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FILTERING OF THE NOISE GENERATED BY SHAFT NECK CONTOUR DEFORMATIONS IN MONITORING SYSTEMS

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The paper presents an applicable, approximate solution to the filtering-prediction problem for the diagnostic signals. It takes into consideration the possibility of compensating the noise generated by the deformations of the surface geometry of a shaft neck. The equations of the Kalman-Bucy model were the basis for the calculations of the structure of the filter-predictor under investigation. It was defined by a stochastic equation of the shaft neck movement around the point of balance which was related to the equation of the monitored courses. Relations resulting from the two-dimensional isothermal model of a hydrodynamic bearing were used. They were the basis for the formulation of equations which define the shape of the signal filtration and prediction module adequate for the geometry of a machine sensor configuration.

1. Introduction

The vibration monitoring of turbo machines, especially of turbine sets with slide bearings, is determined by the monitoring of the bearing bush shaft neck vibrations which are then related to the accepted criteria defining the state gradation of a machine. The analysis of both the vibration changes during the exploitation process and the changes of the Lissajou curves drawn by the shaft neck axis of the object being monitored are symptoms of failure effects which take place in such nodes. This is because the durability and reliability of such nodes depend on the vibration phenomena that accompany the displacements of the centre of the journal around the static balance points.

The proper operation of such systems is determined by correct estimation of variables being monitored (which requires the elimination of the noise that disturbs the measurements) and by evaluation of possible changes in a given time interval. Filtration (Bendat and Piersol, 1971; Cempel, 1989) and prediction (Batko, 1984; Batko and Kaźmierczak, 1985) solutions based on various methods of signal analysis are the basis for the process of estimation. The phenomenon called the mechanical run-out is one of the mechanisms generating the undesired noise, and is related to the

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roughness of the shaft neck surface and to the deformations of the circular contour of the bearing shaft neck. This sort of noise in the operation of the monitoring system sensors may be caused by faulty machining of the journal, by deformations resulting from an improper support of the rotor while storing for a long time, or they may be a consequence of a non-uniform cooling. The traditional methods of compensating the noise of the mechanical run-out by vector zeroing (digital vector filter DVF) or the compensation of run-out (digital compensator of run-out DCR) are not always successful because one cannot guarantee the identity of the results of subtracting the shape deviation vector (its amplitude and phase) measured at a slow roll from the vector measured in working conditions. This is caused by the fact that every change of the axial position of the shaft in relation to a sensor—resulting from a variable load of a machine or from thermal phenomena—imposes a new area of cooperation between the journal and the sensor. Thus, different results are an outcome of such a procedure.

This method of the noise filtration in monitoring systems, which is a partial solution and does not consider other mechanisms that generate the noise, does not guarantee the desired results. The suggestion presented in (Batko and Banek, 1993; 1994) is an optimal solution. It refers to the already existing solutions modelling the shaft neck dynamic movement in the hydrodynamic bearing bush (Kiciński, 1989; 1993; Kurnik and Starczewski, 1985; Muszyńska, 1971) and relates its equations to the observation equation of the courses being monitored. While considering the possible stochastic noise, the equations define the structure of the Kalman filter-predictor which ensures optimal filtration and prediction of the monitored signals being described by stochastic differential equations (Anderson and Moore, 1979). With reference to this direction of research (Batko and Banek, 1993; 1994), the paper presents a solution to an optimum filter problem for a vibration inspection system in slide bearings. It will also render it possible to eliminate the noise generated by errors and deformations of the shaft neck surface. Equations defining the shape of the filter will also be provided.

2. Problem Formulation

The problem of elimination of the noise in vibration monitoring systems of bearings may be related to the problem of unobservable state variables estimation carried out in the presence of noise on the basis of diagnostic signals. For such a formulation of the filtration tasks in the vibration monitoring systems of slide bearings, as suggested in (Batko and Banek, 1993; 1994), a modification of the solutions will be presented that will enable one to eliminate simultaneously the noise generated by the deformations of the shaft neck being monitored. The formulation refers to the results and solutions of the Kalman-Bucy theory of optimal filtration (Anderson and Moore, 1979), which makes the solutions suggested in the paper universal and permits a more penetrating diagnostic analysis of the phenomena being monitored.

