XVI IMEKO World Congress
Measurement - Supports Science - Improves Technology - Protects Environment ... and Provides Employment - Now and in the Future
Vienna, AUSTRIA, 2000, September 25-28

SIMPLE MODEL FOR FORECASTING IN TECHNICAL DIAGNOSTICS

M.Tabaszewski, C.Cempel
Institute of Applied Mechanics
Poznan University of Technology, 60-965 Poznan, Poland

Abstract: The aim of this paper is to present possibility of application of some symptom models for prediction of machine condition. The models were obtained from energy processor (EP) which can describe general energy flaw and processing in machines.
Keywords: modelling of symptoms, prediction of condition.

1 INTRODUCTION

In many cases, in technical diagnostics, prediction of condition is needed. The simplest way to obtain this is to compare a limit value of a symptom with a predicted value of the symptom. It requires choosing a model (models) which can approximate measurements of the symptom. It is possible to use many known methods and models to solve the prediction problem in diagnostics (ARIMA models, neural networks, exponential smoothing etc.). Another possibility, especially for symptoms which grow very rapidly in the last part of a life curve (directly before the brake-down of the machine), is the use of energy processor model [1][2]. If the model of energy processor is correct, it can be a base for models of symptoms behaviour and prediction of future symptom values and should be better in this cases then other general methods.

2 ENERGY PROCESSOR MODEL

The simplest kind of Energy Processor model can be described by differential equation as follows [1]:

$$\frac{dV}{d\Theta} = \frac{b(\Theta)(a-1)V}{1-b(\Theta)(a-1)\Theta} \tag{1}$$

where:
V - externally exported dissipated power, Θ - lifetime, β - function of destructive feedback, α - constant value.

In general observed symptoms of condition are covariant with power V.

The previous model cannot be used in the cases where a control of parameters changes input power Ni. So the next model of EP with additional parameters which allow describing the influence of changing of some parameters on Ni and the observed symptom we can write in the following way:

$$\frac{dV}{d\Theta} = \frac{b\left[(a-1)V + xN_i\right]}{1-b(a-1)\Theta} \tag{2}$$

where: N_i - input power, ξ - constant value.
In this case it is assumed in the first approach that β is constant.
The final form of the model of symptom depends on the relation between the symptom and V and the type of destructive feedback function assumed in modelling process. Here, it was assumed that relation symptom - V can be expressed as follows:

$$S = CV^{h}(\Theta) \tag{3}$$

where C,η are constant values identified in every case.

Considering model (2) it can be very difficult to measure N_i directly, so it is more safely to assume that we can measure a parameter P (for example rotating frequency etc.). So we can assume general formula for case (2) as follows:

$$N_i = C_1 \, P^{\,m} \tag{4}$$

where C_1, m are constant

Considering different propositions of function β it is possible to obtain models of diagnostic symptoms which can be approximate symptoms behaviour observed in practice. Finally, the characteristics of proposed models are shown in figure 1.

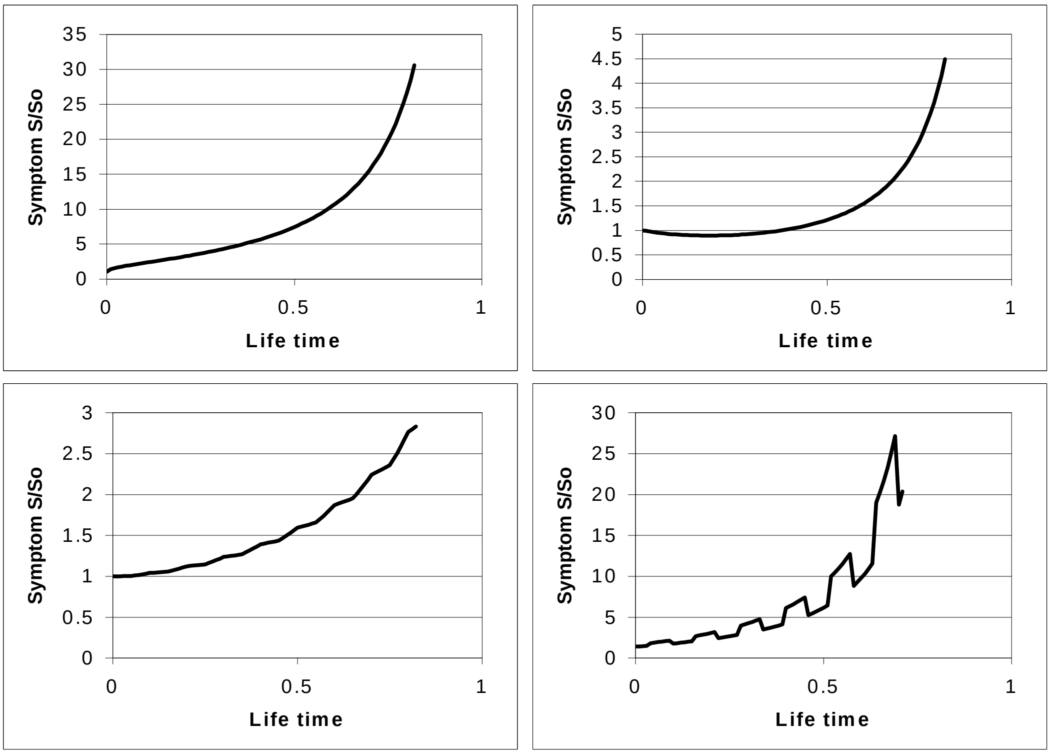

Figure 1. Examples of symptom models obtained from EP models without and with influence of changes of input power (or load of the machine).

