Early Detection of Gear Faults in Variable Load and Local Defect Size Using Ensemble Empirical Mode Decomposition (EEMD)

H. Mahgoun, Fakher Chaari, A. Felkaoui and Mohamed Haddar

Abstract In stationary condition, when a local gear fault occurs, both amplitude and phase of the tooth meshing vibration are modulated. If the rotating speed of the shaft is invariable, the gear-fault-induced modulation phenomenon manifest as frequency sidebands equally spaced around the meshing frequency and its harmonics in vibration spectra. However, under variable load and rotating speed of the shaft, the meshing frequency and its harmonics and the sidebands vary with time and hence the vibration signal becomes non-stationary. Using Fourier transform doesn't allow detecting the variation of the rotating machine and its harmonics which reflect the gear fault. In this study, we propose to use the ensemble empirical decomposition (EEMD) to decompose signals generated by the variation of load and the size of the defect. This method is particularly suitable for processing non stationary signals. By using EEMD the signal can be decomposed into a number of IMFs which are mono component, we use also the spectrum and spectrogram of each IMF to show and calculate the frequency defect.

Keywords Fault detection · Vibration · Ensemble empirical mode decomposition (EEMD) · Gear · Rotating machines

1 Introduction

Gears are widely used in rotating machinery to transmit power. Gear defects are inevitable and considered as one of the major sources of noise and vibration (McFadden 1986) giving rise to abnormal operation and failure of the transmission.

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Vibration analysis is considered as one of the main tools to diagnose gear faults since vibration signals can carry valuable information about the health status of machines (McFadden 1986).

A local gear defect causes both amplitude and phase modulations of the tooth meshing vibration signals (Capdessus 1992). For constant rotational speed, the modulation phenomenon can be characterized in vibration spectra by sidebands equally spaced around the meshing frequency and its harmonics. However, under variable rotating speeds, meshing frequency and its harmonic and sidebands are time varying leading to non-stationary signals (Wu et al. 2012).

The use of the conventional fault diagnosis methods such as the Fourier analysis and the Hilbert transform do not provide valuable results. Methods based on the decomposition of vibration signal into bands are more suitable in these situations.

Until now, many methods were applied to detect the fault at an early stage, among these methods traditional ones including statistical analysis based on the signal itself such as (root mean square, crest factor kurtosis, and so on) and the frequency domain analyses based essentially on the Fourier transform. Therefore, the Fourier analysis gives good results if the vibration signal is stationary and linear and it is inapt to analyze the non stationary signal, which may lead to false information about the mechanical faults (Cohen 1989). To solve this problem new methods have been introduced. The time-frequency analysis methods such as Wigner Ville decomposition (WVD) (Forrester 1989), short Fourier transform (STFT) (Staszeweski 1997) and wavelet transform (WT) (Wang and Mcfadden 1997) seem to be the suitable tool to identify the frequency content and to provide information about its variability. These methods are classified into linear time frequency representation such as STFT and wavelet transform, and bilinear methods such as Wigner Ville distributions. The STFT is appropriate only to analyzing signals with slow variation (Mallat 1998) and it is inefficient for non stationary signals. The WT was widely applied because it's a multiresolution analyses (Mallat 1998), able to detect transient features to extract impulses and denoising. Nevertheless, the wavelet analysis is also a linear transform using functions named wavelets as window function like the STFT. The window changes its width by using a dilatation parameter. Then, at high frequency we have high time resolution and a low frequency resolution. While, at low frequencies we have low time resolution and high frequency resolution. Then, we can't have a good resolution for all time-scale map due to the Heisenberg uncertainty principle (Staszewski 1997). In addition, this method gives a time-scale representation which is difficult to interpret as a time-frequency representation; we must have a relation between the scale and the frequency to understand the obtained results and to identify the fault frequencies. Another limitation of the WT is how to select the mother wavelet used in the analyses of the signal, since different wavelets have different time frequency structures, also, how to calculate the range scale used in the WT is another deficiency of the transform (Liu et al. 2005). Many researchers demonstrated that the use of the WT introduce border distortion and energy leakage.

