Probabilistic Latent Component Analysis for Gearbox Vibration Source Separation

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ABSTRACT

Probabilistic latent component analysis (PLCA) is applied to the problem of gearbox vibration source separation. A model for the probability distribution of gearbox vibration employs a latent variable intended to correspond to a particular vibration source, with the measured vibration at a particular sensor for each source the product of a marginal distribution of vibration by frequency, a marginal distribution of vibration by shaft rotation, and a sensor weight distribution. An expectation-maximization algorithm is used to approximate a maximum-likelihood parameterization for the model. In contrast to other unsupervised source-separation methods, PLCA allows for separation of vibration sources when there are fewer vibration sensors than vibration sources. Once the vibration components of a healthy gearbox have been identified, the vibration characteristics of damaged gearbox elements can be determined. The efficacy of the technique is demonstrated with an application on a gearbox vibration data set.*

1. INTRODUCTION

In a wide variety of mechanical systems, gearboxes transfer power from a rotating power source to other devices and provide speed and torque conversions. Complex gearbox designs are used in order to maximize efficiency, minimize volume, and accommodate automatic transmission designs. An example of a particularly complex gearbox design is the main gearbox in a turboshaft-engine helicopter. This gearbox may have several dozen gears, as many bearings, and five or more shafts rotating at different speeds.

A single-point failure in a gearbox often disables the mechanical system, creating a need for gearbox health monitoring using vibration measurements. Vibrations cannot usually be measured directly at the source, so the exterior of a gearbox may be equipped with one or more accelerometers to measure the composite vibration spectrum of the gearbox. Generally, the number of accelerometers is less than the number of vibration sources on non-experimental machinery.

The capability to separate a measured vibration signal into components corresponding to sources allows for the characterization of the vibration of a healthy gearbox and for the development of condition indicators that are sensitive to component degradation but robust to the normal vibration characteristics of the healthy gearbox.

The development of a new technique for vibration source separation is motivated by the fact that existing techniques for gearbox vibration source separation have important limitations. Consider five characteristics that are desirable features for a gearbox vibration source separation technique: 1) a source separation method should be applicable to cases where there are fewer accelerometers than vibration sources, 2) it should identify the vibration resonance spectrum characteristic of various structural elements in the gearbox, 3) it should allow for the separation of the vibration features of damaged gearbox components from features characteristic of undamaged gearbox components, 4) it should characterize the physical proximity of the vibration source to each of the gearbox accelerometers, and 5) it should identify the periodicity of a vibration features. By identifying the resonance spectrum, the physical proximity, and periodicity of a vibration source, the determination of the physical source is facilitated.

In this work, we apply a technique called Probabilistic Latent Component Analysis (PLCA) to the problem of gearbox vibration source separation. The proposed technique satisfies the five criteria established above. The technique applies to instances where there are fewer sensors than vibration sources. The PLCA technique explicitly estimates the frequency spectra and rotational location characteristics associated with estimated vibration sources. This is not true of the time synchronous average or principal component analysis techniques for vibration source separation.

The paper is organized as follows. Section 2 is a survey of prior work on gearbox vibration source separation. Section 3 describes a model and an algorithm for gearbox vibration source separation using PLCA. Section 4 describes the application of the method to a gearbox data set. Section 5 describes limitations and extensions of PLCA for gearbox vibration source separation.

2. PRIOR WORK ON GEARBOX VIBRATION SOURCE SEPARATION

Vibration-based methods are the most common diagnostic techniques used in gearbox health monitoring for distinguishing the nature of damage in helicopter transmissions. The potential benefits of effective gearbox monitoring have motivated the development of source separation techniques and application to the gearbox domain.

A key feature of gearbox vibration source separation exploited by most techniques is the fact that gearbox vibration typically has one or more cyclostationary components. A basic source separation technique long employed for gearbox health monitoring is the time synchronous average. The time synchronous averaging extracts periodic waveforms from additive noise by averaging vibration signals over several revolutions of the shaft (Stewart, 1977). This can be done in either the time or frequency domains. The time synchronous average technique amplifies vibration features that are synchronous with a particular shaft, and attenuates features that are not synchronous with the shaft. The technique has proved to be useful for monitoring of gear and shaft health. However, a time synchronous average cannot isolate a vibration component among the various components on a particular shaft. Also, the time synchronous average obscures vibration characteristic of bearing degradation that are not cyclostationary.

Specialized techniques for the separation of bearing vibration from other gearbox vibration sources are available. The methods include the high-frequency resonance technique and adaptive filtering. The techniques are not applicable to the more general problem of unsupervised vibration source separation.

Independent component analysis has been applied to separate signals from two independent vibration sources recorded at two separate locations on a gearbox (Zhong-sheng et al., 2004). The utility of this technique is limited to cases where the number of sensors is equal to or greater than the number of vibration sources, a condition that does not generally hold.

Principal component analysis has also been used to identify the number of gearbox vibration sources (Gelle et al., 2003, Serviere et al., 2004). The utility of this dimensionality-reduction technique is limited by the fact that the reduced-dimension vibration features may not have physical significance and thus may not be used to create a mapping between features and physical vibration sources.

3. LATENT COMPONENT MODEL

Latent component models enable one to attribute the observations as being due to hidden or latent factors. The main characteristic of these models is conditional independence – multivariate data are modeled as belonging to latent classes such that the random variables within a latent class are independent of one another. Several models have been proposed that fit this general framework and in this paper, we use Probabilistic Latent Component Analysis (PLCA) as proposed by (Smaragdis *et al.*, 2007).

The model has been used in analyzing image and audio data among other applications (eg: Smaragdis *et al.*, 2007b). Specifically, it has been successfully used in separating audio signals (Smaragdis *et al.*, 2006) which is analogous to the problem addressed in this paper.

3.1 PLCA for gearbox data

The model employed here is probabilistic; the objective is to develop a structured representation for an empirically developed probability mass function $v(\omega, \theta, s)$ characterizing the probability distribution for vibration amplitude "quanta" as a function of vibration frequency ω, gearbox rotational coordinate θ, and sensor identity s.

In a gearbox with a single shaft, the rotational coordinate $\theta \in [0\ 2\pi]$ corresponds to the rotational angle of the single shaft. In a gearbox with multiple shafts, the coordinate $\theta \in [0\ \ \beta\ ]$ can correspond to the rotational position of the slowest shaft, and the maximum value β should be chosen such as the smallest value $\theta \geq 2\pi$ such that every shaft in the gearbox is at the same position at $\theta = 0$ and $\theta = \beta$.

