PRACTICAL APPLICATIONS ELEMENTS OF THE STATE PREDICTION OF TECHNICAL SYSTEMS DESIGN AND CONSTRUCTION

Bogdan ŻÓŁTOWSKI, Henryk TYLICKI, Mariusz ŻÓŁTOWSKI

Abstract: The work introduces the problem of condition-based prognosis algorithms via estimation in machines operating industrial process, this paper aims to exposes a formal mathematical framework on technical condition-based prognosis process to industrial machines, the work is focused on describing the details of each step associated with data processing-analysis, with emphasis on: optimization procedure of diagnostic parameters set; and machine condition prognosis methods. The study has developed a systematic structure of rules basis of machine condition prognosis process based on the technical conditions methods. In order to illustrate an application of the study to a real industrial machine case, this work is applied to researches of combustion engines referenced as type UTD-20, the laboratory test was made in stationary condition.

Keywords: condition - based maintenance, machine condition prognosis, construction state prognosis, procedure of algorithm.

1. Introduction

The online machines condition prognosis process is useful for condition-based maintenance decision making in order to prevent unexpected machine breakdown, human injuries, and costs due to loss of productivity [10].

The main advantage of Preventive Maintenance (PM) strategies based on the scientific approach is that decision making is based on facts acquired through real data analysis. In the literature, PM based on the scientific approach can be classified into two techniques: (i) comprehensive-based; and (ii) specific-based techniques. The specific-based technique, as its name implies, is a specific maintenance technique that has unique principles for solving maintenance problems, examples of specific-based technique are time-based maintenance (TBM) and condition-based maintenance (CBM) [1]. CBM is a maintenance program that recommends maintenance decisions based on the information collected through condition monitoring. It consists of three main steps: (i) data acquisition -information collecting-; (ii) data processing -information handling- analyse the data or signals collected; and (iii) maintenance decision-making [8]. Nevertheless, prognosis is a relatively new area and becomes a significant part of CBM of systems [9].

The machine condition can be either directly observed from monitoring instruments or extracted from raw condition monitoring signals. In a problem of machine condition prognosis, observations of a machine condition Θ_k available up to last measured time point Θ_b are used to predict one at future time point of interest Θ_{b1} [10]. As observations are updated Θ_k, machine condition values are successively predicted for future time observation point Θ_{b1}. This problem is virtually a time series prediction problem. Data-driven approaches can be used to address this problem [8]. Another problem is how many essential observations

Θ_k are used for forecasting the future value, so-called embedding dimension, the value of the dimension should be chosen large enough for the predictor to estimate accurately the future value of machine condition and not too large to avoid the unnecessary increase in computational complexity [12].

Solving these problems depends on many factors relative to: level of machine complexity, application of multi-symptom observations, and exploitation process quality. The machines prognosis is a process which ought to enable to know the *a priori* machine state, basis on an incomplete history of diagnostic tests results. It allows of estimate the time of a faultless machine usage or the value of work done by it in the future. Then, the machine condition prognosis process requires defining the following elements [13]:

– the set of diagnostic parameters $Y=<y_1,...,y_j,...,y_m>$, which depend on the optimization procedure of diagnostic parameters sets, the machine working time, and the quality of recording data time step;
– the machine prognostic method used, which depend on the prognosis horizon, the minimal number of elements of time row indispensable for running the prediction, and the machine working time.

The issue of machine tests for the prognosis process to estimate the technical state, as well as legal acts related to user safety and environmental protections are an impulse for searching new prognostic methods, determining new measures and tools describing the current state in the specific work condition of machines. This paper attempts to summarise the mathematical framework rules basis of machine condition prognosis process based on multi-symptom prognostic methods.