The first and second models can be used in these cases where working parameters are constant or a symptom does not depend on them. The last two models can describe situation where these parameters influence the measured symptoms. Second model can also describe running in of some element of machine.

It is very difficult to verify the energy processor models (1) or (2). So we can only check if the proposed models are useful in the modelling process of some of the diagnostic experiments. In order to check this a simple experiment was made and different methods were compared. The experiment concerned rolling bearings and bad fitting of them which allowed to observe very short live curve. Two cases were considered during the experiment: constant and variable load of the bearing realised by changing the clamp. The most frequent cause of defects of testing bearings was surface fatigue. During the experiment were measured: temperature, acceleration of vibration, level of ultrasounds in narrow band and voltage proportional to ultrasounds in very wide band. Many data were obtained in narrow frequency bands by using digital filters and analysis of envelope of vibration signal, but only some of them could be recognised as good symptoms which monotonically grew in time. For identification of models coefficients the Nelder-Mead simplex algorithm and least mean square method was used. The models based on energy processor model which were considered and estimated parameters are shown in table 1.

Table 1. Proposed of models of symptom behaviour.

	Theoretical values of S	Function b	Estimated parameters
1	$\hat S = \hat S_o\left(1-\left(\frac{\Theta}{\hat\Theta_b}\right)^{\hat m}\right)^{\hat h'}$	$\beta(\Theta)=\beta_0\left(\frac{\Theta}{\Theta_b}\right)^n$	$\hat S_0, \hat\Theta_b, \hat m, \hat h'$
2	$\hat S = \hat S_o\left(\left(1-\frac{\Theta}{\Delta_1}\right)^{\frac{x-1}{2}}\left(1-\frac{\Theta}{\Delta_2}\right)^{\frac{-x-1}{2}}\right)^{\hat h}$	$\beta(\Theta)=\beta_0+\beta_1\Theta$	$\hat h, \hat d, \hat g, \hat S_o$ Δ_1, Δ_2, x are functions of these parameters
3	$\hat S = \hat S_o\left(1-\hat m'_1 f^{\hat m_2}(\Theta)\right)^{\hat h'}$	$\beta(N_i)=\frac{N_i(\Theta)}{\gamma(\alpha-1)}$	$\hat h', \hat m'_1, \hat m_2, \hat S_o$ $(h'<0)$
4	$\hat S = \left(\hat e'_1 + \hat i' P_i^{\hat m}\dot E\right)^{\hat c}\left(1-\frac{\dot E}{\hat{\dot E}_b}\right)^{-\hat h}$	$b = const$	$\hat x', \hat l'_1, \hat\Theta_b, \hat h', \hat m$

In case of model 3 function f is defined as:

$$f(\Theta)=\sum_{k=1}^{N} N_{i_k}\left[t\left(\Theta-\Theta_{n_k}\right)-t\left(\Theta-\Theta_{f_k}\right)\right] \quad (5)$$

$$\tau(\Theta-\mathrm{t})=\begin{cases}\Theta-t & \text{dla } \Theta\ge \mathrm{t}\\ 0 & \text{dla } \Theta<\mathrm{t}\end{cases} \quad (6)$$

Some examples of the result for model 2 and cases with constant load are showed in figure 2.

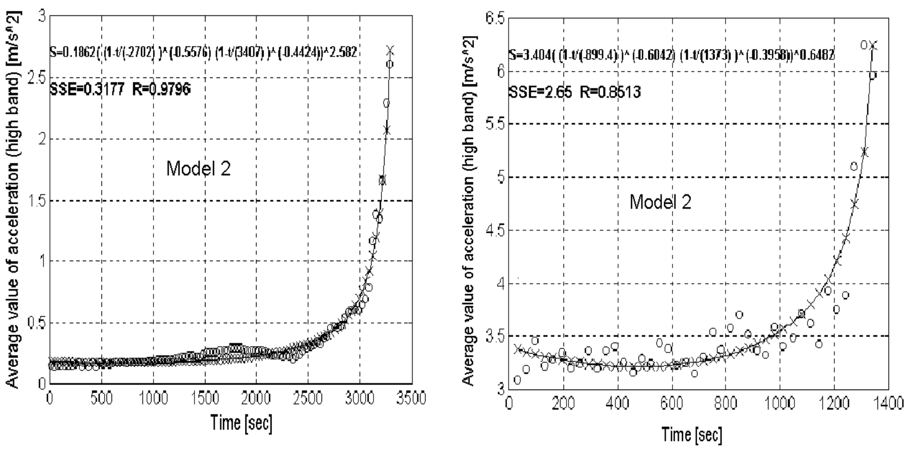

Figure 2. Examples of approximation of measured data by means of model for different life symptoms and different bearings.