The first key aspect of the latent component model is the introduction of the dependence of the vibration distribution on a latent component z taking a finite number of values, small relative to the number of bins for ω and θ

$$v(\omega, \theta, s) = P(\omega, \theta, s, z) = \sum_z P(z) P(\omega, \theta, s|z). \quad (1)$$

It is further assumed that, given a certain latent vibration z, the distribution of vibration as a function of frequency is independent of the shaft rotational coordinate θ and the sensor s:

$$\begin{aligned} v(\omega, \theta, s) &= \sum_z P(z) P(\omega, \theta, s|z) \quad (2) \\ &= \sum_z P(z) P(\omega|z) P(\theta|z) P(s|z), \end{aligned}$$

with $P(\omega|z)$ the marginal distribution for vibration over the frequency domain and $P(\theta|z)$ the marginal distribution for vibration over the rotational coordinate. $P(s|z)$ is a marginal distribution for vibration component by sensor, in effect a "mixing weight" to describe how each vibration component is represented in each sensor measurement.

The intent of the latent component model is that each value of z corresponds to a different vibration source, and that the frequency spectrum $P(\omega|z)$ for that source is independent of the rotational coordinate and the sensor at which the vibration is measured.

To illustrate the intent of this model, consider how it would apply to the characterization of the vibration of a music box. A typical music box has a set of pins arranged on a rotating cylinder that pluck the tuned teeth of a steel comb. The tune repeats with a period corresponding to one rotation of the cylinder. When applying the PLCA methodology to a music box, the number of latent components should be set equal to the number of teeth on the steel comb; the frequency marginal for a given component would correspond to the tone of a particular plucked tooth; and the rotational marginal for the component would correspond to the location on the cylinder of the pins aligned to pluck the particular tooth.

3.2 Data Pre-processing

To develop parameterizations for the latent variable models, the starting point is to develop the empirical distribution for $v(\omega, \theta, s)$. One method for developing the distribution $v(\omega, \theta, s)$ is to apply the Hilbert-Huang transform to time-domain accelerometer data. The first step is to adaptively decompose the signal into a finite set of empirical mode functions, and then apply the Hilbert transform to compute the instantaneous amplitude and frequency for each intrinsic mode function. The amplitude, frequency, and time data is binned to create a probability mass function $v(\omega, t, s)$ in the time domain. The Hilbert-Huang transform may permit better localization of time and frequency features than alternative techniques such as the short-time Fourier transform (Huang, et. al. 1998).

Once $v(\omega, t, s)$ has been parameterized, it is converted to a distribution $v(\omega, \theta, s)$by using a tachometer signal to compute a one-to many mapping from time to the rotational coordinate $\theta(t) \in [0\,\beta]$. Note that this procedure for calculating the empirical distribution $v(\omega, \theta, s)$ *is not* the same as calculating the time synchronous average. Whereas the time synchronous average is the mean vibration signal over multiple rotations, $v(\omega, \theta, s)$ is a probability mass function fully characterizing the distribution of vibration amplitude as observed over multiple rotations.

3.3 Algorithm

Given the empirical distribution $v(\omega, \theta, s)$, an expectation-maximization algorithm can be used to estimate the maximum-likelihood parameterization for the probabilistic latent component model $v(\omega, \theta, s) = \sum_z P(z) P(\omega|z) P(\theta|z) P(s|z)$.

Expectation-maximization is an iterative procedure widely used in a variety of contexts (Dempster et al., 1977, Neal et al., 1998). For example, an expectation-maximization algorithm for parameterization of Hidden Markov models is known as the Baum-Welch algorithm.

Each iteration of the expectation-maximization algorithm has two phases. The expectation phase calculates the probability of a latent component conditioned on frequency, rotation, and sensor, and the current parameterization for the marginal distributions:

$$P(z|\omega, \theta, s) = \frac{P(z) P(\omega|z) P(\theta|z) P(s|z)}{\sum_z P(z) P(\omega|z) P(\theta|z) P(s|z)}. \quad (3)$$

For the first iteration, the marginal distributions can be initialized with randomly generated probability mass functions.

The maximization phase updates the marginal distributions and the total probability of each latent component based on the result of the expectation phase:

$$P(\omega|z) = \frac{\sum_\theta \sum_s v(\omega, \theta, s)\, P(z|\omega, \theta, s)}{\sum_\omega \sum_\theta \sum_s v(\omega, \theta, s)\, P(z|\omega, \theta, s)}, \quad (4)$$

$$P(\theta|z) = \frac{\sum_{\omega}\sum_{s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}{\sum_{\omega}\sum_{\theta}\sum_{s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)},$$
$$P(s|z) = \frac{\sum_{\omega}\sum_{\theta} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}{\sum_{\omega}\sum_{\theta}\sum_{s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)},$$

$$P(z) = \frac{\sum_{\omega,\theta,s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}{\sum_{z,\omega,\theta,s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}.$$

Expectation-maximization produces monotone convergence to a locally optimal solution, and the convergence towards a fixed point can be monitored by calculating the log-likelihood associated with the parameterization for each iteration.

3.4 Characterizing healthy and damaged gearboxes

A gearbox with one or more damaged components operated at the same condition as a healthy gearbox, identical with the exception of the damaged components, should have the vibration components of the healthy gearbox plus some additional vibration components corresponding to the damaged. Principal latent component analysis can be used to identify the vibration components associated with damaged gearbox elements. To do so, the set of latent variables Z is defined as the union of a set of latent variables Z_h corresponding to vibration components of healthy gearbox elements with another set of latent variables with Z_d corresponding to vibration components of damaged gearbox elements, $Z = Z_h \cup Z_d$.

The frequency marginal distribution $P(\omega|z)$ is initialized to that learned for the healthy case for all $z \in Z_h$. The expectation phase of the algorithm is unchanged. The maximization phase is modified so that the frequency marginals are iteratively updated only for $z \in Z_h$, while the marginals for rotation and sensors are updated for all latent components:

$$P(\omega|z) = \frac{\sum_{\theta}\sum_{s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}{\sum_{\omega}\sum_{\theta}\sum_{s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}, \forall\, z \in Z_d; \tag{5}$$

$$P(\theta|z) = \frac{\sum_{\omega}\sum_{s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}{\sum_{\omega}\sum_{\theta}\sum_{s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}, \forall\, z \in Z;$$

$$P(s|z) = \frac{\sum_{\omega}\sum_{\theta} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}{\sum_{\omega}\sum_{\theta}\sum_{s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}, \forall\, z \in Z;$$

$$P(z) = \frac{\sum_{\omega,\theta,s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}{\sum_{z,\omega,\theta,s} v(\omega,\theta,s)\, P(z|\omega,\theta,s)}, \forall\, z \in Z.$$

3.5 Implementation Notes

Let r denote the number of latent variables selected. Let the number of bins along ω, θ and s be m, n and l respectively. Let $P(\omega|z), P(\theta|z), P(s|z)$ and $P(z)$ be represented by multi-dimensional tensors $\boldsymbol{W}_{m\times 1\times 1\times r}$, $\boldsymbol{T}_{1\times n\times 1\times r}$, $\boldsymbol{S}_{1\times 1\times l\times r}$ and $\boldsymbol{Z}_{1\times 1\times 1\times r}$ respectively.