The equations (derived in (Batko and Kaźmierczak, 1985; Batko and Banek, 1993)) of the shaft displacement around the point of balance in the shaft neck of the slide bearing being monitored were accepted as our starting point. They correspond to the description of the behaviour of the bearing node being monitored, defined by a simplified, two-dimensional, and isothermal model presented in (Kurnik and Starczewski, 1985) with its characteristic assumptions, boundary conditions, and reductions. They refer to the conditions of determining the working area of the oil film and hydrodynamic forces.

As regards the description of the model bearing node, the displacement vector changes

$$X = \mathrm{col}\,[\Delta_1,\, W_1 = \dot{\Delta}_1,\, \dot{\Delta}_2,\, W_2 = \dot{\Delta}_2]$$

which describe its state—described by the observation of the changes in the distances Δ_1 and Δ_2 between the shaft neck surface and bearing bush in measurement sensor position respectively (Fig. 2)—can be modelled with the accuracy to some Gaussian processes by eqns. (1) and (2) (Batko and Banek, 1994):

$$\mathrm{d}X_t = (\Lambda + AX_t)\,\mathrm{d}t + \Sigma\,\mathrm{d}B_t \tag{1}$$

$$\mathrm{d}Y_t = HY_t + E\,\mathrm{d}b_t \tag{2}$$

where B and b are Brownian motions of appropriate dimensions,

$$A = \begin{pmatrix} 0 & 1 & 0 & 0 \\ \beta_{11} & \alpha_{11} & \beta_{12} & \alpha_{12} \\ 0 & 0 & 0 & 1 \\ \beta_{21} & \alpha_{21} & \beta_{22} & \alpha_{22} \end{pmatrix} \tag{3}$$

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}, \quad \Sigma = \begin{pmatrix} 0 & 0 \\ \sigma_1 & 0 \\ 0 & 0 \\ 0 & \sigma_2 \end{pmatrix}, \quad E = \begin{pmatrix} \varepsilon_1 & 0 \\ 0 & \varepsilon_2 \end{pmatrix} \tag{4}$$

The coefficients β_{ij} and α_{ij} which appear in the matrix A denote the elasticity and damping coefficients of the oil film, respectively. They may be determined with the use of the perturbation method or its generalised realisation (Kiciński, 1989; 1993) and then corrected adequately (Batko and Banek, 1993) to the axis configuration of sensors in the monitoring system. The matrix H joins the invisible state vector X with the observation vector Y whose components are displacements Δ_1 and Δ_2 (Fig. 2) without the speed measurement. The quantity $\{B1, B2\}$ is a two-dimensional Wiener process denoting the noise caused by the model inaccuracies in the description of the shaft neck movement around the point of balance. The constants $(\Sigma_1,\, \Sigma_2)$ may equal zero (for an undisturbed system) or may be positive when the system is disturbed. Likewise, $\{b_1,\, b_2\}$ is a Wiener process stochastically independent of $\{B_1,\, B_2\}$ and denotes random noise in the monitoring set. The constants

$(\varepsilon_1, \varepsilon_2)$ play the same role as (σ_1, σ_2) in eqn. (1) and model the noise measurement level. The components of vector Λ are given by

$$\Lambda = \begin{pmatrix} \Lambda_1 \\ \Lambda_2 \\ \Lambda_3 \\ \Lambda_4 \end{pmatrix} = - \begin{pmatrix} 0 \\ \beta_{11}\Delta_{10} + \beta_{12}\Delta_{20} \\ 0 \\ \beta_{21}\Delta_{10} + \beta_{22}\Delta_{20} \end{pmatrix} \tag{5}$$

with the discussed above oil film elasticity coefficients β_{ij} and the distance of the centre in the static point of balance recalculated to the distance measured by the sensors.

