NONLINEAR ANLAYSIS OF EXHAUST LOCOMOTIVE ENGINE VIBROACOUSTIC SIGNALS FOR MISFIRE DETECTION – – OBDII/EOBD PERSPECTIVES

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***Abstract*.**

The paper describes the measurements of vibroacoustic exhaust locomotive engine signals for misfire phenomenon simulation and some results of nonlinear analysis of the given time series. The misfire was simulated by disconnection of one cylinder of the engine. The measurements were performed in Rail Vehicles Institute in Poznań. The analysis, besides the classical methods like spectral analysis, consists of nonlinear methods which are based on the deterministic chaos theory. The stimulus for our researches was expected during nearest years introduction of regulations on limits of combustion gases emission and obligatory on-board diagnostic systems in exhaust locomotives.

1. Introduction

The exhaust locomotives are important source of ecological pollution [14]. The emission of destructive combustion gases from non-road sources like combustion locomotives makes a significant contribution in comparison with road vehicles. So far in this area there are no regulations describing the limits of combustion gases emission and no obligatory methods of emission critical damages detection. Such norms have already appeared for automobiles. In the USA in 1996 the OBDII norm was introduced and it became an European standard in 2000 (EOBD). The norm defines the duty of installing on board diagnostic systems and the main function of the systems is a continuous monitoring of basic power transmission system parameters. One of the most important task of the OBDII system is a misfire detection. The misfire detection is important not only because of the combustion gases emission but because of the possibility of catalyst damage. Th following years will bring us the general sharpening of norms on combustion gases emission and they will be carried into vehicles with heavy diesel engines like combustion locomotives. This need to perform some researches in the area of combustion locomotives engines. Hence the important task in this area are researches and the choice of the misfire detection method, which will be adequate to exhaust locomotives. The paper shows the results of the researches on trials of misfire detection which base on the analysis of vibroacoustic signals taken from the exhaust locomotive engine. The misfire was simulated by disconnection of the one cylinder of the engine. The measurement were performed on exhaust locomotive 401Da – 427 in Rail Vehicles Institute in Poznań. The analysis, besides the classical methods like spectral analysis, consists of nonlinear methods which are based on the deterministic chaos theory. The last year show us many evidences that the nonlinear factor appears in the broad spectrum of mechanical devices so the application of nonlinear methods of analysis seems fully reasonable. The base of our method is the Takens-Mane theorem which allows to reconstruct the dynamics of nonlinear system basing on the one-dimensional time series. During our analysis we were applying the time-delay embedding method and the false near neighbor method. We have taken into consideration such parameters like Lyapunov exponents and fractal dimensions.

2. The measurements

The misfire was simulated by the disconnection of one cylinder of locomotive engine. The measurements were preformed in Rail Vehicle Institute TABOR in Poznań on exhaust locomotive 401Da – 427 with an engine 16H12A Henschel – 12V produced by Wola. The acceleration sensor was fixed into the engine frame in the place, where one could define the measurement direction of acceleration. In measurements we used two kinds of apparatuses. First of all, one applied 16-channel digital recorder TA11 produced by Gould provided by Rail Vehicle Institute which bases on piezoelectric sensor 4395 produced by Brűel & Kjær, the data acquisition program Gould Acquire TA-D and results analysis program DASA VIEW II produced by Gould.

The measurement of the locomotive engine was performed in the following circumstances:

1) three rotational velocities
   a) $n_1 = 650 \div 680$ rev/min (idle run),
   b) $n_2 = 1100$ rev/min,
   c) $n_3 = 1500$ rev/min,
2) three measurement phases
   a) phase 1 – sensor is fixed on cylinder 1 – all cylinders are working,
   b) phase 2 – sensor is fixed on cylinder 1 – cylinder 1 is disconnected,
   c) phase 3 – sensor is fixed on cylinder 1 – cylinder 4 is disconnected.

The sensor was fixed on the frame of cylinder 1 (see fig. 1). The signal was registered in three channels, each channel represented a component in one of three directions: parallel to main locomotive axis, horizontal-transversal and vertical-transversal to main locomotive axis.