Let the $m \times n \times l$ tensor $\boldsymbol{V}$ denote the preprocessed data where the entries correspond to the empirical distribution $v(\omega,\theta,s)$. Let the $m \times n \times l$ tensor $\boldsymbol{X}$ denote the approximation of this distribution given by $\sum_z P(z)P(\omega|z)P(\theta|z)P(s|z)$. Let the operators ".*" and "./" represent elementwise multiplication and elementwise division respectively.

The algorithm can be summarized as follows using the matrix *multiprod* notation (de Leva, P., 2005) and MATLAB conventions. Below, *mprod* refers to the *multiprod* function of de Leva that allows matrix multiplications between arrays of matrices.

Initialize $\boldsymbol{W}$, $\boldsymbol{T}$, $\boldsymbol{S}$ and $\boldsymbol{Z}$.
Iterate until convergence
    $\boldsymbol{Zm}$ = *repmat(*$\boldsymbol{Z}$*,[m 1 1 1]);*
    $\boldsymbol{Zn}$ = *repmat(*$\boldsymbol{Z}$*,[1 n 1 1]);*
    $\boldsymbol{Zl}$ = *repmat(*$\boldsymbol{Z}$*,[1 1 l 1]);*
    $\boldsymbol{X}$ = *mprod(mprod(*$\boldsymbol{W}$, $\boldsymbol{T}$*),* $\boldsymbol{S}$.* $\boldsymbol{Zl}$*, 4, 4);*

    nW*=(*$\boldsymbol{W}$.* $\boldsymbol{Zm}$*).*mprod(*$\boldsymbol{S}$*,mprod(*$\boldsymbol{V}$./ $\boldsymbol{X}$, $\boldsymbol{T}$*,2,2),3,3);*
    nT*=(*$\boldsymbol{T}$.* $\boldsymbol{Zn}$*).*mprod(*$\boldsymbol{W}$*,mprod(*$\boldsymbol{V}$./ $\boldsymbol{X}$, $\boldsymbol{S}$*,3,3),1,1);*
    nS*=(*$\boldsymbol{S}$.* $\boldsymbol{Zl}$*).*mprod(*$\boldsymbol{T}$*,mprod(*$\boldsymbol{V}$./ $\boldsymbol{X}$, $\boldsymbol{W}$*,1,1),2,2);*
    nZ*=sum(****nW****);*

    W*=****nW****;* ***T****=****nT****;* ***S****=****nS****;* ***Z****=****nZ****;*
    Normalize $\boldsymbol{W}$, $\boldsymbol{T}$, $\boldsymbol{S}$ *and* $\boldsymbol{Z}$ *appropriately.*

Effective application of the PLCA model requires the selection of a proper number of latent variables. A good starting point is to set the number of latent variables equal to the number of locations where moving surfaces come in contact. Once algorithm results have been produced, the results can be examined to validate the initial choice.

Evidence that there are too few latent components include the absence of any rotational marginals that are strongly periodic, and frequency marginals that include multiple peaks not in a harmonic sequence. Evidence of the use of too many latent variables is two or more latent components with strongly similar rotational marginal distributions.

4. EXPERIMENTS AND RESULTS

4.1 Data

The use of probabilistic latent component analysis for gearbox vibration source separation is illustrated on gearbox data from the 2009 PHM challenge (http://www.phmsociety.org/competition/PHM/09).

The gearbox has three shafts, an input shaft, an idler shaft, and an output shaft, each with an input side and output side bearing, and a total of six gears, one on the input shaft, two on the idler shaft, and one on the output shaft. The frequency ratio of the input, idler, and output shafts is 15:5:3. The helical gear configuration, illustrated in Figure 1, was tested under six different health configurations, as indicated in Table 1.

Table 1: Component health by case

	24-tooth gear	Input shaft output side bearing	Idler shaft output side bearing	Input shaft
Case 1	Good	Good	Good	Good
Case 2	Chipped	Good	Good	Good
Case 3	Broken	Defect	Inner	Bent
Case 4	Good	Defect	Ball	Imbalance
Case 5	Broken	Good	Inner	Good
Case 6	Good	Good	Good	Bent

4.2 Experimental set-up

The PLCA algorithm was applied to the helical gear high torque cases run at an input shaft frequency of 30 Hz. To apply the PLCA algorithm, empirical mode decomposition was performed on each accelerometer signal. The Hilbert transform was applied to each intrinsic mode function to generate a probability mass function $v(\omega, t, s)$. Tachometer data was used to generate a many-to-one mapping from t to θ to generate a mapping $v(\omega, \theta, s)$. The rotational coordinate θ was defined as the rotational angle at the output shaft, with the domain $[0, 6\pi]$ covering three rotations. Three rotations of the output shaft corresponds to an integer number of rotations for the idler shaft (5 rotations) and for the input shaft (15 rotations), and thus vibration features for all three shaft should be cyclostationary over the interval $[0\ 6\pi]$.

For the healthy gearbox, case 1, PLCA was used to identify 7 vibration components. Once the frequency marginal distributions for the healthy gearbox had been identified, the PLCA model was applied to each of the five damaged gearbox cases in order to identify the vibration components associated with the damage. For each of the five damaged cases, the seven frequency marginals for the healthy gearbox were retained and three additional vibration components were identified. The frequency marginals for these seven vibration components were fixed and used as inputs to identify new rotational marginals and three additional vibration components for cases 2-6.

4.3 Results and Interpretation

As described and illustrated below, the source separation results produced by PLCA are plausible and provide insight on the vibration characteristics associated with the gearbox and its degradation modes. The results of the PLCA algorithm for each of the six gearbox conditions are displayed in Figures 2-7.

A number of characteristics of the separated vibration components may be used in interpreting the component and making an assignment of a vibration component to a particular physical source in the gearbox.

