Influence of characteristics of time series on short-term forecasting error parameter changes in real time

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Abstract. The impact of physical factors, such as temperature and others, leads to a change in the parameters of the technical object. Monitoring the change of parameters is necessary to prevent a dangerous situation. The control is carried out in real time. To predict the change in the parameter, a time series is used in this paper. Forecasting allows one to determine the possibility of a dangerous change in a parameter before the moment when this change occurs. The control system in this case has more time to prevent a dangerous situation. A simple time series was chosen. In this case, the algorithm is simple. The algorithm is executed in the microprocessor module in the background. The efficiency of using the time series is affected by its characteristics, which must be adjusted. In the work, the influence of these characteristics on the error of prediction of the controlled parameter was studied. This takes into account the behavior of the parameter. The values of the forecast lag are determined. The results of the research, in the case of their use, will improve the efficiency of monitoring the technical object during its operation.

1. Introduction

The need for the advanced condition monitoring of a technical object to prevent and control the occurrence of emergency situations in order to eliminate them with minimal impact makes the formulation and implementation of the problem of determining the predicted values of the parameters, as well as the projected assessment of the status of the individual parameters of a technical object or a set of real-time, relevant and timely [1-3]. Modern development of microprocessor technology allows one to realize this task using microprocessor modules in information systems engineering of complex objects such as active safety systems and vehicle inertial navigation [4]. Estimates implemented in microprocessor modules provide a high dynamic response to the situation. To perform predictive assessment of the technical parameters of the object by means of the microprocessor module, it is advisable to use simple models to get results in real time without a significant load on the microcontroller module. Of interest are the models, which are based on methods of analysis and forecasting of time series [5-7]. Numerous methods have been developed on the basis of time-series forecasting models [8-12]. However, these models are quite complex to use microcontroller in the background.

This article describes the model and values of the prediction algorithm for rapidly varying physical quantity based on the use of multiple exponential, smoothing its time series [5, 6]. Efficiency of the model and the algorithm is assessed based on the vehicle acceleration vector of projections of the change data values measured by the three-axial accelerometer in actual driving conditions.
2. The process model prediction

When building a prediction algorithm based on the model of smoothing a multiple exponential of time series, it was suggested that the sampling in a data doffing step can be set low so that a change in a parameter for several consecutive steps could be insignificant. This will improve the accuracy of prediction.

Let the values of the controlled parameter of technical object \( y(t) \) be measured by the microcontroller module in discrete moments of time with constant step \( h \). The result is array \( Y = \{y_i\}_{i=0}^n \) of measured parameter values \( y_i = y(t_i) \) at points \( t_0, t_1, ..., t_n \). \( t_i = t_{i-1} + h \). It is necessary to determine value \( y \) at points \( T + kh \), \( k = 1, K \), where \( T \) - current time, the value of which is forecast for the \( k \)-step or period of time \( \tau = kh \), called the delay time [1], and \( K \) - number specifying the prediction range.

As a predictive model, let us use a number of the time series of the first degree of the form [5, 6] characterized by low complexity and with good adaptive properties:

\[
y(t) = a_1 + a_2 t,
\]

Then, predicted value \( y \) at points \( T + \tau \):

\[
\hat{y}(T + \tau) = (2 + \frac{\alpha}{\beta} \tau) S_T - (1 + \frac{\alpha}{\beta} \tau) S_T^{[2]},
\]

where \( S_T \) and \( S_T^{[2]} \) are exponential averages, which are determined at time \( T \) by the formulas:

\[
S_T = \alpha y_T + \beta S_{T-1}, \quad S_T^{[2]} = \alpha S_T + \beta S_T^{[2]},
\]

where \( \alpha \) - smoothing constant which should be selected, \( \beta = 1 - \alpha \).

To start the calculation process, it is necessary to set the initial values of \( S_0 \) and \( S_0^{[2]} \):

\[
S_0 = \bar{a}_{1,0} - \frac{\beta}{\alpha} \bar{a}_{2,0}, \quad S_0^{[2]} = \bar{a}_{1,0} - \frac{2\beta}{\alpha} \bar{a}_{2,0},
\]

where \( \bar{a}_{1,0} \) and \( \bar{a}_{2,0} \) - the initial estimates of coefficients \( a_1 \) and \( a_2 \) to (1).

Let us study the possibility of using an adaptive model of the time series to predict the parameter of a technical object based on data taken from the accelerometer mounted on the car. Acceleration versus time is rapidly changing the alternating function with a significant spread of values. Step data latch is \( h = 0.015625 \text{ sec} \).

3. Adapting the model

It is necessary to investigate the effect of the polynomial model settings of smoothing the time series of forecasting accuracy change of the physical quantity at the initial stage of simulation performed using function \( f = A \cdot \sin(t) \).