Additionally the measurements were performed by using the signal analyzer AMX520. in the following cases:

- for three rotational velocities 650 rev/min, 1100 rev/min i 1500 rev/min,
- in two phase: all cylinders are working and 4 cylinder is disconnected.

The signal analyzer AMX520 with acceleration sensor was made in Automex (Gdańsk, Poland). Analyzer AMX is an autonomous, battery powered, manual device which is capable to signal registration and analysis. The heart of the device is 24-bit signal processor Motorola DSP56002pv80. On board there is fast 14-bit converter A/D, analog band-pass filter system, 128 kB memory FLASH and RAM. In the measurement one applied integrated capacity sensors (20g i 2g) and laptop with program AMX [10].

__Fig. 1.__ The general schema of the locomotive engine

3. Nonlinerity in mechanical systems and engines

The signals obtained in the measurements composed the one-dimensional time series. The time series were processed using in general such methods like spectral analysis and nonlinear analysis, which based on the deterministic chaos theory. Because of the Fourier analysis of this kind of signals usually do not give the satisfactory results, we have focused on nonlinear analysis.

The deterministic chaos theory is a description of nonlinear dynamical systems. So far for improving the monitoring, diagnostic and control of technical devices one was using usually the linear methods. Some elements of nonlinearity were introduced but not directly in classical linear approach (see e.g. [16]). The deterministic chaos theory is quite good for such an analysis because it uses directly nonlinear models.

The deterministic chaos theory is a development of classical theory of linear dynamical systems (see e.g. [2, 17]). The deterministic chaos one can describe as *„unpredictable long time behavior of deterministic dynamical system which is caused by the sensitivity on initial conditions”* or also as *„irregular and unpredictable evolution of many of nonlinear dynamical systems”*.

We must underline that nonlinear chaotic system is a fully deterministic system and it is fully predictable if we have the full knowledge about initial conditions. The chaotic system is very sensitive to even very little changes in initial conditions, hence in most of practical cases, where we know initial conditions only with the given accuracy, it is really unpredictable. The nonlinear chaotic system can produce the signal which is irregular and seems similar to stochastic system but its irregularity has non stochastic nature, and is caused by the internal nonlinearity of the dynamics. Changing the values of parameters of a nonlinear chaotic system one can find the qualitative changes of solution what is especially well seen in the phase space.

Many processes in technical area, describing electric and mechanical devices, contain in their dynamics nonlinear elements (see e.g. [8, 9, 12]). This can be used to improve the monitoring, diagnostic and control of technical devices. One can find in literature term „engineering chaos” for description of deterministic chaos theory application for engineering and industrial purposes (K. Aihara in agree with [8]).

The combustion engines can be a source of many signals which are good for analysis – it is enough to mention vibration signals form sensors attached into engine, all acoustic signals, signals form the ionic currents detectors, signals representing crankshaft angle velocity, pressure signals, and even visual signals which can show e.g. the engine head heating etc. (see e.g. [15, 20]). The combustion engine shows, so called, cyclic variability CV of energy release form one cycle to another. In literature the cyclic variability CV is described in stochastic, linear deterministic or chaotic deterministic way, and all the time one can find the discourse on the real nature of CV [4, 5, 6, 13, 18].

The nonlinear methods started to play an important role in engine dynamic modeling. This approach can allow us to better understanding of dynamic of engine processes (see e.g. [3, 4, 5, 6, 7, 11, 12, 19]).

4. Nonlinear analysis

Assume we have the sampled time signal s(t). The main idea is that the space in which one should see the dynamical signal structure is not one-dimensional space of s(t) values but the dynamics appear in the space of vectors **y**(t) in higher dimension space. The main task is to find the right phase space (the dimension) and try to reproduce in a such phase space the system dynamics (the attractors). What we can do is to identify a space which is formally equivalent to the original phase space. We can do it following the Takensa and Mañé theorem [1, 3, 8].