The first characteristic that is useful for result interpretation is the sensor mixing weights. If the mixing weight of a component is much stronger for sensor 1 than for sensor 2, then the physical source of the vibration is likely to be on the input side of the gearbox. Conversely, if the mixing weight of a vibration component is stronger for sensor 2 than for sensor 1, then the physical source of the vibration is likely to be on the output side of the gearbox.

The second characteristic that is useful for result interpretation is the appearance of known forcing or resonant frequencies in a frequency marginal. For the gearbox analyzed in this study, known forcing frequencies include the frequency of the input shaft rotation (30 Hz), the gear mesh frequency of the input/idler gear pair (480 Hz), and the gear mesh frequency of the idler/output gear pair (240 Hz). Resonant frequencies in this case were not known *a priori*.

The third characteristic that is useful for result interpretation is the nature of the rotational marginal. The appearance of the marginal may be impulsive, sinusoidal, or nearly constant. Impulsive rotational marginals are likely to be due to the impacts associated with bearing or gear defects. Nearly constant rotational marginals are likely to be associated with constant forcing, such as the rotation of a shaft.

The fourth characteristic that is useful for result interpretation is the periodicity of the rotational marginal. If the periodicity of a rotational marginal coincides with the periodicity of a particular shaft, then the vibration source is likely to be associated with that shaft.

The four characteristics discussed above were used to interpret the source separation results and make source assignments, as shown in Table 1 and Table 2.

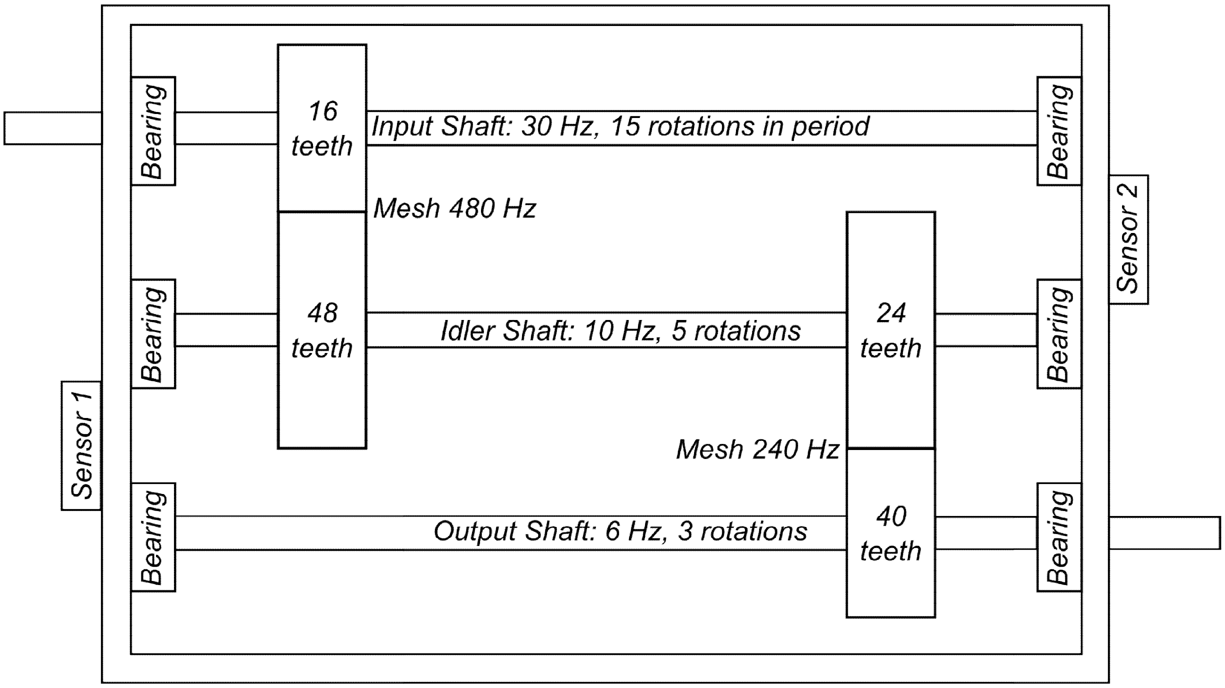

Figure 1: Configuration of the gearbox used to generate vibration data

Table 2: Characteristics of vibration components and source assignments for the nominal gearbox condition*

#	Peak Frequency, Hz	Strongest Sensor Mixing Weight		Content at forcing frequencies			High frequency resonance	Frequency marginal characteristic			Periodicity of rotational marginal, periods per rotational period			Source Assignment
		1	2	30 Hz	480 Hz	240 Hz		Impulsive	Sinusoidal	Sustained	15	5	3	
1	212		X			X								Idler/output gear mesh
2	2089	X					X	X				X		Idler shaft input side bearing
3	985		X		X						X	X		Input/idler gear mesh
4	347		X											Idler/output gear mesh
5	271		X			X								Idler/output gear mesh
6	171	X		X			X			X				Input shaft induced resonance
7	8710		X				X		X		X			Input shaft output side bearing

**The electronic version of this document has embedded sound files which are audio reconstructions of the source-separated vibration components.*

Table 3: Characteristics of vibration components and source assignments for seeded fault conditions*

#	Peak Frequency, Hz	Strongest Sensor Mixing Weight		Content at forcing frequencies			High frequency resonance	Frequency marginal characteristic			Periodicity of rotational marginal, periods per rotational period			Source Assignment
		1	2	30 Hz	480 Hz	240 Hz		Impulsive	Sinusoidal	Sustained	15	5	3	
Case 2: Chipped 24-tooth gear														
8	845		X		X			X						Input/idler gear mesh
9	255	X				X								Chipped 24-tooth gear
10	369		X											Chipped 24-tooth gear
Case 3: Broken 24-tooth gear, input shaft output side bearing defect, idler shaft output side bearing inner race damage, bent input shaft														
8	985		X		X		X							Input shaft output bearing
9	233	X				X								Broken 24-tooth gear
10	341		X			X	X							Idler shaft output bearing
Case 4: defect in input shaft output side bearing, ball fault in idler shaft output side bearing, imbalanced input shaft														
8	331	X		X										Imbalanced input shaft
9	437	X			X									Input / idler gear mesh
10	240		X			X								Idler shaft output side bearing
Case 5: broken 24-tooth gear, inner race defect on idler shaft output bearing														
8	31	X		X										Input shaft
9	244	X				X								Broken 24-tooth gear
10	8844		X				X							Idler shaft output bearing
Case 6: bent input shaft														
8	8844		X	X			X							Input shaft output side bearing
9	222	X				X								Idler/output gear mesh
10	3067		X											Unknown

