fig. 1. Inverse problem presentation.

and, for that reason, impractical. Now the authors propose a parametric method that is suitable for real-time applications.

Theory Underlying Model Inversion

Reconstruction of the input of the system by inverting the system's model is important in multiple applications. Input reconstruction is a technique frequently used in the Internal Model Control (IMC) strategies [11] to invert data-driven parametric models and compensate the dynamics of the tracking process [12], or for metrological purposes [13]. The literature, however, rarely addresses the problem of dynamic inversion [14] based on data-driven parametric models of mechanical structures and systems. Nonetheless, the technique (model inversion) is applicable to the problems of load reconstruction in mechanical systems in order to modify the dynamics of a structure or a system and to achieve better performance, e.g. to lower the level of loading forces [15]. Load prediction in systems for which the force signal cannot be directly measured due to constructional constraints, as in the case of forces being exchanged by a wheel and the road or rail, is considered to be one of the most practical applications of the inverse approach [16-17].

A model and its inverse can have either a parametric or a non-parametric representation in time or in the frequency domain. A non-parametric representation uses a frequency response function (FRF), called the spectral transfer function, or an impulse response function, while parametric representation uses a transfer function or state-space equations. Examples of applications of the frequency response function method are discussed in [18], while an impulse response function method is presented in [19]. The accuracy of inverse non-parametric models depends on the time or frequency resolution, i.e. the number of samples available in a given signal realization. Non-parametric methods are not capable of handling systems with closed-loop feedback [20], or those which are unstable or generate drift caused by the presence of physical or geometrical nonlinearities, like nonlinear stiffness characteristics. Moreover, the windowing technique used in minimizing the frequency leakage causes inevitable distortions of the signals.

An example illustrating the application of this approach to railway tracks, described in [16], reveals some of its shortcomings, i.e. questionable validity at high frequencies and ill-conditioning in multiple input-output inverse models. Parametric methods overcome these shortcomings by providing better robustness in the case of short signal realizations and lower variance of estimated parameters for systems with closed-loop configurations [20]. Moreover, the parametric approach provides a significant advantage in reconstructing an input in time-varying systems represented by a linear model of variable parameters, which are recursively adjusted based on real-time data [21]. For example, the inverse problem of load reconstruction of vehicles moving on a bridge requires time-varying models to properly reconstruct the load [22, 23]. This approach is supported by recursive techniques well-known in system identification theory, e.g. the recursive least square (RLS) or the Kalman-filter approach. This paper considers a trans-

Table 1. Criteria of model structure optimization.

Criterion	Measure	Values
Fit in the frequency domain	Fit measure	Reconstructed input (output of the inverse model)
Fit in the time domain	Fit measure	Output of the direct model
Statistical properties of model residuals	FPE and AIC	Residuals of the direct model

fer function approach adequate for tracking load changes in the frequency domain. The advantage of such an approach is the immediate possibility of its application as a hardware pole-zero filter. The drawback of the parametric approach, compared to the non-parametric one, is the requirement to define a model structure. The model structure has to be parameterized to reflect the dynamics of the system under consideration. This is a challenge in advanced model structures where a priori knowledge concerning disturbances affecting the systems is additionally required. If *a priori* knowledge is not available, a blind search procedure for the best structure can be applied using key measures of the model quality, e.g. best fit, AIC. To conclude, the parametric approach is recommended when first-principle knowledge of the system under investigation exists and the system is stationary, in the sense that its mass, damping, and stiffness properties do not vary significantly. If the stationarity conditions can not be fulfilled, an adaptive system identification approach has to be applied to obtain an inverse adaptive model as presented in [23].

A block diagram of the procedure of inverting a linear model is presented in Fig. 2.

The process of selecting an adequate model structure and an algorithm for estimating model parameters is the initial step. The model structure is selected using the quality indicators of the direct and inverse models' fit to the data in the time and frequency domain, respectively. The selection process is supported by model quality measures and visual inspection as proposed in Table 1.