2. Optimization procedure of diagnostic parameters sets

Given a set of diagnostic parameters Y derived from the set of output parameters, based on tests results, and focused to: get a reduction of useful diagnostic information for the prognosis process; or confirming some included information premise about physical behaviour of the machine. The determination of diagnostic parameters set in the machine condition prognosis process must to have:

– the ability to capture the machine state changes in exploitation time;
– the whole quantity of information on the machine state;
– relevant variability of diagnostic parameters values in the exploitation time.

The above postulates can be presented using the following methods [13, 14].

2.1. Correlation method of diagnostic parameters values

The method consists in examining the correlation procedure between each diagnostic parameter values y_j, and the technical state of the machine W, then $r_j=r(W,y_j)$ – coefficient of correlation of W and y_j. Then, expressing this relationship in terms of the time of machine exploitation, $r_j=r(\Theta,y_j)$, which is written as

$$r_j = \frac{\sum_{k=1}^{K}(\Theta_k - \overline{\Theta})(y_{j,k} - \overline{y_j})}{\sqrt{\sum_{k=1}^{K}(\Theta_k - \overline{\overline{\Theta}})^2 \sum_{k=1}^{K}(y_{j,k} - \overline{y_j})^2}}, \tag{1}$$

$$\text{with } \overline{\Theta} = \frac{1}{K}\sum_{k=1}^{K}\Theta_k , \quad \overline{y_j} = \frac{1}{K}\sum_{k=1}^{K} y_{j,k} , \quad j = 1,\ldots,m ,$$

where r_j –coefficient of correlation between the variables $\Theta_k \in (\Theta_1, \Theta_b)$ (Θ_k –machine exploitation time) and y_j; and in case of lack of data from the set W, data are replaced, assuming that the determination of state recognition procedures is realized within the range of normal wear, with the time of machine exploitation, then $r_j = r(\Theta_k, y_j)$ with $k = 1,\ldots, K$

.

2.2. Informational size of diagnostic parameter method

Method focused to choice of the parameter which provides the largest quantity of information on the machine state. The relevance (in terms of sensitivity to change of state of the machine) of a diagnostic parameter y_j, increases in relation to another y_i, according to the next conditions:

– if y_j is more correlated to W, i.e. $r_j > r_i$;
– if y_j is less correlated to others diagnostic parameters, i.e. $r_{j,n} < r_{i,n}$.

This relation is presented as the size indicator of the diagnostic parameter h_j, which is a modification of the indicator relating to the set of variables explaining the econometric model [15]:

$$h_j = \frac{r_j^2}{1 + \sum\limits_{j,n=1, j\neq n}^{m} \left| r_{j,n} \right|} , \tag{2}$$

$$r_{j,n} = \frac{\sum\limits_{k=1}^{K} (y_{j,k} - \overline{y_j})(y_{n,k} - \overline{y_n})}{\sqrt{\sum\limits_{k=1}^{K} (y_{j,k} - \overline{y_j})^2 \sum\limits_{k=1}^{K} (y_{n,k} - \overline{y_n})^2}} , \tag{3}$$

$$\text{with } \overline{y_j} = \frac{1}{K}\sum_{k=1}^{K} y_{j,k} , \quad \overline{y_n} = \frac{1}{K}\sum_{k=1}^{K} y_{n,k} ,$$

where $r_{j,n} = r(y_j, y_n)$, with $n = 1,\ldots,m$ and $j \neq n$ –coefficient of correlations between the variables y_j and y_n; in case of lack of data from the set W, they are replaced, assuming that the determination of state recognition procedures is realized within the range of normal wear, with the time of machine exploitation.

2.3. Summary of parameters optimization methods

An advantage of the presented methods is the fact that both allow of the choose single-element as well as multi-element sets of diagnostic parameters from the set of output parameters. A single-element set refers case, when the machine is decomposed into units, and it is necessary to choose one diagnostic parameter. A multi-element set is acquired when in presented procedures less strict limitation is used [7], which consists in classifying into the diagnostic parameters set these parameters whose indicator values are higher (lower), accepted respectively for the method, high (low) positive numbers.