In mechanical application, Yang et al. (2011) confirm that this method is highly dependent on the rotational speed and pre-knowledge of the machine. To overcome the deficiencies of these methods empirical mode decomposition (EMD) was proposed by Huang et al. (1998) for nonlinear and non-stationary signals and was applied in fault diagnosis of rotating machinery (Liu et al. 2005; Mahgoun et al. 2010). It does not use a priori determined basis functions and can iteratively decompose a complex signal into a finite number of zero mean oscillations named intrinsic mode functions (IMFs). Each resulting elementary component (IMF) can represent the local characteristic of the signal. However, one of the problems of EMD is mode mixing as a result of intermittency (Huang et al. 2003; Rilling and Flandrin 2008). Mode mixing occurs when different frequencies that should appear separately in different IMFs are presented in one IMF. This problem gives a vague physical significance of the IMF. EMD is unable to separate different frequencies in separate IMFs. Also, the IMFs are not orthogonal each other, which produce end effects. To solve the problem of mode mixing the ensemble empirical mode decomposition EEMD method was proposed by Wu and Huang (2009) by adding several realizations of Gaussian white noise to the signal, and then using the EMD to decompose the noisy signal, multiple IMFs can be obtained and the added noise is canceled by averaging the IMFs. The ensemble empirical mode decomposition (EEMD) proposed by Huang et al. to analyze nonlinear and non-stationary signals. The method was largely applied in fault diagnosis of rotating machinery (Wu et al. 2009; Mahgoun et al. 2012) because it does not use a priori determined basis functions and can iteratively decompose a complex signal into a finite number of intrinsic mode functions (IMFs). Each resulting elementary component IMF can represent the local characteristic of the signal. But all these papers used the EEMD to analyze signals collected from test bench which work under stationary conditions, where the speed of the shaft is constant or slowly variable. The ensemble empirical decomposition (EEMD) can be used for processing non stationary signals.

In this work we analyze vibration signals given by a dynamic modeling of a gear transmission in the case of non stationary load and speed with a variation in the defect size. The spectrum of each IMF is also used to detect the fault frequency.

The structure of the paper is as follows: Sect. 2 introduces the basic of EMD and EEMD. In Sect. 3, the method EEMD and the spectrum are applied for early faults gearbox detection. In Sect. 4, a conclusion of this paper is given.

2 EMD and EEMD Algorithms

The EMD consists to decompose iteratively a complex signal into a finite number of intrinsic mode functions (IMFs) which verify the two following conditions:

(a) The number of extrema and the number of zeros of an IMF must be equal or differ at most by one.
(b) An IMF must be symmetric with respect to local zero mean.

For a given signal $x(t)$ the EMD algorithm used in this study is given in literatures (Huang et al. 1998; Mahgoun et al. 2012).

To alleviate the mode mixing effect of EMD, the EEMD was used. The EEMD decomposition algorithm of the original signal $x(t)$ used in this work is summarized in the following steps (Wu and Huang 2009):

1. Add a white noise $n(t)$ with given amplitude β_k to the original signal $x(t)$ to generate a new signal:

$$x_k(t) = x(t) + \beta_k n(t) \tag{1}$$

2. Use the EMD to decompose the generated signals $x_k(t)$ into N IMFs $IMF_{nk}(t), n = 1, \ldots, N$, where the nth IMF of the kth trial is $IMF_{nk}(t)$.
3. Repeat steps (1) and (2) K times with different white noise series each time to obtain an ensemble of IMFs: $IMF_{nk}(t), k = 1, \ldots, K$.
4. Determine the ensemble mean of the K trials for each IMF as the final result:

$$\mathrm{IMF_n}(t) = \lim_{k \to \infty} \frac{1}{K} \sum_{k=1}^{K} \mathrm{IMF_{nk}}(t), \quad n = 1, \ldots, N \tag{2}$$

3 Application

In this section we will put in evidence the efficiency of EEMD method through simulations performed starting from a dynamic model of bevel gear transmission which is subjected time varying operating conditions (speed and load). Previous analysis of simulated vibration signals from gear models using Wigner Ville (Chaari et al. 2013) or spectrogram (Chaari et al. 2013; Bartelmus et al. 2009) was not able to provide clear information about the presence of local defect at an early stage. This is mainly caused by the fact that impacts induced by this localized defect are masked by the part of the signal with simultaneous amplitude and frequency modulation induced by speed and load variation.

