IMPROVEMENTS IN VEHICLE MAINTENANCE THROUGH VEHICLE CONDITION DIAGNOSIS USING A-PRIORI DATA

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ABSTRACT

This paper describes a prediction technique based on a-priori data of vehicle components, using the Bayes statistical method. The technique increases the accuracy of diagnosis instead of increasing the accuracy of the diagnostic parameter being measured. It is shown that this generally also leads to an increase of prediction accuracy. Assuming that the useful signal and noise are normally distributed, the expressions for the parameter values are obtained. The technique was demonstrated by the calculation of predicted parameters of a vehicle under diagnosis. The braking force of a vehicle diagnosed on a stand was used as an example of the technique.

INTRODUCTION

The prediction of diagnostic parameters is a necessary part of the diagnosis process, which determines the technical condition of a vehicle or its separate components. Under diagnosis, it is necessary to ensure that the object will not reach its limiting condition before the next diagnosis. In other words, it is necessary to be able to predict the diagnostic parameter change in the period between diagnoses. In this paper, only diagnostic parameters, which are characterized by functions monotonic with vehicle mileage are considered. Only "gradual" failures are taken into account, and random failures are not considered.

The prediction accuracy is conditioned by the adequacy of the mathematical model and by the accuracy of the diagnostic parameter. Considering only the second factor, i.e., the accuracy of the diagnostic parameter, we will use the exponential function of time [Kharazov & Krivenko, 1982], as a prediction model. Further, let us consider the question of influence of the diagnostic parameter accuracy on the prognosis accuracy. For this, we will use a-priori data of a component under consideration to increase the diagnostic parameter accuracy.

Noise is always added onto the "useful" signal (the signal is sensitive to the component's technical condition change). This leads to the fact that the measured diagnostic signal Y will be a sum of two random values [Shestov, 1967], the useful signal S and a noise N.

Using statistical data on a-priori distributions of the useful signal and the noise, and also of the component's diagnosis results, it becomes possible to correct the measured signal magnitude, which means that we can approximate the actual value of the useful signal. This problem can be solved using the Bayes statistical method, which combines the corrected magnitude of a useful signal on the one hand, with measured results and with a-priori data of the component on the other hand [Neter & Wasserman, 1966; Bierger, 1978; Shestov, 1967].

The method is based on reducing the measured magnitude ambiguity of a given component, using a-priori data obtained for the group of components of the same class. The increase in measuring accuracy is reached not for each separate component, but for the group as a whole. It can be further noted that for prediction purposes, the above information is needed for objects with a varying lifetime. When using vehicle components, the time element is generally approached by a mileage function.

1. THE PROGNOSTIC MODEL

We will examine the Bayes method in order to obtain a general formula for the a-posteriori mean value of a useful signal $\overline{S}^*$ for mileage l_i. The expression for the a-posteriori density distribution function of the useful signal is [Ajkac & Burmat, 1977; Neter & Wasserman, 1966]:

$$f_{S^*}(S/y) = \frac{f_s(S)\, f_y(y/s)}{\int_{-\infty}^{\infty} f_s(S)\, f_y(y/s)\, ds} \tag{1}$$

where:

Y	the measured value of the diagnostic signal (summary signal which consists of the useful signal and noise);
S	value of useful signal;
$f_s(S)$	a-priori density distribution function of useful signal;
$f_Y(Y/S)$	conditional density distribution function of the summary signal under the conditions in which the useful signal has been measured.

The mean value of the a-posteriori useful signal is as follows:

$$M[S^*] = \overline{S}^* = \int_{-\infty}^{\infty} S f_{s^*}(S/Y)\, ds \qquad (2)$$

where:

$\overline{S}^*$ mean value of the a-posteriori useful signal. Combining expressions (1) and (2), we can obtain the general relation for the mean value of the a-posteriori useful signal:

$$\overline{S}^* = \frac{\int_{-\infty}^{\infty} S \cdot f_s(S) \cdot f_y(y/S)\, dS}{\int_{-\infty}^{\infty} f_s(S) \cdot f_Y(y/S)\, dS} \qquad (3)$$

Equation (3) allows us to obtain the above-mentioned mean-value $\overline{S}^*$, which minimizes the root-mean-square error of $\overline{S}^*$ from actual value of the useful signal.