The general methodology for estimating the optimal parameter set of machine diagnosis consists to next stages [14, 15]:

2.3.1. Data acquisition

- the set of diagnostic parameters values in the function of machine exploitation time $\{y_j(\Theta_k)\}$, acquired in the time of passive-active experiment realization, where $\Theta_k \in (\Theta_1, \Theta_b)$;
- the set of diagnostic parameters values: $\{y_j(\Theta_1)\}$ –nominal values, $\{y_{jg}\}$ –boundary values, j=1,…, m;
- the set of machine technical state $\{\Theta_k: \{s_i\}, k=1, \ldots, K; i=1,\ldots, I\}$ determined in the time of passive-active experiment realization, where $\Theta_k \in (\Theta_1, \Theta_b)$.

2.3.2. The optimization of diagnostic parameters set values

The optimization of diagnostic parameters set values (only in case of large size of Y, e.g. m>10). Diagnostic parameters set estimated via:

- correlation method of technical state diagnostic parameters (exploitation time), $r_j=r(W, y_j)$, $(r_j = r((\Theta, y_j))$; and
- method of technical state diagnostic parameters information quantity h_j.

In order to choose a diagnostic parameters set, the weight values used:

- standardized calculation weights w_{1j},

$$w_{1j} = \frac{1}{d_j}, \quad d_j = \sqrt{(1-r_j^*)^2 + (1-h_j^*)^2}, \tag{4}$$

with $r_j^* = \dfrac{r_j}{\max r_j}, \quad h_j^* = \dfrac{h_j}{\max h_j}$;

- as the criterion of diagnostic parameters selection, the maximization of the values of weights w_{1j}, and the diagnostic parameters selection according to the information quantity h_j, are accepted;
- in order to get a clear methodology, it is necessary to insert the auxiliary weights w_{2j} (standardized values) from the range (0,1) and choose parameters according to the above criterion.

3. Machine condition prognosis methods

The machine technical state prognosis process can be realized by different methods [2 - 6]: forecasted symptom value, machine operation date or another for machine state prognosis (e.g. extrapolation trend methods and adaptative methods). CBM uses the diagnostic parameter value change in function of machine exploitation. then uses the assumption that the phenomenon of the machine technical state worsening is represented by the time row $y_\Theta=<y_1,y_2,\ldots,y_b>$, i.e. the set of discrete observations $\{y_\Theta=\zeta(\Theta); \Theta=\Theta_1,\Theta_2,\ldots,\Theta_b\}$ of a certain non-stationary stochastic process $\zeta(\Theta)$.

An acceptable period of the machine usage is the working time delimited by the boundaries of damage range, then the period of use of the machine is determined in the subset $\Omega^y \subset \Omega$, which is derived from the set of optimized observation parameters $\{y_j(\Theta)\}$ and their prognoses $\{y_{j,p}\}$ according to the accepted predictor $P(y_\Theta,\tau)$ do not exceed the boundary values $\{y_{j,gr}\}$ [16].

The date of the next diagnosis-observation term Θ_{b1} of the machine is therefore determined by the prognosis time horizon τ^* by different methods [14, 16, 18]:

– levelling method of prognosis error value;
– levelling method of the diagnostic parameter boundary value;
– method of determination of diagnostic parameter value change (symptoms method);
– estimation methods of diagnosis and the operations date.

3.1. Levelling method of prognosis error value

For which there will be no excess of the diagnostic parameter boundary value y_{gr} by the boundary of the prognosis error range appointed by the radius r_σ (Fig.1). The acceptable value of next diagnosis-observation term Θ_{b1} are determined by the horizon value τ^*, appointed as the intersection point of the line of diagnostic parameter boundary value y_{gr} with the bottom (with the assumption that $y(\Theta_1) > y_{gr}$) or top (with the assumption that $y(\Theta_1) < y_{gr}$) boundary of the prognosis error range, which is appointed by the radius r_σ for the trust level $1-\gamma = 0.95$ or $1-\gamma = 0.99$, which corresponds to the probability of the value $p = 0.05$ or $p = 0.01$ that in the range appointed by the horizon τ^* the diagnostic parameter will reach the boundary value y_{gr}.