3. State Equations of the Monitored Bearing Node in the Case of Shaft Neck Deviations

The easiest way to define the deviation from the circularity of the shaft neck is to give (Fig. 1) functions by which it is characterised.

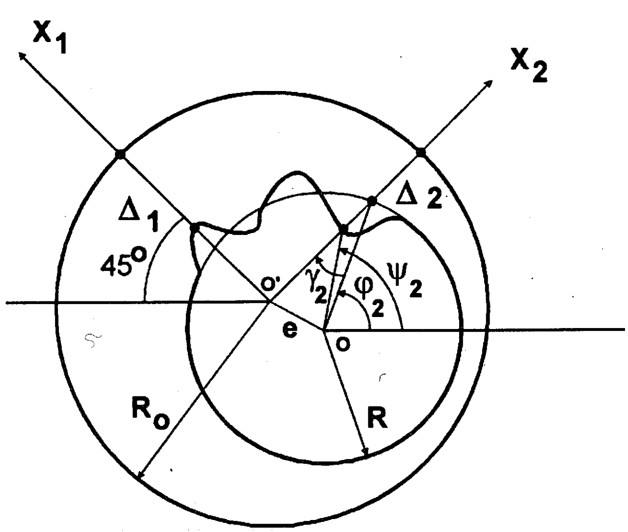

Fig. 1. The scheme of the measuring disturbances caused by the shaft neck profile deformations.

Then the true radius of the shaft neck R_{rz} equals

$$R_{rz}(\varphi) = R - f(\varphi) \tag{6}$$

The considerations concerning the effect of the non-circularity of the shaft neck upon the sensor Δ_1 and Δ_2 indications are clarified by Fig. 2. It is clear from the figure that

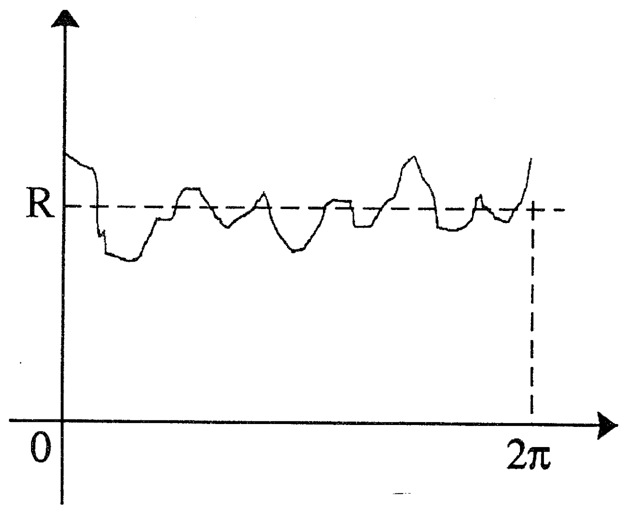

Fig. 2. The characteristics of the shaft neck radius changes in the angular expansion of its profile.

$$\sin\gamma_2 = \frac{X_1}{R} \tag{7}$$

and

$$\varphi_2 = \frac{\pi}{4} + \gamma_2 \tag{8}$$

Thus

$$\varphi_2 = \frac{\pi}{4} + \arcsin\frac{X_1}{R} \tag{9}$$

The analysis of the geometrical dependencies presented in Fig. 2 results in

$$\tau_2^2 = [f(\psi_2)]^2 + \left[2R\sin\frac{\psi_2 - \varphi_2}{2}\right]^2 \tag{10}$$

We also have

$$\frac{\tau_2}{\sin(\psi_2 - \varphi_2)} = \frac{R - f(\psi_2)}{\sin\gamma_2}$$

The comparison of the last two formulae results in

$$[f(\psi_2)]^2 + \left[2\,R\sin\frac{\psi_2 - \varphi_2}{2}\right]^2 = \frac{[R - f(\psi_2)]^2\,R^2\,\sin^2(\psi_2 - \varphi_2)}{X_1^2} \tag{11}$$