Let's consider a bevel gear transmission model driven by a squirrel cage electric motor and having the characteristics given in Mahgoun et al. (2016). The transmission is loaded with a torque having sawtooth shape with frequency $f_L = 5$ Hz as presented in Fig. 1a.

The variation of load leads to a fluctuation in the rotational speed (Fig. 1b) and consequently to variation of the mesh frequency. The mean value of the motor rotational speed is $n_r = 1320$ rpm which corresponds to a mean mesh frequency $f_{gm} = 308$ Hz. A crack on one pinion tooth is considered leading to defect frequency of 22 Hz and a period of 0.045 s.

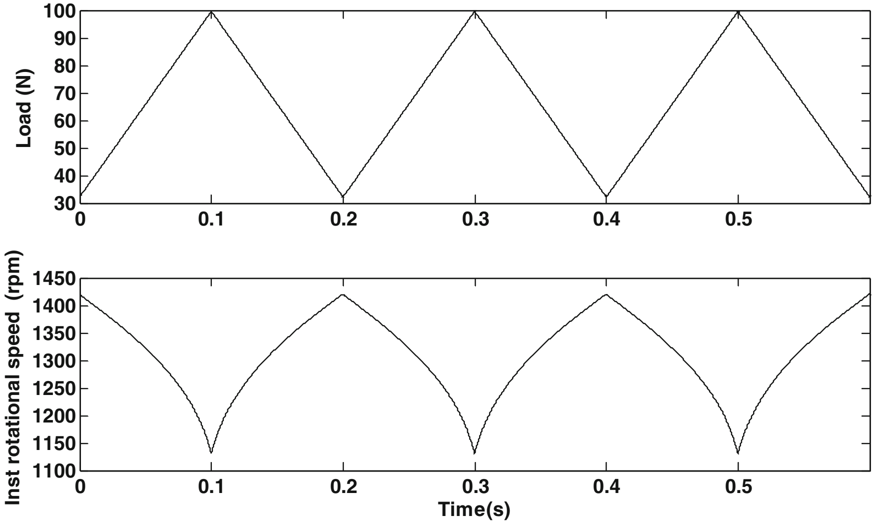

Fig. 1 **a** Evolution of the applied load, **b** evolution of the instantaneous rotational speed

The sampling frequency is 30,800 Hz for all signals. A crack is simulated by a decrease in the gear mesh stiffness function when the defected tooth meshes. In this work we propose to study acceleration signals on pinion bearing for different loads (constant load, load fluctuation of 10 % and load fluctuation of 50 %). We have considered also different severities of crack defect as following:

(a) *Healthy gear*
(b) *gear with an incipient defect (1 % loss in mesh stiffness)*
(c) *gear with a medium defect (5 % loss in mesh stiffness)*
(d) *gear with an important defect (10 % loss in mesh stiffness).*

So, we will have twelve signals that are decomposed by using the EEMD method.

The acceleration signals for healthy gear and faulty gear for early and advanced stage for a fluctuation of load 50 % are given in Fig. 2.

From literature the spectrum of a gear transmission running under constant loading conditions is dominated only by the gear mesh frequency and its harmonics with eventual sidebands induced by the presence of defects (Capdessus et al. 1992). For non-stationary conditions, family of sidebands will be noticed around the mesh frequency f_{gm} and its harmonics induced by the non uniformity of the gear mesh period (Fig. 3) and this can be thought to be a frequency modulation of the gear mesh stiffness.

The zoom around the mesh frequency for the defect cases (Fig. 3b–d) shows many asymmetric sidebands around this frequency, which indicate a frequency modulation.