Then, it is possible to infer the following statements:

– not exceeding the controlled diagnostic parameter the boundary appointed by the radius $r_{\sigma 0.01}$ is interpreted as the alarm signal for thorough and more accurate diagnostic observation of the industrial machine unit or system;
– exceeding the controlled diagnostic parameter the boundary appointed by the radius $r_{\sigma 0.01}$ is interpreted as the lack of alarm signal for thorough and more accurate diagnostic observation of industrial machine (alert threshold);
– the moment of exceeding by the controlled diagnostic parameter the boundary appointed by the radius $r_{\sigma 0.01}$ is interpreted as the time Θ_{b1} –the operation date of the industrial machine unit or system (alert threshold).

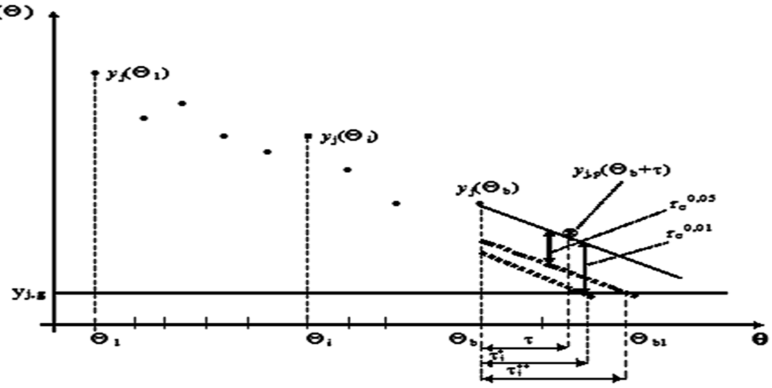

Fig.1. Graphic interpretation of determining the date of next diagnosis-observation term Θ_{b1}: Θ_1 – the beginning of machine's exploitation, Θ_b –last operation of the machine, Θ_{b1} – the date of next diagnosis-observation term

In such situation, the time range (Θ_1, Θ_b) will be estimate period of the prognosis error expected value e_p and the boundary radius of the prognosis error range r_σ , whilst the time period after Θ_b will be the period of the active prognosis, i.e. estimation of: (i) the prognosis value of diagnostic parameter after prognosis horizon time τ, $y_{jp}(\Theta_b+\tau)$; (ii) the estimation of the value of boundary radius of the prognosis error range $r_\sigma(\Theta_b+\tau)$; and (iii) the estimation of the next diagnosis-observation term Θ_{b1}.

3.2. Levelling method of the diagnostic parameter boundary value

For which there will be no excess of the diagnostic parameter boundary value y_{gr} by the forecasted value of the diagnostic parameter (Fig. 2). The date of the next diagnosis-observation term Θ_{b1} is determined by the horizon value τ^*, and estimated as the intersection point of the diagnostic parameter trend line $y(\Theta)$ with:

– bottom (with the assumption that $y(\Theta_{\mathrm{b}}) > y_{\mathrm{gr}}$) limit of the boundary value y_{gr}^*,

$$y_{gr}^* = \frac{1}{10}\left| y(\Theta_1) - y_{\mathrm{gr}} \right| + y_{\mathrm{gr}}, \tag{5}$$

– or top (with the assumption that $y(\Theta_{\mathrm{b}}) < y_{\mathrm{gr}}$) order of the boundary value y_{gr}^*,

$$y_{gr}^* = y_{gr} - \frac{1}{10}\left| y(\Theta_1) - y_{\mathrm{gr}} \right|. \tag{6}$$