The method to determine the conditional density distribution function (from (3)), is based on the assumption that the probability of a summary signal with the value Y_i is equal to the probability of a noise signal with a value $N_i = Y_i - S_i$, as shown in Fig. 1. Thus (3) can be expressed as follows:

$$\overline{S}^* = \frac{\int_{-\infty}^{\infty} S \cdot f_s(S) \cdot f_n(Y-S)\, dS}{\int_{-\infty}^{\infty} f_s(S) \cdot f_n(Y-S)\, dS} \qquad (4)$$

where $f_n(Y-S)$ is the unconditional density distribution function of the noise signal. Expression (4) is a general formula, suitable for any distribution of noise and a-priori useful signal. Here, we will limit the application of the technique to the often met normal distribution both for the useful signal and for the noise. In this case, expression (4) will be as follows:

$$\overline{S}^* = \frac{\sigma_n^2 \cdot \overline{S} + \sigma_s^2 \cdot Y}{\sigma_n^2 + \sigma_s^2} \qquad (5)$$

where: $\bar{S}$ and σ_s are the mean value and root-mean-square value of the a-priori useful signal, respectively;
σ_n the root-mean-square value of the noise;
Y the result of diagnostic parameter measured, i.e., the summary signal.

From probability theory, assuming a normal distribution of the a-priori useful signal and the noise, it follows that the distribution of the a-posteriori useful signal is also normal with mean value $\bar{S}^*$ (which is defined by (5)) and with root-mean-square value σ_{s*} :

$$\sigma_{s^*}=\frac{\sigma_n \cdot \sigma_s}{\sqrt{\sigma_n^2+\sigma_s^2}} \tag{6}$$

Moreover, let us examine the accuracy of the value from the diagnosis results. Let a diagnosis interval be constant $-l_d$ with known measured values Y_i for the mileage l_i and Y_{i+1} for mileage l_{i+1}.

Taking into consideration that the diagnostic signal change as a function of mileage can be described as an exponential function, we obtain:

$$y(l_i)=A-Bl_i^{\alpha} \tag{7}$$

where A,B coefficients, which are taken as constants;
α exponent index, which is characteristic for a certain vehicle component.

The mileage will be measured from the moment - l_i. Thus:

$$l_{i+1} = l_i + l_d, \text{ and } l_{i+2} = l_i + 2l_d$$

and one can write:

$$\begin{cases} Y_i=A-B\cdot 0^{\alpha} \\ Y_{i+1}=A-B\cdot l_d \end{cases} \tag{8}$$

From equation (8), we can define A and B for the range of prediction :

$$\begin{cases} A = Y_i \\ B = \dfrac{Y_i - Y_{i+1}}{l_d^{\alpha}} \end{cases} \tag{9}$$

Furthermore, combining (7) and (9), we can obtain the following expression for the predicted mileage l_{i+2} :

$$Y_{i+2} = 2^{\alpha} \cdot Y_{i+1} + (1 - 2^{\alpha}) \cdot Y_i \tag{10}$$

where the term "2^{α}" derives from the relation :

$$l_{i+2} - l_i = 2\, l_d$$

For example, for the mileage $l_{i+3} = l_i + 3\, l_d$, a term "3^{α}" will be presented in expression (10) instead of term "2^{α}".

Under the normal distribution assumption of a-priori data, the mean value Y_{i+2} can be determined from mean values Y_{i+1} and Y_i. The predicted variance is determined with a noise value for mileage l_{i+2} and is equal to $\sigma^2_{n_{i+2}}$.