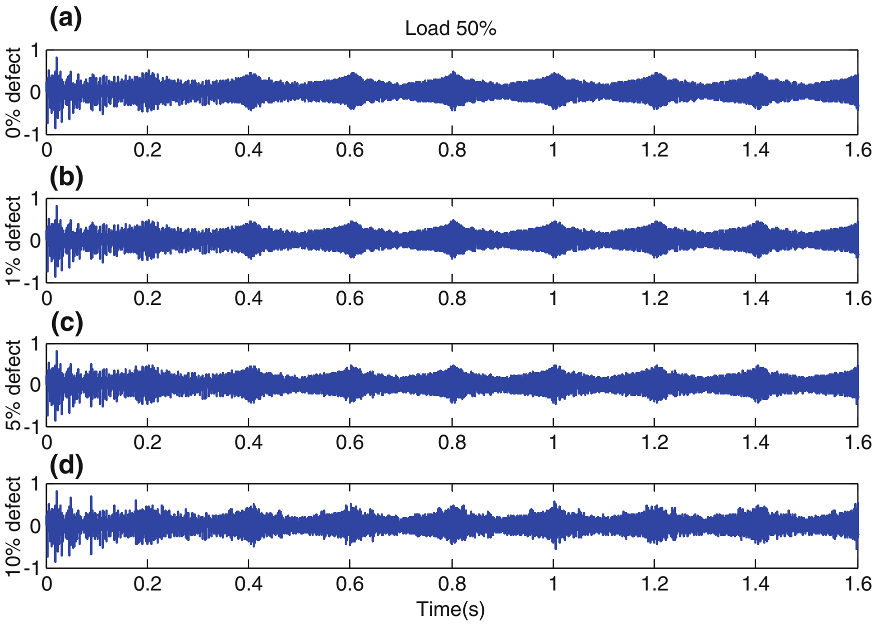

Fig. 2 Acceleration signals for 50 % of load **a** healthy gear, **b**–**d** faulty gear

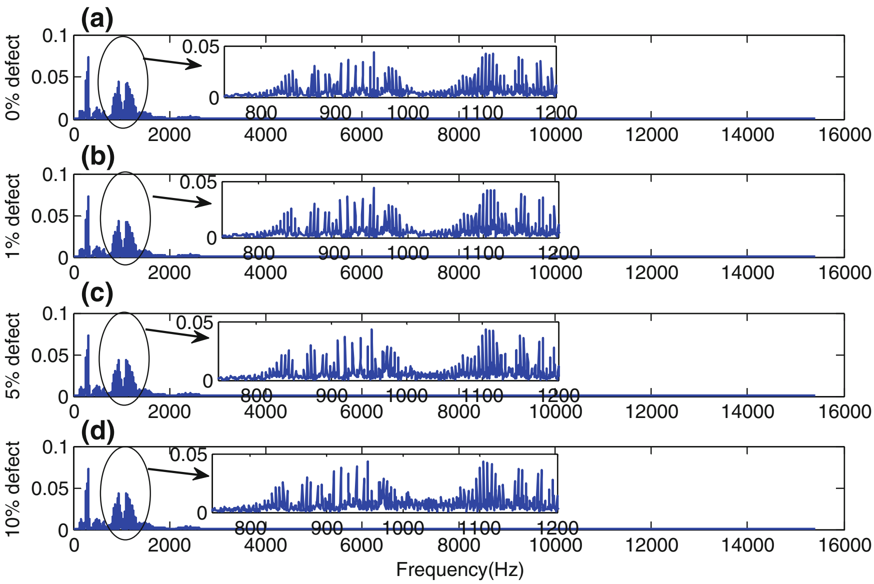

Fig. 3 Spectrum of the signals for 50 % of load **a** healthy gear, **b**–**d** faulty gear

From the presented zoomed spectrum (Fig. 3a) for healthy case, we can observe also presence of sidebands which may cause confusion with the defected case when diagnosing the transmission.

In order to overcome this difficulty, we propose to use EEMD to analyze such signals. The objective is to look at the efficiency of this method and its limits especially in the presence of an excessive load variation.

Figure 4 presents the first IMF of four signals in the case of a constant load. From this figure we can clearly observe for the case of faulty gear the position of impacts starting from 5 % of severity.

Figure 5 presents the first IMF of four studied signals in the case of a load fluctuation of 10 %. From this figure we can observe the impulses due to the defect if the severity is greater than 5 %.

Figure 6 presents the first IMF of four studied signals in the case of a load fluctuation is 50 %. From this figure we can observe the position of the variation of the load which can hide the impulsions due to the defect and precisely at early stage (1 and 5 % defect). It is possible to observe the impulses due to defect if the severity is greater than 5 %. The period between two impulses is 0.045 s which is equivalent to the frequency defect.

The spectrogram of this IMF gives an idea on the variation of the load (Figs. 7 and 8) and gives also information of the position of the maximum load. It shows clearly the position of the impulses due to the fault. The periodicity of the defect can be clearly observed for 5 % of defect better than 1 % of defect.