The values $S_p(\Theta_b+\tau)$ and Θ_{b1} are estimated with one of the prognosis methods, whilst the date of diagnosis and operation according to the relation

$$\Theta_{b1} = \Theta_b + \frac{\tau \left(y_{gr}^* - y(\Theta_{\mathrm{b}})\right)}{y(\Theta_b + t) - y(\Theta_b)}. \tag{7}$$

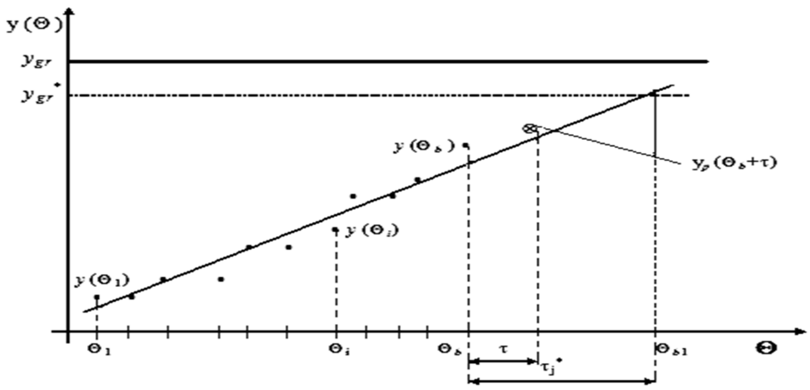

Fig.2. Determining the date of next operation of the devices Θ_{b1} with the method of diagnostic parameter boundary value levelling for $y(\Theta_b) < y_{gr}$

3.3. Method of determination of the diagnostic parameter value change

For which there will be no excess of the diagnostic parameter boundary value y_{gr} by the estimated value of the diagnostic parameter (Fig.3). The method has the following assumptions:

- exponential decomposition of the diagnostic parameter at the time Θ_b;
- probability of the machine reliable work P_r: $1 < P_r < 0.8$;
- dynamics of the parameter S growth in the time (with $S(\Theta) < S_{gr}$),

$$S(\Theta) = \frac{S(\Theta_b)}{S_{gr} - S(\Theta_b)}, \tag{8}$$

and the value Θ_{b1} is estimated as:

$$\Theta_{b1} = \frac{(1 - P_r)(S_{gr} - S(\Theta_b))}{S(\Theta_b)} \Theta_b . \tag{9}$$

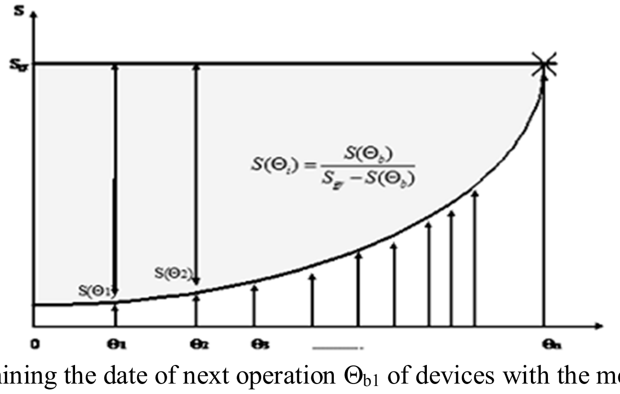

Fig.3. Determining the date of next operation Θ_{b1} of devices with the methods of the determining the diagnostic parameter change for $S_{gr} > S(\Theta_b)$ (periodicity of diagnosis in symptom depiction)

3.4. Estimation method of diagnosis and operation date

In the date estimation method Θ_{b1} the effort to simplify the procedures of date estimation Θ_{b1} led to creating the date estimation method Θ_{b1}, in which there is no need to estimate the prognosis value of the parameter y_p. In this method, like in the levelling method of the boundary value, a certain level of the boundary value y_{gr}^* is determined, different from the boundary value y_{gr}, e.g. according to the equations (5, 6) and compared to it the diagnostic parameter value. Then, as the date of the next diagnosis-observation term Θ_{b1} it is suggested to accept the value of working time (course) of the machine, determined by the horizon value τ^*, estimated as the intersection point of the diagnostic parameter value $y(\Theta_b)$ with the value y_{gr}^*,

$$\Theta_{b1} = \Theta_b, \tag{10}$$

for which there will be no excess of the diagnostic parameter boundary value y_{gr}^* by the value of the diagnostic parameter at the observation time Θ_b (Fig. 4).