**The electronic version of this document has embedded sound files which are audio reconstructions of the source-separated vibration components.*

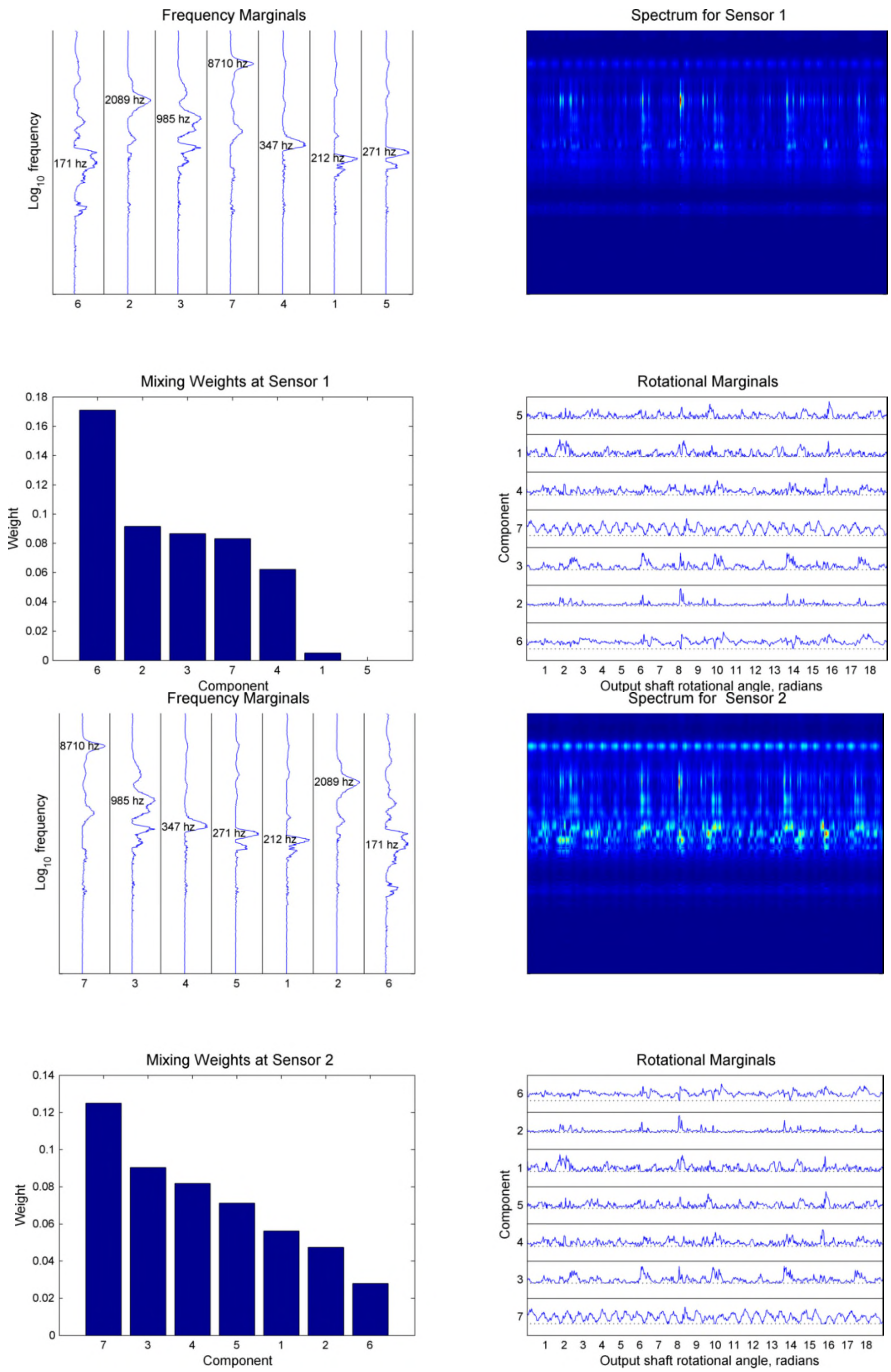

Figure 2: Source separation results for the baseline gearbox condition

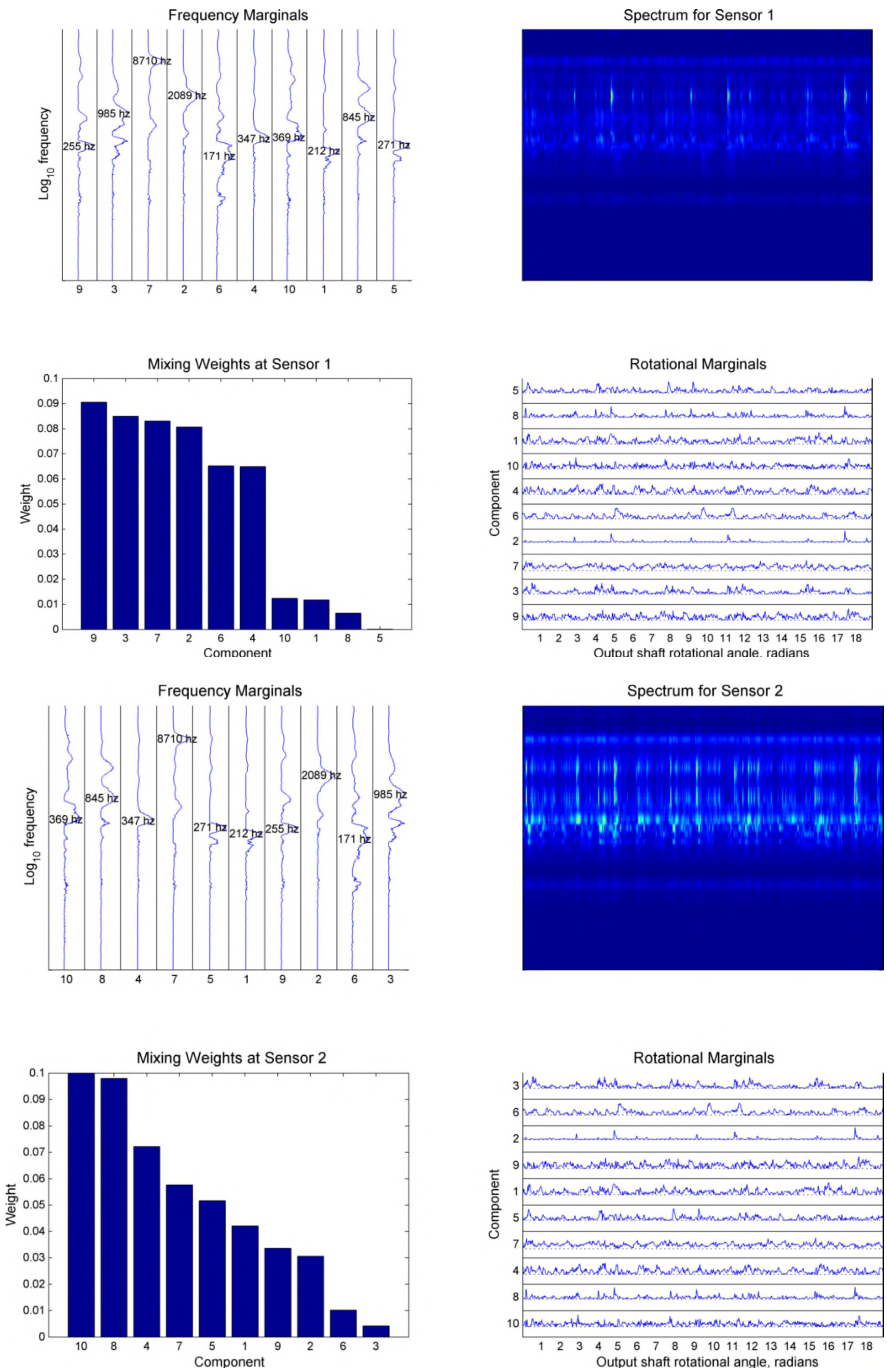

