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# THE CONCEPT OF PROCEDURES STATE FORECASTING USAGE IN REDUCTION LINE MACHINES LIFE MAINTENANCE

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Summary

The following article presents an original method of resolving the problem connected with production line machines life maintenance with the use of state forecasting procedures. The research problem undertaken in this article focuses on defining and describing how to maintain a usability state for production line machinery used in industries on the example of the Philips Lighting Poland S.A. in Piła. The defined problems could probably be eliminated by shifting from a planed-preventive strategy to a state-based machinery usage strategy. To implement the second course of action it is necessary to develop suitable procedures monitoring the state of machines used in production lines, including procedures of their state evaluation and state prognosis.

Keywords: production line machines, machine state forecasting, condition maintenance

KONCEPCJA WYKORZYSTANIA PROCEDUR PROGNOZOWANIA STANU W UTRZYMANIU ZDATNOŚCI MASZYN LINII PRODUKCYJNEJ

Streszczenie

Artykuł przedstawia autorską metodę rozwiązania problemu wynikającego z utrzymania zdatności maszyn linii produkcyjnej przy wykorzystaniu procedur prognozowania stanu. Problem badawczy podejmowany w artykule określony został poprzez zdefiniowanie i opisanie problematyki utrzymania stanu zdatności maszyn linii produkcyjnej w zakładach przemysłowych na przykładzie Philips Lighting Poland S.A. w Pile. Zdefiniowane problemy można prawdopodobnie wyeliminować poprzez przejście ze strategii obsługiwania planowo – zapobiegawczej na strategię obsługiwania według stanu maszyn. Aby ją zaimplementować konieczne jest opracowanie odpowiednich procedur monitorowania stanu maszyn linii produkcyjnej, w tym procedur oceny stanu oraz prognozowania stanu.

Słowa kluczowe: maszyny linii produkcyjnej, prognozowanie stanu maszyn, utrzymanie stanu zdatności

## 1. INTRODUCTION

Increasing requirements in production systems quality need implementing new procedures for monitoring of their state which allow making rational decisions that shape safety and exploitation costs. These opportunities are created by developing and implementing the production machine state system, which generates various problems which resolution are attempted in this article. One of the most important problems is a process of machine destruction during exploitation which requires the need for their state change supervision which in case of maintenance the fitness of production line machines includes:

a) definition of machine state (state evaluation) at present time basing on diagnostic test results which allows the control of state and localization of defects in case of machine inability;
b) forecasting of machine state in the future time (state forecasting) basing of diagnostic tests, which allows estimating date and range of the next machine maintenance;
c) development of forecasting diagnostic information usage in a maintenance system of production line machines.

The result of these solutions should be development of a concept of state monitoring which would generate information about technical state of production line machines within state evaluation and state forecasting having influence on safety and economics of the production process

## 2. CHARACTERISTICS OF THE ISSUE

Physical processes going on in production line machines have essential influence on their state change and are associated with their usage and exploitation. These processes are the source of diagnostic signals emission. Their analysis allows generation of information about technical state as well as about state of processes in the systems. Such examples are systems developed in our country (DIADYN, RSTM - Machine Technical State Recognition) and abroad (HUMS – Health and Usage Monitoring System) [3,4,6,7,8,14].

Presently the operation of production line machines in Philips Lighting Poland in Piła

(HOR6000, PLR and VELLO lines) goes according to planned and preventive strategy where once a week there is a necessary standby of a production line in order to perform planned activities which ensure fitness of production line. Additionally, binary sensors mounted in production line machines inform operators about malfunctioning (for example component misfeeding, conveyer stop, synchronization of manipulator), which is recorded as a defect and results in stopping the production line [13,14]. Single bit information does not give possibility to analyze the state of machine system, which limits diagnosis only to state of defect without its localization. Some support is given from process data, which allows observation of selected machine states, however, because of lack of adequate procedures [14]:

a) it does not generate exploitation decisions (for example localization of defected machine systems, date of next maintenance or reasons of defects);
b) range and character of information gained by them are set by a diagnostic technician, at initial stage it is often the machine operator;
c) in most of production line machines the systems of process diagnostics generate information about electrical and electronic systems, but nearly almost mechanical systems are omitted;
d) currently used monitoring systems applied in production line state realize only single elements proposed in function project (for example machine fitness state), but there are no functions associated with state forecasting that generate dates of maintenance of transport means which decreases universality of proposed solutions.