It is very important to compare the obtained results to other methods to proof that the proposed models can be more useful in some cases then in others. So this comparison is based on prediction error, determination coefficient and sum of square calculated in each step of approximation. In most cases model 2 reached results measured in these categories as good as neural networks, autoregresive models (ARIMA) and exponential smoothing and much better than exponential or polynomial models. Some examples of approximation obtained with model 2, neural network and polynomial model is shown on figure 3.

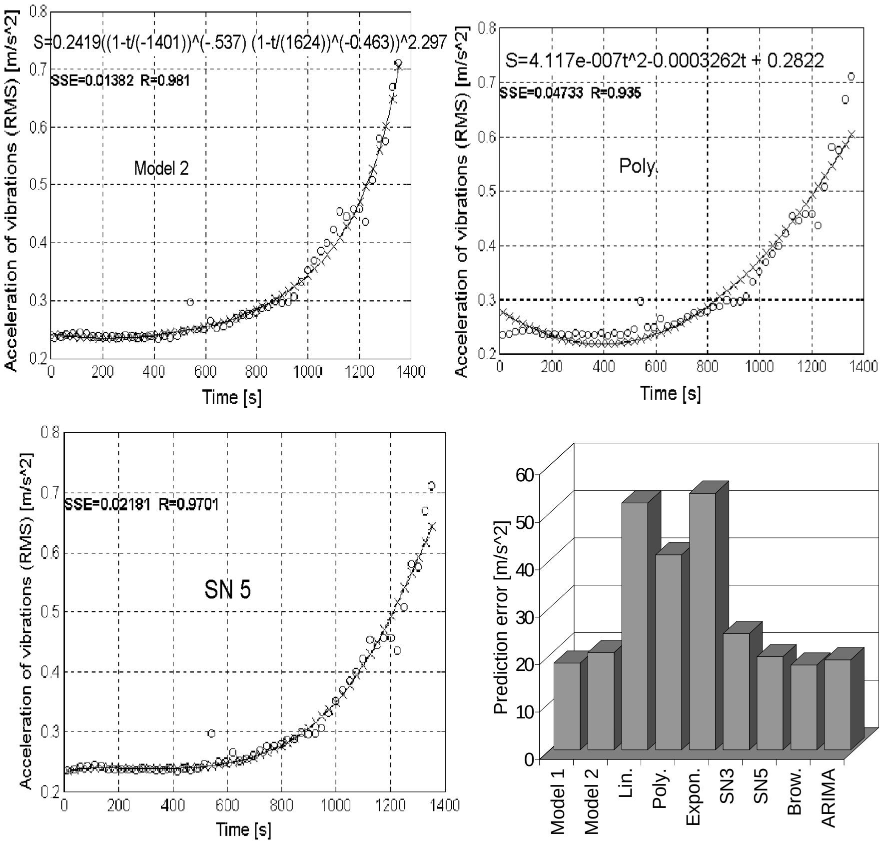

Figure 3. Comparison of chosen models for a symptom obtained in the experiment. First three figures: model 2, approximation with polynomial and neural network. In the next: prediction error. From left: model 1, model 2, linear model, polynomial model, exponential model, neural network models for 3 and 5 neurons in the hidden layer, exponential smoothing model and ARIMA (2,1,1) model.

To check the adequacy of models the changeability of identified parameters during approximation and normality of rests were also observed. In most cases (some of the symptoms and some of the bearings) model 2 was adequate and this model appeared to be much better then model 1. It means that linear form of feedback function in the energy processor model describes better the reality.

Model 3 was not adequate for obtained symptoms but it can be useful for others. So it is needed to take it to account in other diagnostic experiments. Model 4 gave also promising results especially comparing with exponential and linear multiregressional methods so it is possible to use it when a symptom grows rapidly near the breakdown and when a symptom depends on the load.

REFERENCES

[1] C.Cempel, Theory of Energy Transforming Systems and Their Application in Diagnostics of Operating Systems, Applied Mathematical Computational Science 3, (1993) 533-548

[2] C. Cempel, H.G. Natke, System Life Cycle -System Life: The model Based Technical Diagnostics, a View on Holistic Modelling, System Research, Vol. No 9, pp 53 -63

AUTHORS: Institute of Applied Mechanics, Poznan University of Technology, ul. Piotrowo 3A, 60-965 Poznan, Poland, fax +48 61 6652 307, E-mails:
cempel@put.poznan.pl., mactab@neur.am.put.poznan.pl