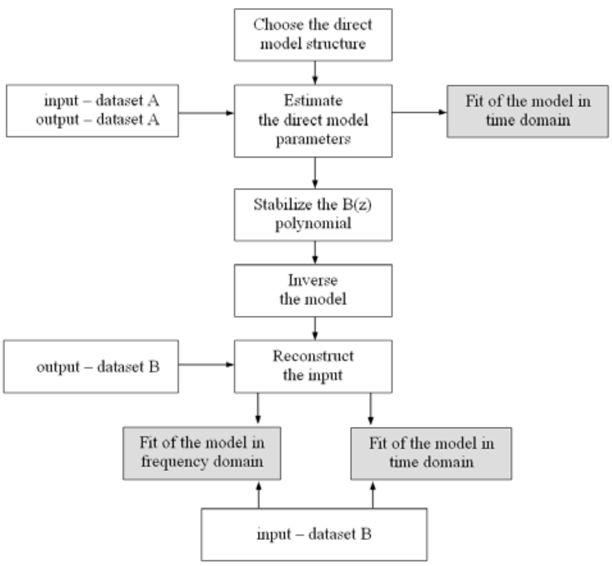

Fig. 2. Block diagram of the inversion procedure of a linear model.

The next step, estimation of the parameters of the selected model, is performed using the available input-output data, and a one-step-forward prediction of a direct model output is computed. The adequacy of model structures is then evaluated by means of two measures, referred to in the literature as the final prediction error (FPE) and the Akaike information criterion (AIC). The more accurate the model is, the smaller the values of the FPE and the AIC measures are. Additionally, in order to detect the presence of abnormalities in the frequency domain, a visual inspection of the Bode plot of the input-to-output transfer path and the spectra of model residuals (the disturbance-to-output transfer path) was performed for each identified model structure. Analysis of the extensive quantity of such visual indicators (not presented here due to a lack of space) indicates the presence of no abnormalities. Visual evaluation of model quality might also be supported by pole-stability diagrams, plotted as a function of the orders of selected polynomials. The major criterion for model order selection is, however, comparison of fit quality of the reconstructed inputs. The purpose of selection is to obtain a suitable inverse linear filter capable of providing the best possible reconstruction of the input signals with respect to the optimality criteria listed in Table 1. The strategy implemented for optimizing selection of the model structure is the systematic search for a set of model structures that would satisfy the criteria listed in Table 1.

The inverse linear model is unstable if at least one of the zeros of the direct transfer function is located outside the unit circle or inside the unit circle, for z^{-1} or z operators respectively. These zeros create a non-minimum phase transfer function, and hereafter are referred to as non-minimum phase zeros. The inverse transfer function can be stabilized, however, by factorization of the numerator $B(z)$, as discussed in [20]. The advantage of such a stabilization method is the lack of phase error and delay, while the only disadvantage is a small gain error that is, moreover, negligible if the output signal consists of low frequency components [20]. This stabilization technique was applied to load reconstruction by [16, 17].

The procedure of inverting a model does not correspond to any physical phenomenon and, therefore, inverse models always have a tendency to be unphysical. As all physical systems have a time delay as well as limited bandwidth, an exact inverse advances the signal as a result of the delay and amplifies high frequency noise without any bound, if the bandwidth is not restricted to the upper frequency band of the inversing load. This phenomenon is the so-called ill-posedness of the inversion and requires regularization techniques to be used to correctly estimate the load up to a certain bandwidth, typically given by the frequency at which amplitudes of the signal and the noise are equal. A standard solution of the regularization problem is to use low-pass 'noise' filters that lead to a model and its realized approximation to the prototype of inversion that are both strictly proper. This fact suggests that the sampling rate of input and output signals has to be adapted to the maximum frequency of the reconstructed signal, although a very low sampling rate can result in severe aliasing. On the other hand, the sampling rate should allow the most important dynamics represented by vibration modes of the structure to be captured correctly. The significance of identified modes can be classified according to their energy levels while the structure is operating, which allows the most powerful ones to be selected and the sampling rate to be defined.