The above mentioned statements result in conclusion that monitoring of production line machines, in suggested range is very limited and generation of exploitation decisions is hardly possible. Moreover, an unplanned production break because of unfitness of one of machines generates high costs associated with a quick repair in order to keeping delivery dates, and in extreme cases, while realizing 'just-in-time' deliveries can result in loosing a customer and high penalty costs for breach of a contract.

These problems can be probably eliminated by switching from plan and preventive strategy to maintenance according to state strategy. In order to implement it there is a need to develop adequate procedures of monitoring the production line machine state, including state evaluation procedures and forecasting of production line machine state. In connection with the above there is a need to develop a system of state monitoring, which on the level of subsystems and systems of production line machines would generate information about their technical condition, date and scope of the next maintenance.

In this paper a problem of setting dates and scope of next maintenance was undertaken and developing procedures using the diagnostic information in a system of maintenance of fitness of production line machines.

## 3. FORECASTING OF PRODUCTION LINE MACHINE STATE

The process of forecasting of machine state depends on setting changes of diagnostic parameter values, characterizing the process of state degrading in the future [2,3,4,5,11]. In this method the technical state of a machine, is showed by a vector function: $Y(\Theta)= [y_1(\Theta),...,y_j(\Theta),...,y_m(\Theta)]$, of discrete or analogue course at time $\Theta_1,..., \Theta_b$ ($\Theta_1$- time of machine exploitation start, $\Theta_b$ - time of machine test), and there are known values of functions $Y(\Theta_1),..., Y(\Theta_b)$ at this time. Next, there should be defined the course of function $Y(\Theta_b+\tau)$, while the forecast can refer function $Y(\Theta)$, as well as each its component $y_j(\Theta)$. But then it is assumed that the course of function $Y(\Theta_b+\tau)$ is 'similar' to the course of function $Y(\Theta_1),..., Y(\Theta_b)$, which is made with assuming that there is existing continuity of changes of value for diagnostic parameters under examination. Such conclusion can be well-founded only with proper recognition of course of the changes, for example in the period of normal wearing and not taking into account discontinuities resulting from changes and adjustment of machine subsystems. One of possible ways is formulation of forecasting conclusions about the machine state basing on comparison of forecasting of diagnostic parameters with their limit values (setting for example the fitness and unfitness state classes) and setting the prognosis as for example the date of next maintenance in a strategy of machine exploitation according to state.

The machine state $W(\Theta_{n+\tau})$ at time $\Theta_{n+\tau}$ can be characterized by a set of values of diagnostic parameters $\{y_j(\Theta)\}]$. The machine at time $\Theta_{n+\tau}$ is in the fitness state $W^0$, when condition (1) is fulfilled [3,7,12]:

$$W(\Theta_{n+\tau})=W^0 \Leftrightarrow \forall(j=1,m)[\{y_{j,d}\}\leq\{y_j\,(\Theta_{n+\tau}\,)\}\leq \{y_{j,g}\}] \quad (1)$$

where: $\{y_{j,d}\}$, $\{y_{j,g}\}$ - sets of lower and upper limit values symptoms.

Set elements $\{y_j\,(\Theta_{n+\tau}\,)\}$ are unknown and thus it is necessary to forecast them at a assumed period of time $\tau$. The value of $\tau$ designates the time period for which the forecasting process is realized ( $\tau$ is also called prediction or 'time horizon of forecast'). In this approach the evaluation of time of transfer to unfitness state is defined by results of forecast of diagnostic parameters $\{y_j(\Theta_{n+\tau})\}$, signaling overrunning limit values, what will probably enable defining the date and scope of maintenance of production line machines. It uses assumption that the worsening of the machine technical state is represented by the time series $y_\Theta = <y_1, y_2, ..., y_b>$, i.e. a set of discrete observations $\{y_\Theta = \zeta(\Theta);\ \Theta = \Theta_1, \Theta_2,..., \Theta_b\}$ of a certain non-stationary stochastic process $\zeta(\Theta)$. As an acceptable period of machine exploitation it is assumed then its working period, in which limits of error range for particular forecasts defined on subset $\Omega^y \subset \Omega$ of available realizations of observed parameters $\{y_j(\Theta)\}$ and their forecasts $\{y_{j,p}\}$ according assumed predictor $P(y_\Theta,\tau)$ do not overrun limit values $\{y_{j,gr}\}$. Then the date of the next machine maintenance $\Theta_{b1}$ defines the time horizon of the forecast $\tau^*$ [5,6,11]:

1. For which there will not occur overrunning the limit value of the diagnostic parameter $y_{gr}$ through a limit of forecast error range set by a radius $r_\sigma$ (forecast error leveling method).
2. For which there will not occur overrunning the limit value of diagnostic parameter $y_{gr}$ through the forecast value of diagnostic parameter (method of limit value leveling of diagnostic parameter).