For the discrete dynamical system

$$\mathbf{x}(n) \to \mathbf{x}(n+1) = \mathbf{F}(\mathbf{x}(n))$$

where the phase space of **x**(n) is multidimensional the Takensa and Mañé theorem poses that if we can observe the single scalar value h(•) which depends on some vector function of dynamical variables **g**(**x**(n)) then the geometrical structure of multidimensional dynamics can be transform from scalar measurements h(**g**(**x**(n))) into the space created with new vectors with components consist of h(•) applies to powers of **g**(**x**(n))

$$\mathbf{y}(n) = \left[\ h(\mathbf{x}(n)), h(g^{T_1}(\mathbf{x}(n))), h(g^{T_2}(\mathbf{x}(n))), \ldots\ldots, h(g^{T_{d-1}}(\mathbf{x}(n)))\right]$$

For quite general conditions on smoothness of function h(•) i **g**(**x**) one shows that if d is enough high, then many important features of unknown system (which is the source of our signal) is reproduced in new space of vectors **y**(n). In particular one shows that the sequence of points **y**(n) → **y**(n+1) (time evolution) is performed in agree with unknown dynamic **x**(n) → **x**(n+1). The new space is mapped from original by smooth and differentiable transformations. All invariants of motion are the same in original and reconstructed space. The main problem is to find the time delays and dimension. To this purpose one applies time-delay embedding and false nearest neighbors method. The time delay is usually found as the first zero of autocorrelation function or as the first minimum of averaged mutual information [1].

In practice we take one time interval τ and it increasing multiples

$$s(t),\ s(t+\tau),\ s(t+2\tau),\ s(t+3\tau),\ \ldots..$$

If we consider time series s(n) with sample time t_p

$$s[n] \equiv s(nt_p)$$

then the sequence of delay vector components started from time t_i we can write as

$$\begin{aligned} &s[i] = s(t_i),\\ &s[i+T] = s(t_i+\tau),\\ &s[i+2T] = s(t_i+2\tau),\\ &\text{etc.} \end{aligned}$$

where $T=\tau/\tau_p$. In general beginning with t_1 the successive points in n-dimensional phase space created from n delay components one can write as

$$\mathbf{y}_1 = (s[1], s[1+T], s[1+2T], \ldots.., s[1+nT])$$
$$\mathbf{y}_2 = (s[2], s[2+T], s[2+2T], \ldots.., s[2+nT])$$

$$\vdots$$
$$\mathbf{y}_j = (s[j], s[j+T], s[j+2T], ... , s[j+nT])$$
$$\vdots$$

The dimension will be choosen well if the geometrical structure created in successive phase spaces (two, three and more dimensional) will be fully unfolded, what means that the near distance of all points is the result of only the dynamics, not of the projection into space of lower dimension. To find the right dimension one applies then the false nearest neighbour method where we choose as the right dimension this for which the percentage of false neighbours (which are the result of projection) decrease to zero [1].

The time delay and the dimension are parameters which can also appear important from the diagnostic point of view. But usually to diagnostic purpose one uses the parameters which describe the dynamic in the phase space (attractors). In our researches we have used the parameters called Lyapunov exponents. The Lyapunov exponents are the measure of a trajectory convergence and divergence in the phase space. The Lyapunov exponent is an average convergence speed (divergence speed) of two neighbor trajectories. One have a convergence for $\lambda>0$ and divergence for $\lambda<0$. We expected that for two points in the phase space $\mathbf{x}(t)$ i $\mathbf{y}(t)$, their distance in time t' after the chaotic evolution will be as following

$$|\mathbf{x}(t') - \mathbf{y}(t')| \approx |\mathbf{x}(t) - \mathbf{y}(t)| \exp(\lambda|t' - t|),$$

where λ is Lyapunov exponent.

In nonlinear system with d degrees of freedom (d dimensional phase space) we have d Lyapunov exponents $\lambda_1>\lambda_2,...,\lambda_d$. Usually if one of the Lyapunov exponents is positive we can expect the chaotic behaviour. Analysis of Lyapunov exponents can give us information on bigger or smaller chaotic contribution in the system. Anyway the Lyapunov exponents can be treated as the parameters which can be directly applied during diagnostic process to differ one system state from another [1].