System Identification

A linear time-invariant (LTI) system, mapping a single input onto a single output (SISO) and in discrete time-steps, is represented by difference equations [20]. These equations take the form of (1), where $G(z^{-1})$ and $H(z^{-1})$ are discrete-time transfer functions containing adjustable coefficients and represent the input-to-output dynamics and the disturbance-to-output dynamics, respectively. The transfer functions $G(z^{-1})$ and $H(z^{-1})$ are rational functions of the operator z^{-1} that take the form shown on the right-hand-side of the equation [20].

$$y(i) = G(z^{-1})u(i) + H(z^{-1})e(i) = \frac{B(z^{-1})}{A(z^{-1})F(z^{-1})}u(i) + \frac{C(z^{-1})}{A(z^{-1})D(z^{-1})}e(i) \tag{1}$$

The polynomials $A(z^{-1})$, $B(z^{-1})$, $C(z^{-1})$, $Dz^{-1})$, and $F(z^{-1})$ are used for model parametrization. Special cases of the LTI SISO general model structure (2) are listed below as predefined model structures using the function notation to state their characteristic structural numbers [20];

$$\begin{gathered} \mathrm{PEM}(nA, nB, nC, nD, nF, k) \\ \mathrm{BJ}(nB, nF, nC, nD, k) \\ \mathrm{ARMAX}(nA, nB, nC, k) \\ \mathrm{ARARX}(dA, dB, dD, k) \\ \mathrm{OE}(nB, nF, k) \\ \mathrm{ARX}(nA, nB, k) \end{gathered} \tag{2}$$

...where nA, nB, nC, nD, and nF are polynomial orders and k is the input-to-output delay [20].

Experimental Verification

Kinematic excitation in the form of rail roughness is directly interconnected with rail-wheel contact force. The measurements were taken on a self-dumping cargo vehicle of the Fals series, type 665 4 011-4. The authors are aware of the fact that this type of car is not the best choice for the rail roughness assessment due to it braking system, which can cause some wheel irregularities. However, that was the only possibility to measure the experimental data. The measurements were performed excluding the braking phase of the cargo vehicle as this can affect the measurements due to additional forces generated by braking systems in the form of friction between the wheels and braking blocks. The cargo vehicle was empty during tests. In Fig. 3, the placement of accelerometers on the axle-boxes is shown.

During the test rides, the time histories of two forces were recorded: vertical and horizontal, both acting in the rail-wheel contact point in the first wheel set on the right-hand side. Together with the forces, 6 vibration accelerations measured on the axle boxes and the frame of the vehicle were stored. Additionally, information regarding vehicle velocity, and its gyroscopic moments, was collected for the ride profile recognition. Forces were measured in an indirect form during the tests. Displacements of the vehicle axles were the measured quantity. They were measured using the strain gauges set and further recalculated to obtain the bending moments of the axles. These moments were next transformed into the rail-wheel contact forces. The values obtained in the presented method were compared with the identified ones. Eight data sets, which corresponded to the eight rides of the vehicle with different velocities, were collected on the rail with varying quality. Each test ride took less than 20 s. Sampling frequency was set to 150 Hz.

Inversion of the model was conducted according to the scenario shown in Fig. 2. The measured random force is required at the input of a direct model and measured acceleration is required at its output. The orders of particular polynomials of a linear model were selected using the quality indicator of the direct model's fit to the data in the time domain as proposed in Table 1.

To compare the results of direct measurements and those obtained with the procedure of model inversion, the correlation coefficients were computed for both the lateral and vertical forces. The results of this comparison of measured and reconstructed rail-wheel contact force are presented in Table 2.