## 4. METHODS OF FORECASTING OF DIAGNOSTIC PARAMETER VALUES

### 4.1. Regression function method

On basis of diagnostic parameter value $y_j$ at time $(\Theta_1, \Theta_b)$ it is estimated by the smallest square method, the function of linear regression method for changes of diagnostic parameters according to relationship [2,3,13]:

a) for linear function: $y_{p\tau} = \alpha\Theta + \beta$ ;
b) for exponential function of second grade, $\beta$=2: $y_{p\tau} = \alpha\Theta^\beta$ ;
c) for exponential function of third grade, $\beta$=3: $y_{p\tau} = \alpha\Theta^\beta$ ;
d) for exponential function: $y_{p\tau} = e^{\alpha\Theta + \beta}$.

The radius of limit range of forecast error value $r_\sigma$ for forecast horizon $\tau$:

$$r_\delta = q\sqrt{\frac{1}{k-2}\sum_{i=1}^{k} e_{p,i}^2\left[1+\frac{1}{k}+\frac{(\Theta_k+\tau-\overline{\Theta})^2}{\sum_{i=1}^{k}\left(\Theta_i-\overline{\Theta}\right)^2}\right]} \qquad (2)$$

### 4. 2. Adaptive methods

1. Brown-Mayer method of exponential equaling grade 1.

The forecast value of parameter $y_{p\tau}$ is calculated with assumption of linearity of variable trend y(t), from relation [2,3,14,17]:

$$y_{p\tau} = a_t^{(0)} + \alpha\, a_t^{(1)} \qquad (3)$$

where: $\alpha$ - parameter of exponential smoothing, $\alpha \in <0,1>$

The radius of forecast error range $r_\sigma$:

$$r_\sigma \cong ab \qquad (4)$$

$$a = q\sqrt{\frac{1}{k-2}\sum_{i=1}^{k} e_{p,i}^2}$$

$$b=\sqrt{\frac{\alpha}{(2-\alpha)^3}\left[1+4(1-\alpha)+5(1-\alpha)^2+2(4-3\alpha)\tau^2+2\alpha^2\tau^2\right]}$$

2. Brown - Mayer method of exponential equaling grade 2.

The forecast value of parameter $y_{p\tau}$ is calculated with assumption of linearity of variable trend y(t), from relationship:

$$y_{p\tau} = a_t^{(0)} + \alpha\, a_t^{(1)} + \alpha^2 a_t^{(2)} \qquad (5)$$

The radius of forecast error range $r_\sigma$:

$$r_\sigma \cong q\sqrt{\frac{1}{k-2}\sum_{i=1}^{k} e_{p,i}^2}\ \sqrt{2\alpha+3\alpha^2+3\alpha^3\tau^2} \qquad (6)$$

3. Holt method.

The value of forecast parameter $y_{p\tau}$ is calculated, with stating two parameters $\alpha$ and $\beta$ according relationship [9]:

$$y_{p\tau} = F_t + T_t \qquad (7)$$

where: $F_t = \alpha y_{t-1} + (1-\alpha)\, y_{pt-1}$

$T_t = \beta(F_t - F_{t-1}) + (1-\beta)\, T_{t-1}$

The radius of forecast error range $r_\sigma$:

$$r_\sigma(q(k;0.05)) = abc \qquad (8)$$

$$a = q\sqrt{\frac{1}{k-2}\sum_{i=1}^{k} e_{p,i}^2}$$

$$b = \sqrt{\frac{\alpha}{(2-\alpha)^3}\left[1+4(1-\alpha)+5(1-\alpha)^2+2(4-3\alpha)\tau^2+2\alpha^2\tau^2\right]}$$

$$c = \sqrt{\frac{\beta}{(2-\beta)^3}\left[1+4(1-\beta)+5(1-\beta)^2+2(4-3\beta)\tau^2+2\beta^2\tau^2\right]}$$

While analyzing on literature research [2,3,4,5,6,7] and performed own research [8,9,10] the above introduced methods of defining the value of forecast diagnostic parameters it was stated that the most suitable methods are:

a) methods of regression function (linear, exponential, power function grade 1, 2, and 3);
b) adaptive methods (Brown – Mayer grade 1 and Holt methods).