5. Results

The calculation were performed by using program NDT (Nonlinear Dynamics Toolbox) and the package CDA (Chaos Data Analyzer). The delay time τ was calculated both as the first zero of the autocorrelation function and as the first minimum of an averaged mutual information. Anyway the results of mutual information were taken as the most significant because of their nonlinear background.

For the first part of signals (obtain by Gauld recorder with piezoelectric sensors) the values of time delay are in the range $\tau = 12 \div 14$ with $\bar{\tau} = 12.78$. The dimension d was in the range $5 \div 6$ with $\bar{d} = 5.5$. The general found tendency is that the dominant Lyapunov exponents DLE are bigger for the cases with all cylinders working (see table 1).

For the second part of signals (obtain by analyzer AMX520 with capacity sensors) the values of time delay were $\tau = 3$, and the dimension d=5. The general results show the same tendency for DLE like the previous results. And it is worth underlying that one can find the confirmation of this tendency in literature and in other our measurements (e.g. for car engines).

Table 1

The results of the dominant Lyapunov exponents calculation with using the program NDT (Nonlinear Dynamics Toolbox) for the case with all cylinder working and the case with one cylinder (no. 1) disconnected.

Rotational speed (in rev/min) and sensor number	Dominant Lyapunov exponent		
	the case with all cylinder working	the case with one cylinder disconnected	the difference
1500 1	0.573	0.519	0.054
1500 2	0.292	0.197	0.095
1500 3	0.524	0.500	0.024
1100 1	0.581	0.542	0.039
1100 2	0.355	0.327	0.028
1100 3	0.417	0.501	-0.084
650 1	0.456	0.385	0.071
650 2	0.262	0.299	-0.037
650 3	0.508	0.434	0.074

But the table 1 shows this tendency not for all cases. It seems that the main problems are to eliminate noise which gives a big component to the signal and to extract the relevant part of the signal which gives us the real information about the dynamic. The influence of the noise can be found during the analysis of the phase space portraits. For all signals the phase space portraits were in the form of cloud but with more or less regularities outside (see fig. 2). The cloud shows the big influence of noise which seems is possible to be eliminated.

6. Conclusion

The results of the analysis appear quite interesting. First of all, the dominant Lyapunov exponents for all signals were positive what means that one can find some chaotic components in the signals and their dynamics. The calculated values of time delay τ and dimension d appeared quite reasonable. The d was not to
high what gives us the hope to find some low-dimensional chaotic behaviour. It is worth to underline that the significant difference for dominant Lyapunov exponents for the case with all cylinders working and the case with one cylinder disconnected. Taking into account the measurement presented in the paper and literature data one can conclude that the Lyapunov exponents can be used as diagnostic parameters. The only problem is to perform the good and reasonable reprocessing consisting of denoising and filtering. But the reprocessing should be performed with a great care because the inconsiderate elimination of some signal components can deprive us of relevant dynamical information.

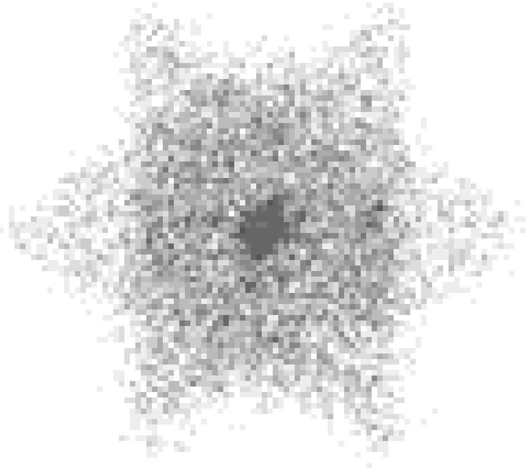

Fig. 2. *Phase space portrait for the case with 4 cylinder disconnected for 1500 rev/min*

We also observe some interesting behaviour during application of the false nearest neighbour FNN method. The result dimension of FNN depend on the criterion threshold which classify neighbours as false or truth. But in the plot of dimension d against the criteria threshold one can find a broad plateau what gives us the possibility of reasonably choice of threshold and result dimension.

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