Figure 3: Source separation results for case 2, which has a chipped gear tooth on the 24-tooth gear on the idler shaft

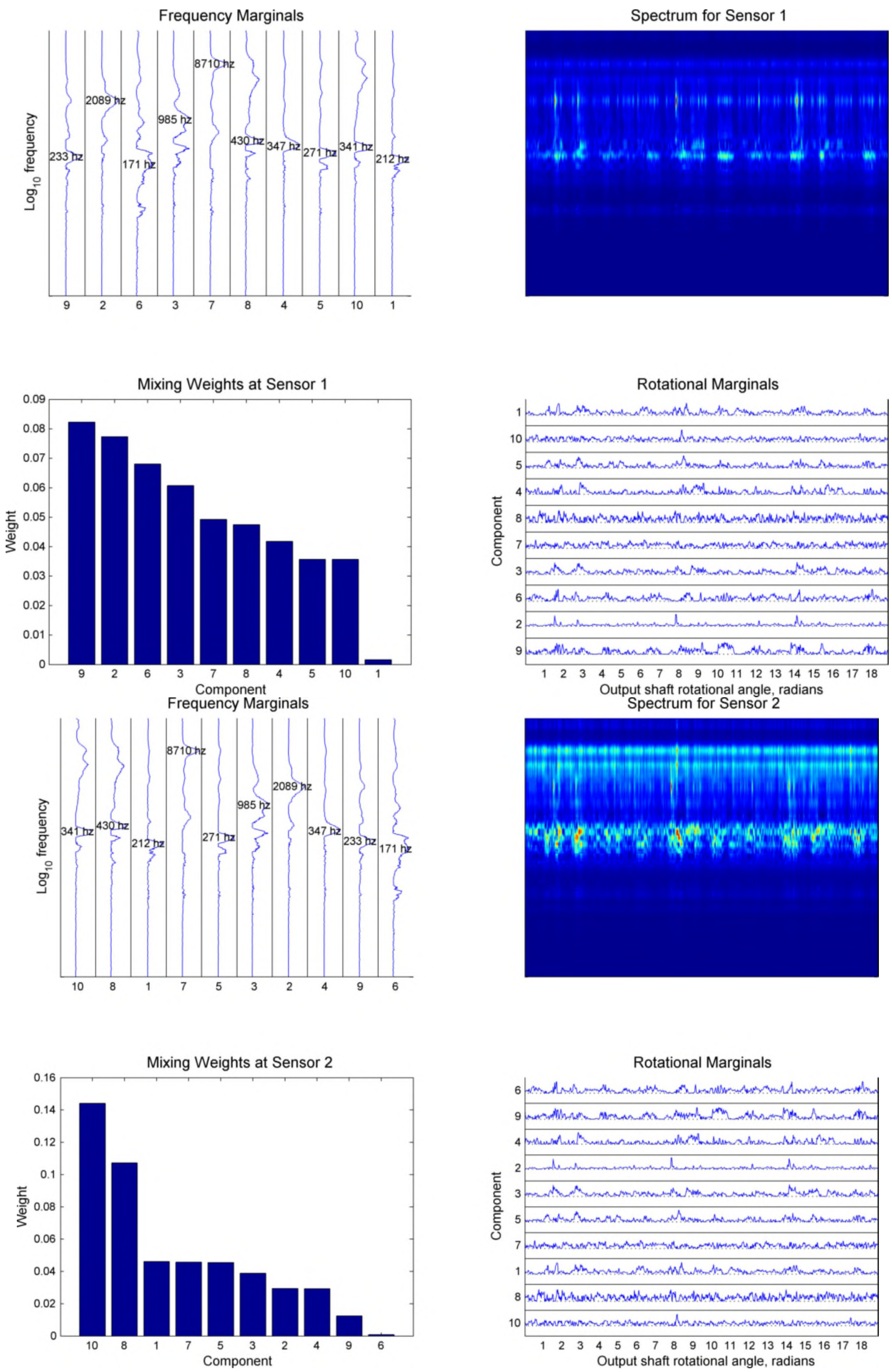

Figure 4: Source separation results for case 3, which has a broken gear tooth on the 24-tooth gear on the idler shaft, a bent input shaft, and bearing faults on the output side of the input and idler shafts