Since, for small angles α, $\sin\alpha \approx \alpha$, formulae (10) and (11) may be respectively rewritten as

$$\tau_2^2 = [f(\psi_2)]^2 = R^2(\psi_2 - \varphi_2)^2 \tag{12}$$

and

$$X_1^2 = \frac{R^2[R - f(\psi_2)]^2(\psi_2 - \varphi_2)^2}{R^2(\psi_2 - \varphi_2)^2 + [f(\psi_2)]^2} \tag{13}$$

From similar considerations for the first sensor, one obtains

$$\tau_1^2 = [f(\psi_1)]^2 + R^2(\psi_1 - \varphi_1)^2 \tag{14}$$

and

$$X_2^2 = \frac{R^2[R - f(\psi_1)]^2(\psi_1 - \varphi_1)^2}{R^2(\psi_1 - \varphi_1)^2 + [f(\psi_1)]^2} \tag{15}$$

The geometrical dependencies shown in Figs. 1 and 2 result in

$$\begin{aligned} &(X_1 - R_0 + \Delta_1)^2 + X_2^2 = R^2 \\ &X_1^2 + (X_2 - R_0 + \Delta_2)^2 = R^2 \end{aligned} \tag{16}$$

After solving the above system one obtains

$$\begin{aligned} X_1^{\mp} &= \frac{1}{2}(R_0 - \Delta_1) \mp (R_0 - \Delta_2)\sqrt{\frac{4R^2 - (R_0 - \Delta_1)^2 - (R_0 - \Delta_2)^2}{(R_0 - \Delta_1)^2 + (R_0 - \Delta_2)^2}} \\ X_2^{\mp} &= \frac{1}{2}(R_0 - \Delta_2) \mp (R_0 - \Delta_1)\sqrt{\frac{4R^2 - (R_0 - \Delta_1)^2 - (R_0 - \Delta_2)^2}{(R_0 - \Delta_1)^2 + (R_0 - \Delta_2)^2}} \end{aligned} \tag{17}$$

Substitution of (9) and (17) into (13) and (15) results in a complex relation between angles ψ_1, ψ_2 and R, R_0, Δ_1, Δ_2. The relation, although possible to be defined, results in insignificant deviations due to insignificant differences between φ_1, ψ_1, and φ_2, ψ_2. That is why it is assumed that

$$\psi_1 = \varphi_1, \qquad \psi_2 = \varphi_2 \tag{18}$$

Thus, the first approximation yields

$$\tau_1 = f(\varphi_1), \qquad \tau_2 = f(\varphi_2) \tag{19}$$

where

$$\varphi_1^{\mp} = \frac{3}{4}\pi + \arcsin\frac{X_2^{\mp}}{R}, \quad \varphi_2^{\mp} = \frac{\pi}{4} + \arcsin\frac{X_1^{\mp}}{R} \tag{20}$$

Thus, true deviations measured by the sensors equal to A_1 and A_2, respectively, where

$$A_1 = \Delta_1 + \tau_1, \qquad A_2 = \Delta_2 + \tau_2 \tag{21}$$

and τ_1, τ_2 are given by (19).

Further approximations in (17) result in

$$\begin{aligned} X_1^{\mp} &= \frac{1}{2}(R_0 - \Delta_1) \mp (R_0 - \Delta_2)\bar{R} \\ X_2^{\mp} &= \frac{1}{2}(R_0 - \Delta_2) \mp (R_0 - \Delta_1)\bar{R} \end{aligned} \tag{22}$$

where $\bar{R} = \sqrt{2(R/R_0)^2 - 1}$.