## 5. METHODS OF SETTING THE MACHINE MAINTENANCE DATE

### 5.1. Method of setting the forecast error value leveling

For value $\Theta_{b1}$ there is assumed the value of time period of machine working time defined by time horizon $\tau^*$, set by a crossing point of a line of limit value of diagnostic parameter $y_{gr}$ with lower (assuming that $y(\Theta_b) > y_{gr}$) or upper (assuming that $y(\Theta_b) < y_{gr}$) is a limit of forecast error range set by the radius $r_\sigma$ for the trust level 1-$\gamma$=0.95 or 1-$\gamma$=0.99, which corresponds probability of value p=0,05 or p=0.99, that in the range set by horizon $\tau^*$ the diagnostic parameter will reach limit value $y_{gr}$. Then, there are possible the following interpretations of obtained dates [10,12,17]:

1. Not exceeding the limit set by radius $r_\sigma^{0.01}$ by the controlled parameter is interpreted as a lack of alarm signal to detailed and more precise diagnostic observation of a machine part or subsystem.
2. Exceeding the limit set by radius $r_\sigma^{0.01}$ by the controlled parameter is interpreted as a signal to detailed and more precise diagnostic observation of a machine part or subsystem (alert threshold).

3. Exceeding the limit set by radius $r_\sigma^{0.05}$ is interpreted as time $\Theta_{b1}$ - date of machine subsystem or system maintenance (alarm threshold).

In such situation the time period ($\Theta_1$, $\Theta_b$) will be a period of estimation of expected value for forecast error $e_p$ and limit radius of forecast error range $r_\sigma$, while the time period after $\Theta_b$ will be a period of active forecast, i.e. setting [8,9,10]:

a) forecast value of diagnostic parameter after forecast horizon time $\tau$, $y_{jp}(\Theta_b+\tau)$;
b) setting the radius value of forecast error range limit $r_\sigma(\Theta_b+\tau)$;
c) setting the date of the next machine maintenance $\Theta_{b1}$.

### 5.2. Method of diagnostic parameter limit value leveling

The date of next maintenance of a machine $\Theta_{b1}$ is defined by horizon value $\tau^*$, set by a crossing point of parameter trend line $y(\Theta)$ with [13,14,16]:

a) lower (with assumption that $y(\Theta_b) > y_{gr}$) limit of limit value $y_{gr}^*$:

$$y_{gr}^* = \frac{1}{10}\left| y(\Theta_1) - y_{gr}\right| + y_{gr} \tag{9}$$

b) or upper (with assumption that $y(\Theta_b) < y_{gr}$) limit of limit value $y_{gr}^*$:

$$y_{gr}^* = y_{gr} - \frac{1}{10}\left| y(\Theta_1) - y_{gr}\right| \tag{10}$$

Values $y_p(\Theta_b+\tau)$ and $\Theta_{b1}$ are set by one of forecast methods, and diagnosis and maintenance dates according to relation:

$$\Theta_{b1} = \Theta_b + \frac{\tau\ (y_{gr}^* - y(\Theta_b))}{y(\Theta_b+\tau) - y(\Theta_b)} \tag{11}$$

### 5.3. Method of estimation of diagnostic parameter change

Assuming [9]:

a) exponential distribution of diagnostic parameter at time $\Theta_b$;
b) that probability of reliable machine work $P_r$: $1 < P_r < 0.8$;
c) that dynamics of parameter increase $y_j$ at time (with $y_j(\Theta) < y_{jgr}$):

$$y(\Theta) = \frac{y_j(\Theta_b)}{y_{jgr} - y_j(\Theta_b)} \tag{12}$$

The value $\Theta_{b1}$ is set as:

$$\Theta_{b1} = \frac{(1-P_r)(y_{jgr} - y_j(\Theta_b))}{y_j(\Theta_b)}\Theta_b \tag{13}$$

### 5.4. Method of date $\Theta_{b1}$ estimation

Aspiration to simplify procedures of setting date $\Theta_{b1}$ caused development of a procedure for setting the date $\Theta_{b1}$, in which there is not necessary to set forecast value of parameter $y_p$. In this method there is set a certain level of limit value $y_{gr}^*$ different from limit value $y_{gr}$ and equals to it the value of diagnostic parameter [10]. Then as a date of next machine maintenance $\Theta_{b1}$ it is proposed to assume value of machine working time defined by horizon value $\tau^*$, defined as a crossing point of diagnostic parameter $y(\Theta_b)$ with value $y_{gr}^*$.

$$\Theta_{b1} = \Theta_b \tag{14}$$

Analyzing the results of own research [8,9,10] in this range it was decided that the most proper methods are:

a) method of forecast error leveling;
b) method of diagnostic parameter limit value leveling.