The initial data for modeling: modeling with interval \( 0 \leq t \leq \pi \); simulation step (discrete interval) is \( h_m = \pi / 400 \); the amplitude of the sine wave is \( A = 1 \). Let us consider the behavior of the adaptive model of the time series of the first degree when \( h = hm \) is a prediction step.

Coefficients \( a_1 \) and \( a_2 \) of the initial submission of \( y(t) = a_1 + a_2 t \) of the original function significantly affect the duration and amplitude of the stage adaptation of the model to forecast the behavior of the function. Since at small angles to the sine of the angle, valid approximation of \( \sin(t) \approx t \), is to reduce the impact of this set on the following values for coefficients \( a_1 = 0.0; a_2 = \pi / 400 \). The absolute error of approximation of the initial representation of the function in this case is negligible (about \( 10^{-5} \)), the relative error is \( 10^{-5} \) or 0.001\%.
Analysis of the effect of smoothing coefficient \( \alpha \) on the prediction error indicates that the change of \( \alpha \) has no significant effect on the error in the initial part of the prediction (in the range of \( 0 \leq t \leq 0.7 \)). However, the \( \alpha \) decreases with an increasing error in the central part of the prediction range (on plot \( 0.7 \leq t \leq 1.8 \) error varies from 0.008 when \( \alpha = 0.09 \) to 0.0015 when \( \alpha = 0.3 \)) and there is a tendency of a slight increase in the error at the edge of the range (from 0.014 at \( \alpha = 0.09 \) to 0.016 when \( \alpha = 0.3 \)). Graphs of changes in the absolute values of reduced error for different values of \( \alpha \) with the "strict" setting the initial submission of the original features are shown in figure 1.

![Graph showing changes in absolute error with different \( \alpha \) values](image)

**Figure 1.** Graphs of changes in the absolute value of the above approximation error in the "strict" setting the values of the initial submission of the original function.

Consider the effect of factors \( a_1 \) and \( a_2 \) of the initial submission of the original function. If the determination of these coefficients is to use a linear approximation over an interval greater than \( \pi/400 \), then the coefficients will be different from the previously defined. Take the point \( t = \pi/400 \) and \( t = \pi/40 \). Then the coefficients have the following values: \( a_2 = 0.99 ; \; a_1 = 8.8 \times 10^{-6} \). Step \( h \) previous prediction. The error of approximation of the initial representation of the function in this case is much larger than the error of the previous presentation (3 orders) and is (maximum) relative error amounts to 0.0007 or 0.07%. Smoothing factor \( \alpha \) varied from a minimum value \( \alpha = 0.09 \) to the value \( \alpha = 0.29 \).

The simulation showed that under inaccurate reference values of the function at the initial time series forecasting adaptation period setting decreases with increasing \( \alpha \) (from 0.6 at \( \alpha = 0.09 \) to 0.15 with \( \alpha = 0.29 \)). In this case the amplitude of the surge and spike amplitude ratio to the value of the function is also decreased (by 3.7 and 37, with \( \alpha = 0.09 \) to 0.8, and 27, with \( \alpha = 0.29 \), respectively). The table and the relative error is also reduced (by 0.007 and 0.008 with \( \alpha = 0.09 \) to 0.002 and 0.002 with \( \alpha = 0.29 \) co-responsibility). However, predicting the extremes observed errors rise to a few percent.

Thus, the prediction procedure using the continuous function of smoothing the time series is the adaptation period, which depends on the accuracy of setting the initial count approximation coefficients \( \alpha_{1,0} \) and \( \alpha_{2,0} \) in (1). It is characteristic that an inaccurate reference initial approximation coefficients \( a_1 \) and \( a_2 \) only affects the duration of the adaptation of the site and shape of the predictor depending \( \tilde{y}(t) \) on this sector and has virtually no effect on prediction accuracy beyond.

### 4. Modelling of process of forecasting changes in the technical object parameter

Studies have shown that within the selected time series model prediction error outside the area of adaptation to a large extent determined by the choice of smoothing constant. Figure 2 shows the
results of prediction anticipation time $h$ experimental time series characterizing the change in acceleration over time, for different values of the smoothing constant $\alpha$.

**Figure 2.** Forecasting results for different values of $\alpha$.

Figure 2 shows: curve 1 - experimental acceleration versus time; curve 2 - result prediction at $\alpha = 0.55$; curve 3 - at $\alpha = 0.35$; curve 4 - at $\alpha = 0.15$

Graphs analysis shows that an increase in $\alpha$ predictive curve accurately reproduce the shape of the experimental curve. However, for each dependency there is a certain value of $\alpha$, which determines the border capacity model in terms of prediction accuracy. Error corresponding to the above results and illustrating this conclusion are shown in figure 3.