As it may happen that $X_1, X_2 > 0$ or $X_1, X_2 < 0$, it can be assumed that

$$\begin{aligned} X_1 &= \frac{1}{2}(R_0 - \Delta_1) - (R_0 - \Delta_2)\bar{R} \\ X_2 &= \frac{1}{2}(R_0 - \Delta_2) - (R_0 - \Delta_1)\bar{R} \end{aligned} \tag{23}$$

Thus the approximate form of (21) is given by

$$\begin{aligned} A_1 &= \Delta_1 + f\left(\frac{3}{4}\pi + \arcsin\frac{X_2}{R}\right) \\ A_2 &= \Delta_2 + f\left(\frac{\pi}{4} + \arcsin\frac{X_1}{R}\right) \end{aligned} \tag{24}$$

Considering the assumed reduction

$$\frac{X_1}{R}, \frac{X_2}{R} \simeq 0, \quad \arcsin\frac{X_1}{R} = \frac{X_1}{R}, \quad \arcsin\frac{X_2}{R} = \frac{X_2}{R}$$

one obtains

$$\begin{aligned} \dot{A}_1 &= \dot{\Delta}_1 + f'\left(\frac{3}{4}\pi + \arcsin\frac{X_2}{R}\right)\frac{1}{R}\dot{X}_2 \\ &= \dot{\Delta}_1 + f'\left(\frac{3}{4} + \arcsin\frac{X_2}{R}\right)\frac{1}{R}\left[-\frac{1}{2}\dot{\Delta}_2 + \bar{R}\dot{\Delta}_1\right] \end{aligned} \tag{25}$$

$$\begin{aligned} \dot{A}_2 &= \dot{\Delta}_2 + f'\left(\frac{1}{4}\pi + \arcsin\frac{X_1}{R}\right)\frac{1}{R}\dot{X}_1 \\ &= \dot{\Delta}_2 + f'\left(\frac{1}{4} + \arcsin\frac{X_1}{R}\right)\frac{1}{R}\left[-\frac{1}{2}\dot{\Delta}_1 + \bar{R}\dot{\Delta}_2\right] \end{aligned} \tag{26}$$

which, after some arrangements, can be rewritten as

$$\begin{aligned} \dot{A}_1 &= \dot{\Delta}_1\left[1+\frac{\bar{R}}{R}f'\left(\frac{3}{4}\pi+\frac{X_2}{R}\right)\right]-\frac{1}{2R}f'\left(\frac{3}{4}+\frac{X_2}{R}\right)\dot{\Delta}_2 \\ \dot{A}_2 &= -\frac{1}{2R}f'\left(\frac{1}{4}\pi+\frac{X_1}{R}\right)\dot{\Delta}_1+\left[1+\frac{\bar{R}}{R}f'\left(\frac{1}{4}\pi+\frac{X_1}{R}\right)\right]\dot{\Delta}_2 \end{aligned} \tag{27}$$

4. Optimal Filtration and Prediction of Monitored Signals

The state vector will be defined as

$$Z := \begin{pmatrix} A_1 \\ \dot{A}_1 \\ A_2 \\ \dot{A}_2 \end{pmatrix} = \begin{pmatrix} \Delta_1 \\ \dot{\Delta}_1 \\ \Delta_2 \\ \dot{\Delta}_2 \end{pmatrix} + \begin{pmatrix} f\left(\frac{3}{4}\pi+\frac{X_2}{R}\right) \\ \frac{1}{R}\dot{X}_2 f'\left(\frac{3}{4}\pi+\frac{X_2}{R}\right) \\ f\left(\frac{\pi}{4}+\frac{X_1}{R}\right) \\ \frac{1}{R}\dot{X}_1 f'\left(\frac{\pi}{4}+\frac{X_1}{R}\right) \end{pmatrix} \tag{28}$$

which, having applied (24) and (25), can be rewritten as

$$Z = \begin{pmatrix} A_1 \\ \dot{A}_1 \\ A_2 \\ \dot{A}_2 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1+\frac{\bar{R}}{R}f'\left(\frac{3}{4}\pi+\frac{X_2}{R}\right) & 0 & -\frac{1}{2R}f'\left(\frac{3}{4}\pi+\frac{X_2}{R}\right) \\ 0 & 0 & 1 & 0 \\ 0 & -\frac{1}{2R}f'\left(\frac{\pi}{4}+\frac{X_1}{R}\right) & 0 & 1+\frac{\bar{R}}{R}f'\left(\frac{\pi}{4}+\frac{X_1}{R}\right) \end{pmatrix} \begin{pmatrix} \Delta_1 \\ \dot{\Delta}_1 \\ \Delta_2 \\ \dot{\Delta}_2 \end{pmatrix}$$

$$+ \begin{pmatrix} f\left(\frac{3}{4}\pi+\frac{X_2}{R}\right) \\ 0 \\ f\left(\frac{\pi}{4}+\frac{X_1}{R}\right) \\ 0 \end{pmatrix} = CX + F \tag{29}$$