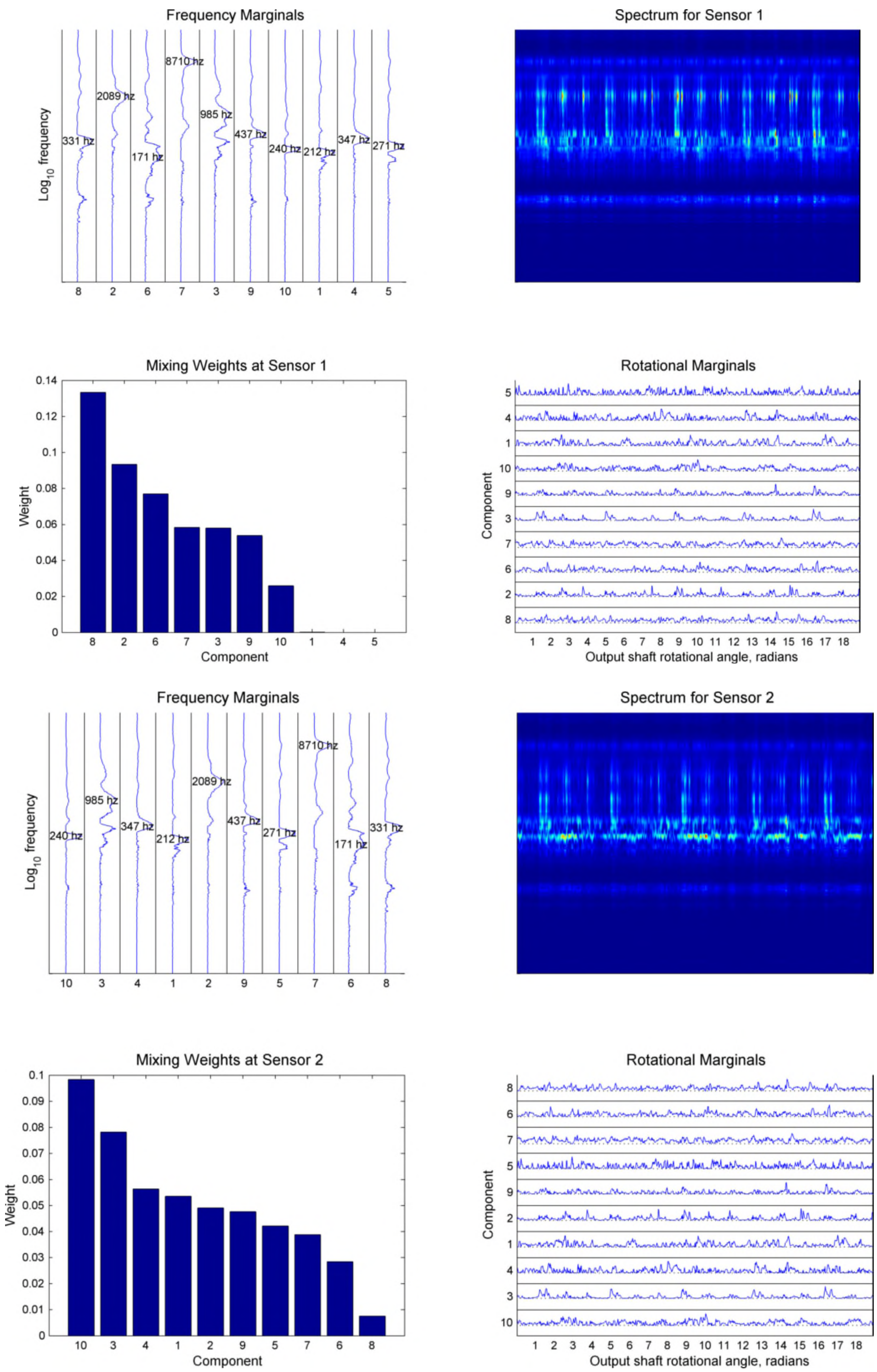

Figure 5: Source separation results for case 4, which has an imbalanced input shaft and bearing faults on the output side of the input and idler shafts

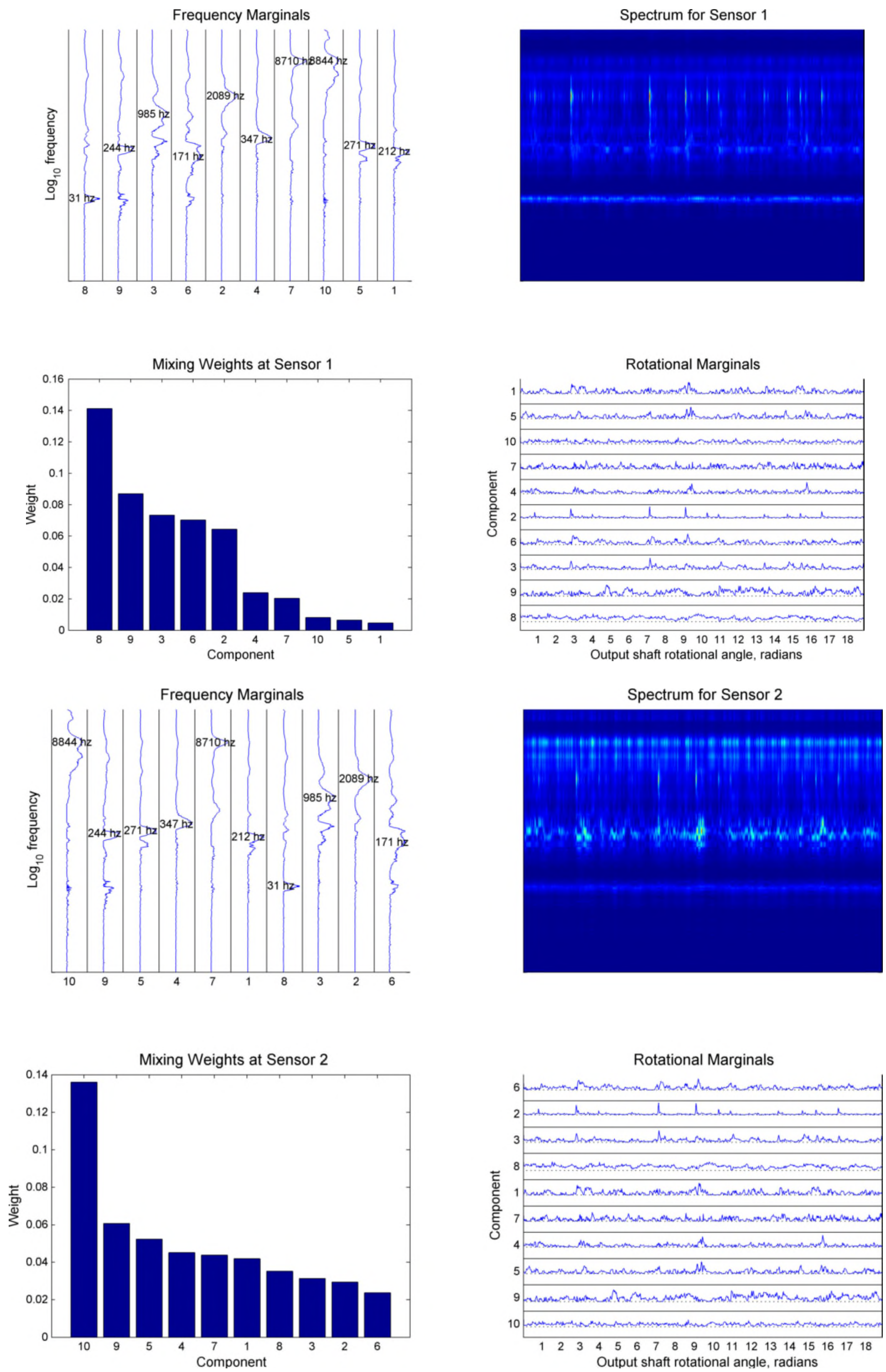

Figure 6: Source separation results for case 5, which has a broken 24-tooth gear and an inner-race defect on the idler shaft output side bearing