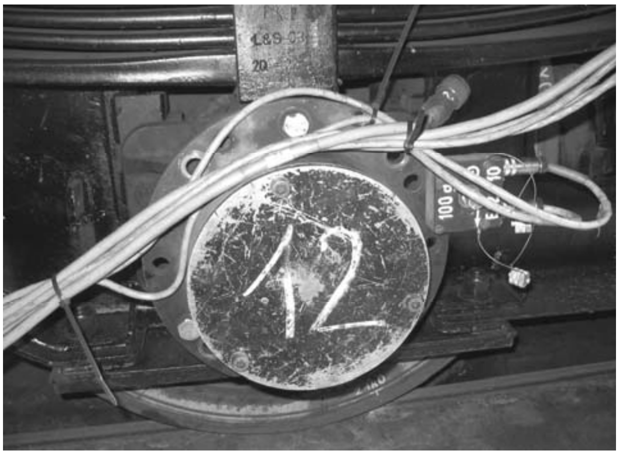

Fig. 3. Measurements of acceleration vibrations on the vehicle axle box.

Table 2. Validation results for linear model ARX(33,29,1) at vehicle velocity v=60 km/h.

Force	Correlation coefficient	
	right side of vehicle	left side of vehicle
Lateral force	65%	63%
Vertical force	71%	72%

Besides Table 2, the exemplary results of load reconstruction are presented graphically in Fig. 4 in the frequency domain.

Conclusions and Final Remarks

Our paper addresses questions concerning the feasibility of reconstructing the excitation of the mechanical systems, which is difficult to measure directly. The purpose of this work is to advocate model inversion based on a parametric linear model as an alternative method for applying this class of problem to non-parametric models [8, 9, 15]. The paper summarizes the theory and discusses case studies of inverting data-driven models of mechanical systems. Experimental validation tests confirm that the methodology proposed herein, i.e. parametric system identification and model inversion, is valid for operational data. Nevertheless, the validation process can be improved using a vehicle where the braking system does not affect wheel roughness. This approach requires, however, another vehicle to be selected and the proposed constructional modifications to be implemented in the suspension system of the vehicle.

Results provided by data-driven parametric model structures are sufficient to constitute foundations for implementing them as inverse models in the form of fixed-point filters on a DSP platform. The model implemented in such a form is capable of filtering the responses of a mechanical system into a reconstructed input, which is further converted into the frequency domain by a standard DFFT algorithm.

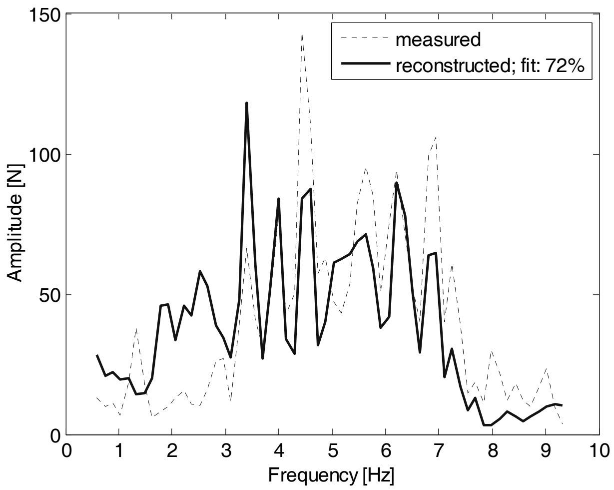

Fig. 4. Results of load reconstruction presented in the frequency domain at the left side of the vehicle in the vertical direction obtained with the use of ARX(33,29,1).

Nomenclature

i – discrete time
A, *B*, *C*, *D*, *E*, *F* – polynomials used for the representation of the transfer function
nA, nB, nC, nE, nF – order of polynomials used for the representation of the transfer function
z – operator of the Z transformation
e – disturbance variables in the model
u – input variables in the model
u_0 – inverse input
y – output variables in the model
G(z), G(z^{-1}) – transfer function

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