The above presented methods of diagnostic parameter value forecast and setting the machine maintenance date determine a lot of problems, which are:

a) defining the optimum set of diagnostic parameters describing change of machine state in function of exploitation time;
b) defining of weight function for multi-element set of diagnostic parameters;
c) defining the “best” method of diagnostic parameter value forecasting;
d) defining the “best” method setting the date $\Theta_{b1}$.

## 6. ALGORITHM OF USING THE STATE FORECASTING PROCESS IN MAINTENANCE OF PRODUCTION LINE MACHINE FITNESS

### A. Data acquisition

During the data acquisition there are gained [13,14,15]:

a) set of diagnostic parameters in function of machine exploitation time $\{y_j(\Theta_n)\}$, collected during exploitation, where $\Theta_n \in (\Theta_1, \Theta_b)$;
b) set of values of diagnostic parameters: $\{y_j(\Theta_1)\}$ – nominal values, $\{y_{jg}\}$ - limit values, $j=1, \ldots, m$;
c) set of machine states $\{\Theta_n: \{s_i\}, n=1, \ldots, N; i=1,\ldots, I\}$ collected during exploitation, where $\Theta_n \in (\Theta_1, \Theta_b)$;
d) set of machine process parameters in function of machine exploitation time $\{y_p(\Theta_n)\}$, collected during exploitation, where $\Theta_n \in (\Theta_1, \Theta_b)$;
e) set of machine environment parameter values in function of machine exploitation time $\{y_o(\Theta_n)\}$, collected during exploitation, where $\Theta_n \in (\Theta_1, \Theta_b)$;
f) set of additional events in function of machine exploitation time $\{z_d(\Theta_n)\}$, collected during exploitation time, where $\Theta_n \in (\Theta_1, \Theta_b)$.

### B. Optimization of the diagnostic parameter value set

The set of diagnostic parameters is defined by [13,14,17]:

a) method of correlation of diagnostic parameter values with the machine state (with machine exploitation time), $r_j = r(W, y_j)$, $(r_j = r((\Theta, y_j))$;

b) methods of diagnostic parameter information quantity about machine state $h_j$;
c) reduction of diagnostic parameter set by method of 'ideal point' from the group of Pareto compromising solution;
d) definition of weight value $w_j$.

**C. Forecast of diagnostic parameter value $y_j^*$**

a) by Brown - Mayer adaptive method grade 1 (B-M1) with coefficient $\alpha$= (0.1 – 0.6) and for forecast horizon $\tau$ = (1 – 3)$\Delta\Theta$ set for time period ($\Theta_1$,$\Theta_b$),
b) by Holt adaptive method with coefficient $\alpha$=(0.1 – 0.4) and $\beta$=(0.1 – 0.6) for forecast horizon $\tau$ = (1 – 3)$\Delta\Theta$ defined for a time period ($\Theta_1$,$\Theta_b$),
c) by analytic methods (exponential and power methods of the first, second, and third grade) for time horizon $\tau$ = (1 – 3)$\Delta\Theta$ set for a time period ($\Theta_1$,$\Theta_b$).

**D. Setting of next machine maintenance $\Theta_d$ :**

a) $\Theta_{d1}$ by method of forecast error leveling $r_p$ (for essentiality level $\gamma_1$=0.05) according to relationship [13,14,17]:

for $y_j(\Theta_b) > y_{jg}$ :

$$\Theta_{jd1} = \Theta_{jb} + \frac{\tau\lfloor y_j(\Theta_b) - y_{jg} - r_\sigma \rfloor}{y_j(\Theta_b) - y_{j,p}(\Theta_b + \tau)} \quad (16)$$

for $y_j(\Theta_b) < y_{jg}$ :

$$\Theta_{jd1} = \Theta_{jb} + \frac{\tau\lfloor y_j(\Theta_b) - y_{jg} \rfloor}{y_{j,p}(\Theta_b + \tau) - y_j(\Theta_b) + r_\sigma} \quad (17)$$