In order to obtain a filter and evolution equation for the vector Z, transformation (29) and state equation (1) will be given a vector-matrix form

$$\begin{aligned} Z &= CX + F \\ \mathrm{d}X_t &= (\Lambda + AX_t)\,\mathrm{d}t + \Sigma\,\mathrm{d}B_t \end{aligned} \tag{30}$$

where F and Λ are heterogeneities.

By Ito's differential rule we obtain

$$\mathrm{d}Z_t = \dot{F}(t)\,\mathrm{d}t + C\,\mathrm{d}X_t = \big(\dot{F}(t) + C\Lambda + CAX_t\big)\mathrm{d}t + C\Sigma\,\mathrm{d}B_t \tag{31}$$

and

$$\mathrm{d}Z_t = \Big[\dot{F}(t) + C\Lambda + CAC^{-1}Z_t - CAC^{-1}F\Big]\,\mathrm{d}t + C\Sigma\,\mathrm{d}B_t \tag{32}$$

where

$$F := \mathrm{col}\Big[f\Big(\frac{3}{4}\pi + \frac{X_2}{R}\Big),\, 0,\, f\Big(\frac{\pi}{4} + \frac{X_1}{R}\Big),\, 0\Big] \tag{33}$$

$$C := \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1+\frac{\bar{R}}{R}f'\Big(\frac{3}{4}\pi+\frac{X_2}{R}\Big) & 0 & -\frac{1}{2R_0}f'\Big(\frac{3}{4}\pi+\frac{X_2}{R}\Big) \\ 0 & 0 & 1 & 0 \\ 0 & -\frac{1}{2R}f'\Big(\frac{\pi}{4}+\frac{X_1}{R}\Big) & 0 & 1+\frac{\bar{R}}{R}f'\Big(\frac{\pi}{4}+\frac{X_1}{R}\Big) \end{pmatrix} \tag{34}$$

Equation (32) describes evolution of the state vector Z that defines the shaft neck location and speed related to both sensors, in view of shaft neck contour errors. The ovalization of the shaft neck is given by the function $f(\phi)$ and is effective in eqn. (32). If $f(\cdot) \equiv 0$, then $B = I$ and $F \equiv 0$, thus $Z \equiv X$. As a result, eqn. (32) is reduced to the basic equation (1).

By the non-linear function f, transformation (30) is also nonlinear, since all the terms in the matrix B and the vector F depend on the function f whose arguments are variables (X_1, X_2) which depend on the coordinates of the vector $X := \mathrm{col}(\Delta_1, \dot{\Delta}_1, \Delta_2, \dot{\Delta}_2)$ through relations (23).

Unfortunatelly, all known monitoring systems can only measure displacements A_1 and A_2 without speed measurement, so we must assume the following observation model:

$$\mathrm{d}\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} A_1 \\ \dot{A}_1 \\ A_2 \\ \dot{A}_2 \end{pmatrix} \mathrm{d}t + \begin{pmatrix} \varepsilon_1 & 0 \\ 0 & \varepsilon_2 \end{pmatrix} \mathrm{d}\begin{pmatrix} b_1 \\ b_2 \end{pmatrix} \tag{35}$$

where $\{b_1, b_2\}$ is a Wiener process stochastically independent of $\{B_1, B_2\}$.