In the case examined, the prediction accuracy is determined by the departure value from the mean value Y_{i+2} for a given level of confidence. So far as the value Y_{i+2} is normally distributed, the predicted magnitude Y_{i+2} is in the range:

$$Y_{i+2} = \overline{Y}_{i+2} \pm t_{\beta} \cdot \sigma_{n_{i+2}} \tag{11}$$

where t_{β} is the percentage point of the normal distribution under the confidence probability β.

Let us now consider the prediction for above described technique, subject to known a-priori data regarding the useful signal and the noise. For that, we will employ the expressions (5) and (6), acccordingly, for the predicted values of the mean value Y_{i+2} and of the variance $\sigma^2_{n_{i+2}}$. Thus we obtain:

$$\overline{S}^{*}_{i+2} = \frac{\sigma^2_{n_{i+2}} \overline{S}_{i+2} + \sigma^2_{s_{i+2}} \cdot y_{i+2}}{\sigma^2_{n_{i+2}} + \sigma^2_{s_{i+2}}} \tag{12}$$

$$\sigma^{*}_{s_{i+2}}=\frac{\sigma_{n+2}\cdot\sigma_{s_{i+2}}}{\sqrt{\sigma^{2}_{n_{i+2}}+\sigma^{2}_{s_{i+2}}}} \tag{13}$$

where $\sigma_{s_{i+2}}$ the root mean square deviation of the a-priori useful signal;

$\overline{S}_{i+2}$ is the mean value for a given mileage l_{i+2};

$\overline{S}^{*}_{i+2}$, $\sigma_{s^{*}_{i+2}}$ are the mean value and roof-mean square deviation of the a-posteriori predicted useful signal for the same mileage.

Combining equations (10) and (12), one obtains the final expression for $\overline{S}^{*}_{i+2}$:

$$\overline{S}^{*}_{i+2}=\frac{\sigma^{2}_{n_{i+2}}\cdot\overline{S}_{i+2}}{\sigma^{2}_{n_{i+2}}+\sigma^{2}_{s_{i+2}}}+\frac{\sigma^{2}_{s_{i+2}}\left[2^{\alpha}y_{i+1}+(1-2^{\alpha})y_{i}\right]}{\sigma^{2}_{n_{i+2}}+\sigma^{2}_{s_{i+2}}} \tag{14}$$

This last expression uses a-priori data about the noise and the useful signal under the mileage l_{i+2} and also uses the results of the diagnosis under the mileages l_i and l_{i+1}. The same initial data are necessary for the calculation of $\sigma_{s^{*}_{i+2}}$. For the corresponding mileages it is possible to substitute the magnitudes $\overline{S}^{*}_{i}$ and $\overline{S}^{*}_{i+1}$, which are defined with (5) instead of the magnitudes Y_i and Y_{i+1}. This will allow us to determine the mean predicted value $\overline{S}^{*}_{i+2}$ more accurately.

The confidence interval is determined in the following way:

$$S^{*}_{i+2}=\overline{S}^{*}_{i+2}\pm t_{\beta}\sigma_{s^{*}_{i+2}} \tag{15}$$

One can show that invariably:

$$\sigma_{s^{*}_{i+2}}<\sigma_{n_{i+2}}$$

In other words, comparing the derivation of the predicted value subject to a-priori data under (15) with the derivation using the conventional technique (11), leads to the conclusion that the confidence interval of predicting is narrowed, and the scattering centre $\overline{S}^{*}_{i+2}$ is determined more reliably than $\overline{Y}_{i+2}$. As a result of that, the prediction accuracy is increased.

3. EXAMPLE

We will illustrate the method developed above by using the given technique on the brake force as a diagnostic parameter. It was measured on a braking stand - KI-4988. The examination was carried out for the front wheels of a ZIL truck. The efficiency of the proposed technique can be examined for the presented data of diagnosis results with the above parameter.