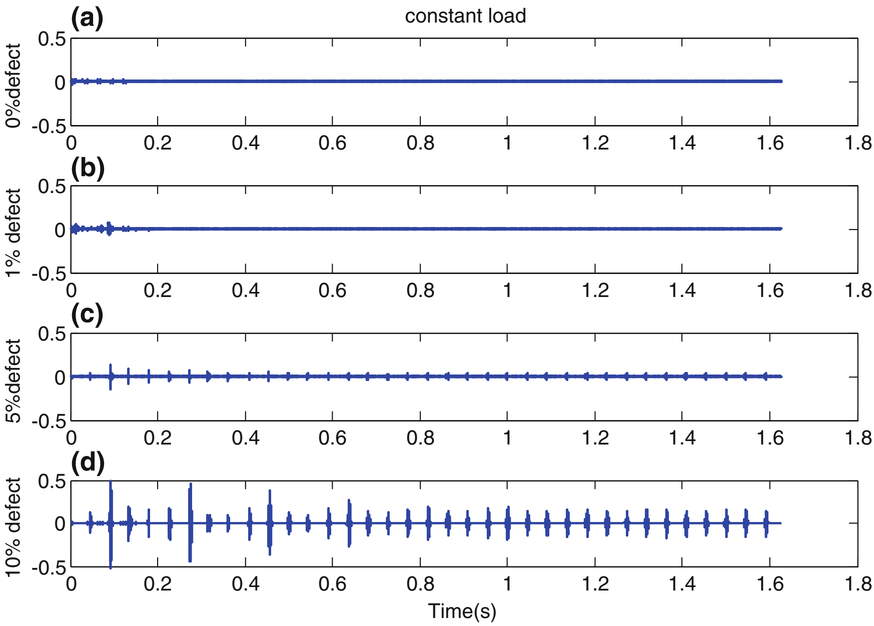

Fig. 4 IMF1 of signal regular load **a** healthy gear, **b–d** faulty gear

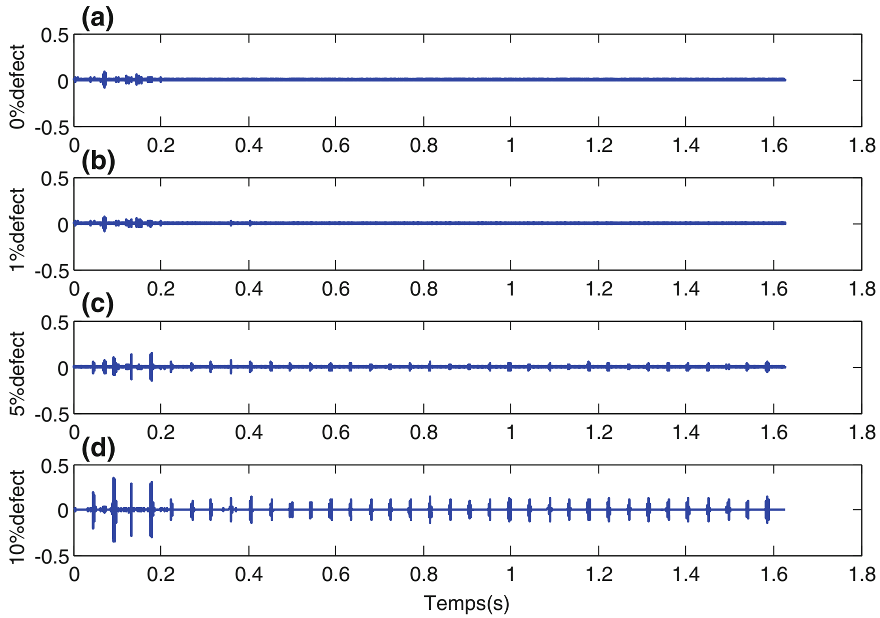

Fig. 5 IMF1 of signal for 10 % of load **a** healthy gear, **b–d** faulty gear

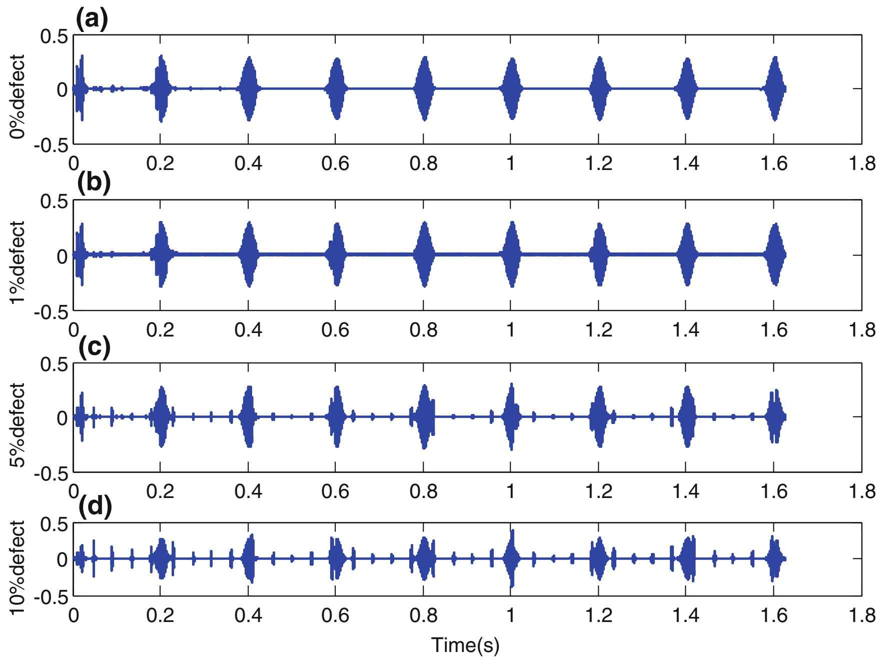

Fig. 6 IMF1 of signal for 50 % of load **a** healthy gear, **b–d** faulty gear

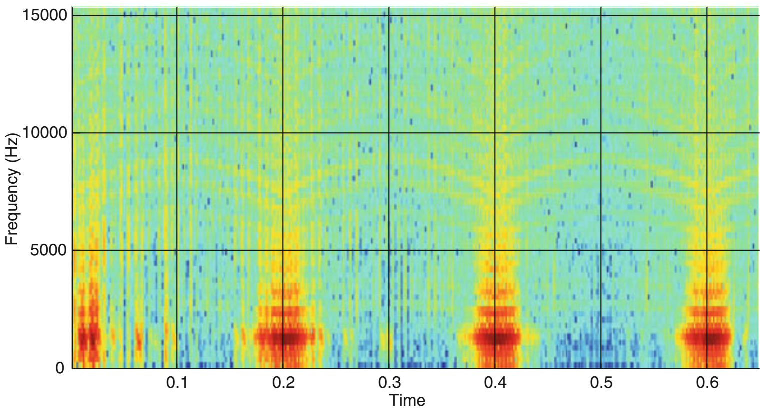

Fig. 7 Spectrogram of the first IMF for 1 % of defect and 50 % of load

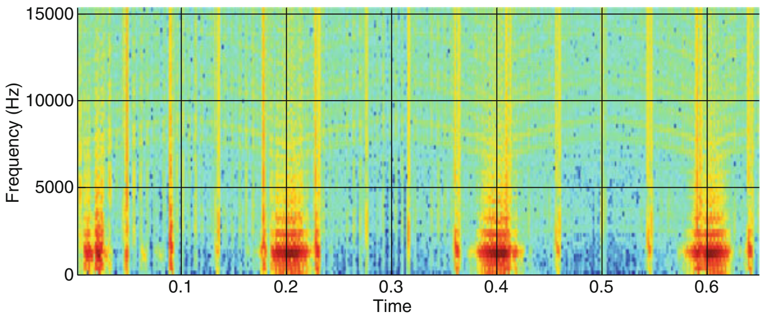

Fig. 8 Spectrogram of the first IMF for 5 % of defect and 50 % of load

4 Conclusion

In this study we have used the EEMD method to analyze non-stationary signals that give information about the variable conditions such as variable speed and load. The EEMD method achieves good modes separation. To detect the fault masked by simultaneous variation of load and presence of defect, EEMD showed successful separation of the different modes that correspond to the variation of load and the effect of fault. We have also used the spectrogram to detect the period of the impulses due to the fault, and we have observed that the huge load (50 %) cover information if the defect is less than 5 % in severity.

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