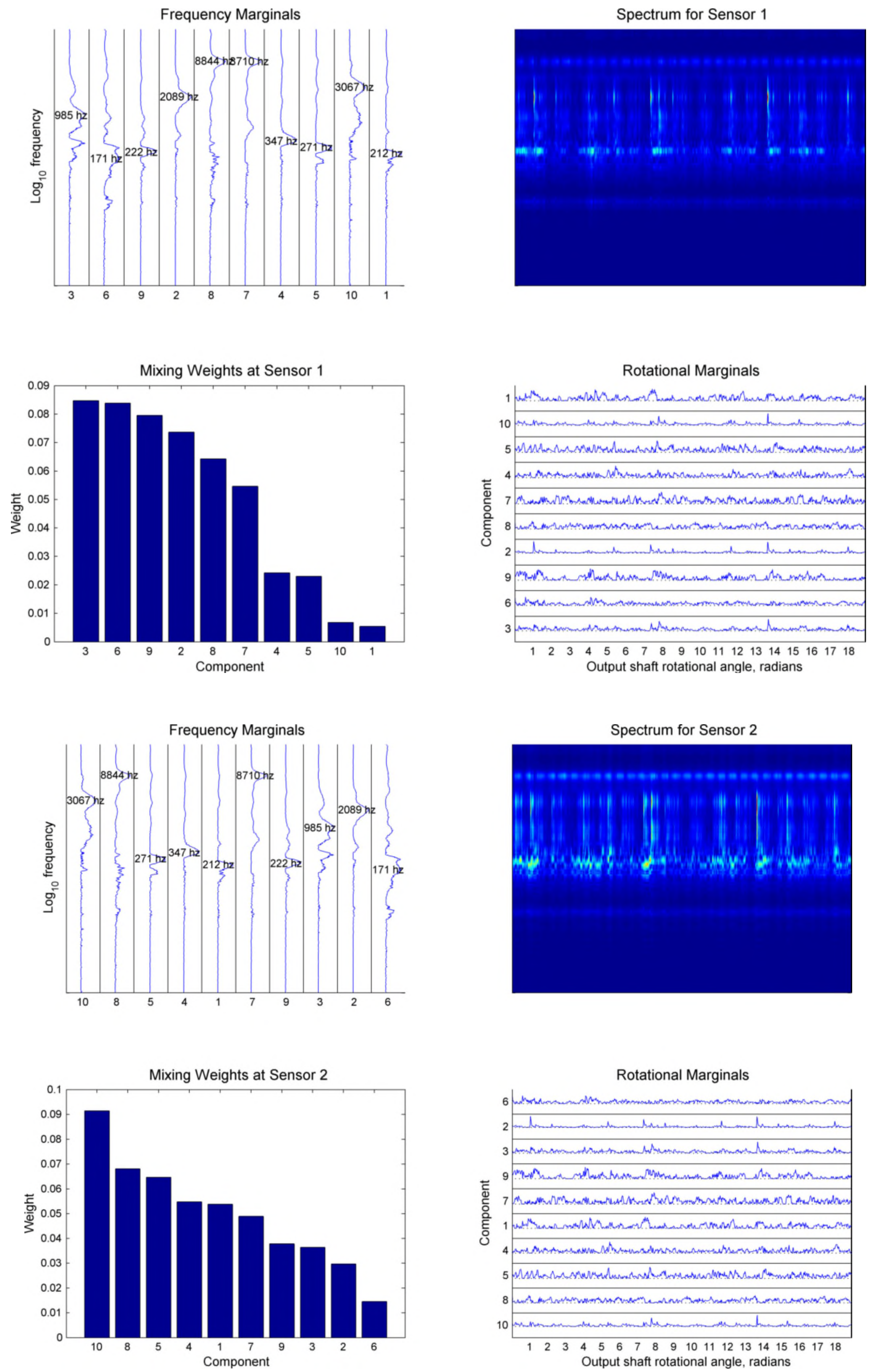

Figure 7: Source separation results for the cyclostationary spectra for case 6, which includes a bent input shaft

5. LIMITATIONS AND EXTENSIONS

The PLCA method has been illustrated as a technique for source separation of the cyclostationary component of gearbox vibration, but could be extended for analysis of the non-stationary vibration components. This may be useful for additional characterization of bearing defects which are not cyclostationary. There are least two possible methods for integrating cyclostationary spectrum analysis with time-spectrum analysis. The first method is to identify vibration components associated with cyclostationary spectrum, fix the frequency marginals of these components and use these as inputs for analysis of the time spectrum, and identify additional vibration components unique to the time spectrum. A second potential method is to 1) use the frequency marginals of cyclostationary vibration components to attempt to reconstruct the time spectrum, 2) subtract the reconstructed time spectrum from the original time spectrum, and 3) apply PLCA to the residual time spectrum to identify new vibration components.

The model employed here for the mixing of vibration components in a sensor signal is simple, and more complicated models could be employed for better fidelity at the cost of increased complexity. For example, one could formulate a convolutive mixing model that allows for delays in the propagation of vibration from source to sensor.

Finally, although the experimental results presented here make plausible the efficacy of PLCA as a technique for vibration source separation, further validation of the technique could be obtained experimentally using laser Doppler vibrometery to measure gearbox component vibrations at the source.

6. CONCLUSIONS

Probabilistic latent component analysis has been developed as a technique for gearbox vibration source separation. Unlike independent component analysis, the method is applicable when there are fewer sensors than vibration sources. The method identifies the frequency spectrum and rotational marginal distribution associated with vibration components. Experimental results make plausible the effectiveness of the source separation performance, and it was shown that the technique could be used to identify the characteristics of a healthy gearbox, and then used to isolate vibration components associated with gearbox damage.

NOMENCLATURE

$P(\cdot)$ Probability
s Sensor
$v(\cdot)$ Probability distribution for vibration amplitude
z Latent variable
β Period for cyclostationary vibration component
θ Rotational coordinate
ω Frequency

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