An important question that arises is how to determine the distribution characteristics of the a-priori useful signal and of the noise. For simplification, we will assume that the noise distribution is invariant and does not depend on the mileage, so that $\sigma_{n_i}(l_i)$ = const (the real noise distribution can be characterized only with an increase of σ_n with mileage, which would lead to a more efficient use of the technique in the sense of diagnosis reliability). The noise statistical characteristics were determined in the following way:

Frequent (N>30) measurements of the diagnostic parameter - the braking force - were carried out for a randomly chosen truck. The experimental distribution obtained was then compared with the theoretical one, and finally with the χ^2 criterion. The normal distribution was selected as appropriate. Its parameters are:

$$\overline{Y}_i = 5000 \text{ N} \quad \text{[Newton]}$$
$$\sigma_n = 200 \text{ N}$$

The deviations of the measurement results are associated with the noise and determine the value σ_n. Here, we consider that mean value of the noise is equal to zero, which means that the deviation of the measurements will not depend on mileage. Also, we assume that the braking force mean value will reduce by 1% during the period l_d , so that

$$\overline{Y}_{i+1} = 4950 \text{ N}$$

Taking into account that the exponent index for a brake system is $\alpha = 0{,}9$ [Kharazov & Krivenko, 1982], we can calculate $\overline{Y}_{i+2}$ with equation (10):

$$\overline{Y}_{i+2} = 2^{0.9} \cdot 4950 + (1 - 2^{0.9}) \cdot 5000 = 4907 \text{ N}$$

The distribution density of the predicted magnitude (without a-priori data) Y_{i+2} is expressed by :

$$f(y_{i+2}) = \frac{1}{\sqrt{2\pi\sigma_n}} \exp\left[-\frac{(y_{i+2}-\tilde{y}_{i+2})}{2\sigma_n^2} \right] \qquad (16)$$

where $\tilde{Y}_{i+2}$ is the centre of the measured value distribution which is determined using expression (10). The diagnosis results for the mileages l_i and l_{i+1} are accordingly:

$$Y_i = 5400 \text{ N}; \quad Y_{i+1} = 4750 \text{ N}$$

Then from (10) we will obtain:

$$\tilde{Y}_{i+2} = 4187 \ N$$

For the calculation of the predicted value with the suggested technique one needs to know the values $\overline{S}_{i+2}$, σ_{n_i} - the characteristics of a normally distributed a-priori useful signal. For this purpose, the large group of trucks with mileage l_{i+2} was chosen. As stated, the measuring magnitude of a diagnostic signal Y is represented as a sum of two random uncorrelated values; the useful signal and the noise. From that the following expressions are derived:

$$\overline{S} = \overline{y}; \quad \text{as} \quad \overline{n} = 0, \qquad (17)$$
$$\sigma^2_{s_{i+2}} = \sigma^2_{y_{i+2}} - \sigma^2_n$$

where $\sigma_{y_{i+2}}$ - root-mean square deviation of the measuring diagnostic parameter which was obtained from a group of trucks.

The investigation results of the group of vehicles with mileage l_{i+2} show that:

$$\overline{S}_{i+2} = \overline{Y}_{i+2} = 4907 \text{ N}$$

and also: $\sigma_{y_i} = 490N$, $\sigma_{y_{i+1}} = 495N$, $\sigma_{y_{i+2}} = 500N$.

Then: $\sigma_{s_i} = 447 \ N$, $\sigma_{s_{i+1}} = 453 \ N$, $\sigma_{s_{i+2}} = 458 \ N$,

$$\overline{S}_i^* = 5333 \text{ N}, \quad \overline{S}_{i+1}^* = 4783 \text{ N}.$$

The distribution density of the a-posteriori (corrected) predicted value is calculated as:

$$f(S^*_{i+2}) = \frac{1}{\sqrt{2\pi}\sigma_{S^*}} \exp\left[-\frac{(S^*_{i+2}-\bar{S}^*_{i+2})^2}{2\sigma^2_{S^*}}\right] \tag{18}$$

Still assuming that the useful signal is described by a normal distribution, where $\bar{S}^*_{i+2}$ and σ_{s*} are determined by (13) and (14), and are equal to:

$$\bar{S}^*_{i+2} = 4403 \text{ N}; \quad \sigma_{s*} = 170 \text{ N}$$

The calculation results are presented in Fig. 2.