Let the matrices H, Σ, E be as in (1) and the matrix $R(t)$ be the solution of the Riccati differential equation

$$\frac{\mathrm{d}}{\mathrm{d}t}R = \Sigma\,\Sigma^T + CAC^{-1}R + R(C^{-1})^T A^T C^T - RH^T\Big(\Sigma\,\Sigma^T\Big)^{-1}HR \tag{36}$$

with boundary condition $R_0(0) = R_0 = E[Z_0 - EZ_0][Z_0 - EZ_0]^T$, where $Z_0 = CX_0 + F_0$. Then the Kalman-Bucy optimum filter equation for the state estimator of monitored variables $Z_t = E(Z_t|Y_t)$ is given by

$$\mathrm{d}\hat{Z}_t = \left(\dot{F} + C\Lambda - CAC^{-1}F + [CAC^{-1} - RH^T(EE^T)^{-1}H]\hat{Z}_t\right)\mathrm{d}t$$
$$+RH^T(EE^T)^{-1}\,\mathrm{d}Y_t \tag{37}$$

The above structure of the Kalman-Bucy filter, adequate for the technical problem under investigation, generates the optimal mean-squared state estimator if three fundamental conditions are met:

- linear state equation,
- linear observation equation,
- Gaussian boundary conditions.

If any of these requirements is not fulfilled, the suggested Kalman-Bucy filter is no longer optimal. The first condition is not met because of the shape errors given by the function $f(\varphi)$. However, if the components in the matrix B and the vectors F and $\dot{F}$ change insignificantly, then the existing nonlinearities produce minor effects, and the properties of the filter differ insignificantly from the optimum. A similar situation occurs in the case of the second condition. It is due to the variable properties of the oil film, characterised by four damping and rigidity coefficients. However, if their values that appear in the matrix A and the vector F change insignificantly, which may happen in the case of insignificant vibrations of the shaft neck in relation to the bearing bush, the existing nonlinearities will produce minor effects and the properties of the suggested filter will be insignificantly different from the ones of an optimal filter.

It should be stressed that the optimum filter in the general non-linear case cannot be given by a finite system of equations. Very few cases of filtration for non-linear systems which have been investigated, e.g. the Benes filter and its generalisations provided in (Zeitouni, 1984), do not conform to the case under investigation.

When errors of the shaft neck contour appear, optimal prediction $Z(\tau,t)$ with fixed t and changing $\tau > 0$ for $\tau \geq 0,\, t \geq 0$, (defined with mean-squared error on the assumptions that have been discussed above in detail) is given by the formula

$$\frac{\partial Z(\tau,t)}{\partial \tau} = \dot{F} + C\Lambda - CAC^{-1}F + CAC^{-1}Z(\tau,t) \tag{38}$$

The initial value $Z(0,t) = Z_t$ at the moment t is given from the Kalman-Bucy filter defined by eqn. (37). All variables of (38) are measured at moment τ. Thus the estimation of predictable changes of the monitored courses is given by the Cauchy formula, with application of the fundamental matrix, or by the solution of recurrent eqn. (38) coming from the initial condition obtained from the Kalman-Bucy filter given by formula (37).

5. Concluding Remarks

The basic result of the present paper is the elaboration of an alternative method of disturbance filtration and prediction of changes of symptoms being monitored for a vibration monitoring system of slide bearings. It permits simultaneous compensation of noise generated by the deformations of the shaft neck contour.

The method differs from the existing solutions to the problem of elimination of mechanical run-out noise, which are applied when testing machines. Having analysed the generation of changes in the courses, an adaptation filter-predictor for diagnostic signals was constructed. It is related to the known mathematical solutions that define the dynamics of slide journal bearings and to mathematical solutions in the field of the theory of optimal filtration and prediction of signals defined by stochastic differential equations. In a coherent way—with application of one model—it makes the tasks of filtration, prediction, and diagnosis possible. The solution presented in the paper constitutes a base for constructing programs for diagnostic system monitoring sets. Contrary to previous solutions, the algorithmic solution presented in the paper is characterised by a high degree of unification and modest computing requirements. As a result, it may be applied when designing sets to monitor any bearing nodes and their proper dynamic operation.

The solution of filtration presented here may constitute a factor leading to an increase in the reliability of monitoring systems under as well as reliability of the set that measures the stochastic noise generated by the deformations of the contour of the shaft surface included.

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