**Figure 3.** Errors of prediction for different values of $\alpha$.

Figure 3 shows: curve 1 - the error at $\alpha = 0.15$; curve 2 - at $\alpha = 0.35$; curve 3 - at $\alpha = 0.55$.

Simulation results show that in areas with a sharp increase of the controlled parameter (fig. 2, the time interval from 8.4 to 8.5 sec.) gives a lower prediction error model with constant high value smoothing and, on the contrary, in the case of small fluctuations decrease parameter prediction error associated with a decrease smoothing constant (for example, the section from 8.0 to 8.4 sec., fig. 3).

Forecasting can be carried out using the model on the time $\tau = kh > h$. Prediction results for the $\tau$ different and smoothing constant $\alpha = 0.35$ shown in fig. 4.
Figure 4. Predicting results at $\alpha = 0,35$ and different values of $\tau$.

Figure 4 shows: curve 1 - experimental acceleration versus time; 2 - result curve acceleration prediction for $\tau = 3h$; Curve 3 - $\tau = 5h$; Curve 4 - $\tau = 10h$.

Analysis of the simulation results showed that the forecast graphs for different values of the delay time generally the same shape as the experimental curve with lag, which is greater, the greater the value of pre-emption of time. For sites with a long time (over 4-5 $h$) increase or decrease in acceleration, for example, site-defined time interval from 8.4 to 8.5 seconds. (fig. 3), the time delay is proportional to the forecast lead time.

Prediction error in areas with a long time increasing or decreasing the maximum for graphics acceleration corresponding to $\tau = 10h$, and in areas with slightly changing trend of the prediction error for the same schedule as a whole smaller in comparison with other predictive curves corresponding $\tau < 10h$.

It should be noted that the prediction delay time decreases with increase in the smoothing constant $\alpha$. However, the use of $\alpha > 0.5 - 0.55$ to reduce the delay time is not effective.

5. The algorithm implementation process of forecasting changes in the technical object parameter

The study features of the model allowed to synthesize a generic algorithm for its setting and performance prediction:

1. In accordance with the relationship (1) defined by the initial evaluation of $a_{1,0}$ and $a_{2,0}$ values for $a_1$ and $a_2$ coefficients. For this purpose, the parameter $y_0(t_0)$ and $y_1(t_1)$, recorded on the prediction model initial settings.

2. Set the initial value of the smoothing constant in the range from 0.15 to 0.25. The value of $\alpha$ selected from the range, can serve as a point of reference for the selection of the most appropriate value of $\alpha$ in terms of further minimizing the prediction error of the controlled parameter $y$ in the process of setting up a model.

3. After determining the $\alpha$, $a_{1,0}$, and $a_{2,0}$ of $S_0$ and $S_1$, calculated from the formula (4).

4. For each $T \in [t_2, t_3, ..., t_n]$ for a fixed $\alpha$ performed forecasting lead time $\tau$, forecasting as of $T + \tau$. Forecasted value $\tilde{y}(T + \tau)$ calculated according to (3) and (2) respectively. The forecasting process is allocated adaptation portion when the predicted value $\tilde{y}(T + \tau)$ differ significantly from the measured values $y(T + \tau)$. Planning and forecasting, respectively, the end of the adaptation section can be identified by the predictive behavior of the curve, which in this area seek to get closer to the
dependence \( y(T + \tau) \). This prediction error, on average virtually unchanged or change very slowly in comparison with the dynamics as reported on the adaptation of the site.

5. After determining the site must minimize the prediction error of the prediction by varying the smoothing parameter \( \alpha \). By increasing or decreasing the \( \alpha \), depending on the expected dynamics change depending \( y(T) \) define the minimum (estimated) value of the error in the prediction area. Smoothing \( \alpha \) should be reduced if projected slowly changing dependency and increase otherwise. The resulting \( \alpha \) value can be used to predict future values \( y(T) \) using the model time series smoothing \( \tilde{y}(T) \).

6. Conclusions

Thus, the model of short-term forecasting algorithm and changes rapidly changing physical quantity characterizing the state of the technical object. The features of setting up and using the model, in particular, to ensure a good prediction accuracy is necessary to select the smoothing constant, the corresponding dynamics of the process being forecast, to eliminate or minimize the area of adaptation and extension of time-series forecasting section should accurately define the initial values of the original depending approximation coefficients. Also model constraints are defined.

These ratios, and short-term prediction circuit oriented data processing performance microprocessor in the microcontroller module in real time. The simulation showed the effectiveness of the proposed approach to forecasting changes in process parameters. The results can be useful in the development of software and algorithmic means monitoring systems and security technology, such as active safety systems and vehicle inertial navigation

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