4. CONCLUSIONS

1. The method offered presents an alternative decision process providing improved vehicle fleet diagnosis for maintenance as an alternative to the employment of expensive, highly accurate measuring devices. It is recommended to employ a broad programme of diagnostic posts where there is a real opportunity to accumulate a-priori data relating to "useful" signal and noise data for the automobile diagnosis;
2. The employment of a-posteriori "useful" signal values increases the diagnostic significance, and in some cases, when the necessary accuracy is obtained at the expense of repeated measurements, the proposed method allows for a reduction in measurement quantity without increasing the errors;
3. Keeping in mind a-priori information for the diagnostic parameter prognosis allows us to correct both a pointing estimation of the prognosis and to diminish the confidence interval value under the given confidence probability. This increases the significance of the prognosis;
4. All calculations on which the given method is based are easily computed.

Note: The measurements were conducted while the first author (Dr. Anilovich) was in the Soviet Union. Therefore, all data relate to Russian vehicles. However, this does not affect the generality of the methods developed in any way.

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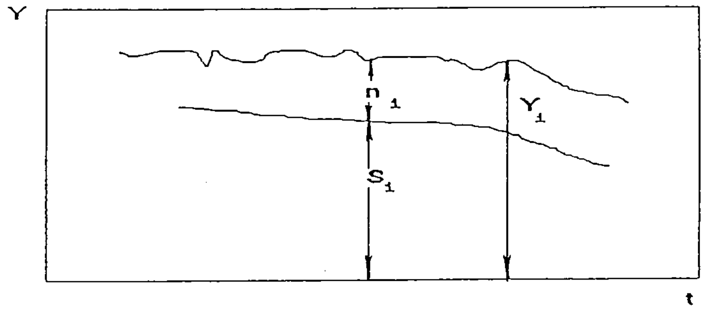

Figure 1: Summary Diagnostic Signal Y_i and its Components: The Useful Signal S_i and Noise n_i

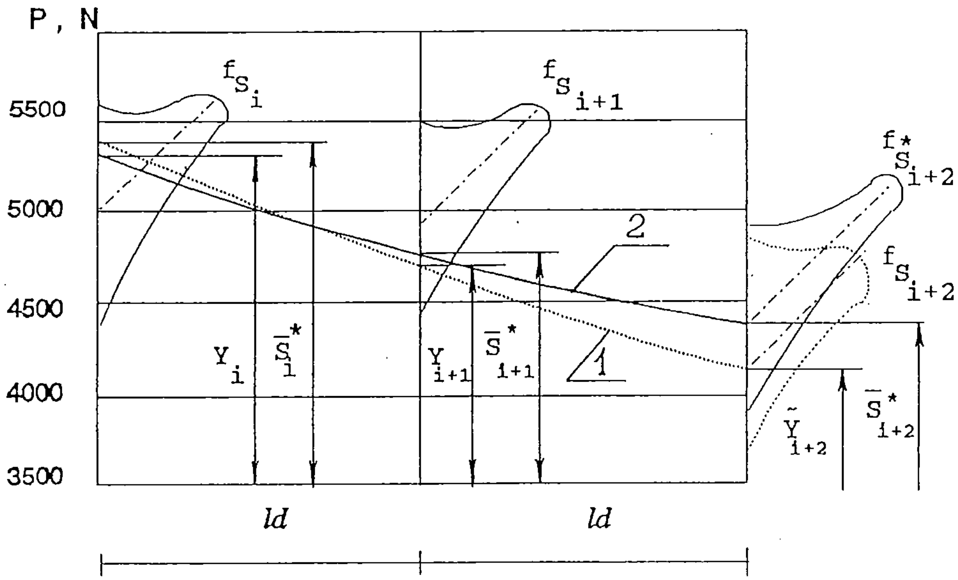

Figure 2: Prediction under the Conventional Technique (Curve 1) and under the Suggested Technique (Curve 2)