where: $r_\sigma$ - radius of forecast error range (calculated a posteriori corresponding to each method of setting the forecast value $y_{j,p}(\Theta_b+\tau)$);

b) $\Theta_{d2}$ by method of diagnostic parameter limit value leveling ($y_{jg1}$= $y_{jg}$; $y_{jg1}$=$y_{jg}$+$\gamma$($y_{jn}$–$y_{jg}$) for $y_{jn}$ > $y_{jg}$ and $y_{jg1}$= $y_{jg}$; $y_{jg1}$=$y_{jg}$–$\gamma$($y_{jg}$–$y_{jn}$) for $y_{jg}$ > $y_{jn}$), for example for $\gamma$=0.1:

for $y_j(\Theta_b) > y_{jg}$ :

$$\Theta_{jd2} = \Theta_{jb} + \frac{\tau\lfloor y_j(\Theta_b) - y_{jg1} \rfloor}{y_j(\Theta_b) - y_{j,p}(\Theta_b + \tau)} \quad (18)$$

for $y_j(\Theta_b) < y_{jg}$ :

$$\Theta_{jd2} = \Theta_{jb} + \frac{\tau\lfloor y_{jg1} - y_j(\Theta_b) \rfloor}{y_{j,p}(\Theta_b + \tau) - y_j(\Theta_b)} \quad (19)$$

d) setting the date of next machine maintenance and diagnosing: $\Theta_d^*$=min ($\Theta_{d1}$, $\Theta_{d2}$).

The above presentation of possibilities for setting dates and scope of machine maintenance lets formulate following conclusions:

1. All methods presented in the algorithm of machine state forecast let define optimum (according to assumed criterion, diagnostic parameter forecast values ($\Theta_1$,$\Theta_b$), and for further research it is proposed:

a) by Brown-Mayer adaptive method grade 1 (B-M1) with coefficient $\alpha$= 0.6 and for the forecast horizon $\tau$ = 3$\Delta\Theta$ defined for time period ($\Theta_1$,$\Theta_b$),
b) by Holt adaptive method with coefficient $\alpha$ = 0.4 and $\beta$ = 0.6 for forecast time horizon $\tau$ = 3$\Delta\Theta$ defined for time period ($\Theta_1$,$\Theta_b$),
c) by exponential analytic method for forecast horizon $\tau$ = 3$\Delta\Theta$ defined for time period ($\Theta_1$,$\Theta_b$).

Choice of method according minimum value of forecast error radius (matching error).

2. Assuming as basic methods of setting maintenance date the method of forecast error leveling for forecast error radius $r_\sigma$ (for significance level $\gamma_1$=0.05) – result $\Theta_{d1}$ and methods of leveling the limit value of diagnostic parameter – result $\Theta_{d2}$ setting a deadline for the next machine maintenance: $\Theta_d^*$= min ($\Theta_{d1}$, $\Theta_{d2}$).

3. Algorithm of realization the forecast of machine state contains the following stages:

a) data acquisition and optimizing of diagnostic parameters;
b) forecasting of diagnostic parameter set values {$y_j^*$} in time period ($\Theta_1$, $\Theta_b$);
c) setting the machine maintenance date $\Theta_d^*$= min ($\Theta_{d1}$, $\Theta_{d2}$).

## 7. CONCLUSIONS

Reassuming the above discussed issues we can formulate the following conclusions:

1. All presented procedures let setting the optimal, due to the adopted criterion, forecast values of diagnostic parameters and dates of the next machine maintenance.
2. In forecast of machine state it was focused on setting the date of the next maintenance, where the following methods were reviewed:

a) in area of diagnostic parameter forecast: the method of regression function and adaptive methods;
b) in area of setting the date of the next maintenance: the method of forecast error, method of diagnostic parameter limit value leveling, method of diagnostic parameter value estimating, method of next diagnosing and maintenance date estimation.

3. In order to define the diagnostic parameter forecast value there were selected three adaptive methods (Holt, Brown – Mayer grade 1) and regression function methods (linear, exponential, and power), while in order to define date for the next diagnosis and maintenance (method of forecast error leveling and method of diagnostic parameter limit value leveling).

4. Due to the above in order to define the forecast values of diagnostic parameters and dates for next machine maintenance it is recommended to implement the above algorithms and verify them.

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