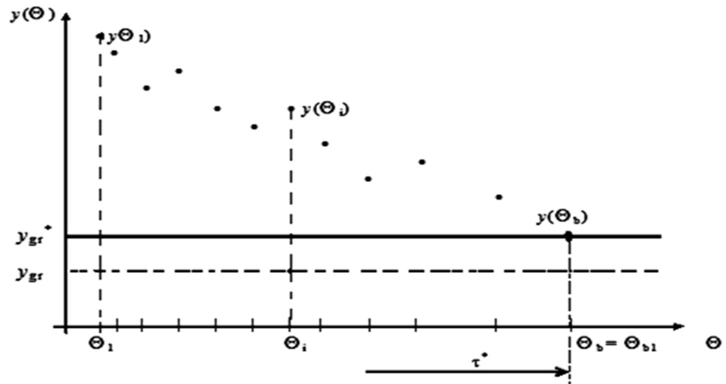

Fig.4. Determining the date of next operation of devices Θ_{b1} with the method of value estimation Θ_{b1}

3.5. Summary of machine condition prognosis methods

The estimation of the date Θ_{b1} on the basis of the presented methods is determined by many problems, most important of which are:

- the determination of the optimal diagnostic parameter set describing the change of the machine state in function of its "lifetime";
- the determination of weight function for a multi-element optimal set of diagnostic parameters;
- the determination of "the best" method for date estimation Θ_{b1}.

The solution of the above problems, as it show in [14, 16, 19] requires the use of appropriate multi-criteria optimization methods and prognosis methods enabling the estimation of the prognosis value of the diagnostic parameter $y_{j,p}$ and the necessity to know the boundary value of the diagnostic parameter y_{gr}.

The suitable methods to technical state prognosis and to find the operation term estimation are: method of levelling the prognosis damage; and method of levelling the diagnostic parameter boundary value. The algorithm of machine state prognosis includes the following stages [14, 17]:

The prognosis of the diagnostic parameter value y_j^*:

- via Brown-Mayer adaptation method type 1 (B-M1) with the coefficient $\alpha = (0.1 - 0.8)$, the prognosis horizon $\tau = (1 - 3)\Delta\Theta$ determined by the time range (Θ_1,Θ_b),
- via Holt adaptation method with the coefficient $\alpha_1 = (0.1 - 0.8)$ and $\alpha_2 = (0.1 - 0.8)$, the prognosis horizon $\tau = (1 - 3)\Delta\Theta$ determined by the time range (Θ_1,Θ_b),
- via analytical methods (linear, exponential, etc.), the prognosis horizon $\tau = (1 - 3)\Delta\Theta$ determined by the time range (Θ_1,Θ_b);

The estimation of the next diagnosis-observation term Θ_d:

- Θ_{d1} via prognosis error levelling method for the radius of the prognosis error r_p (for the importance level $\beta = 0.05$) according to the relation

$$\text{for } y_j(\Theta_b) > y_{jg} \quad \therefore \quad \Theta_{jd1} = \Theta_{jb} + \frac{\tau\left[y_j(\Theta_b) - y_{jg} - r_\sigma\right]}{y_j(\Theta_b) - y_{j,p}(\Theta_b + \tau)}, \tag{11}$$

$$\text{for } y_j(\Theta_b) < y_{jg} \quad \Theta_{jd1} = \Theta_{jb} + \frac{\tau\left[y_{jg} - y_j(\Theta_b) - r_\sigma\right]}{y_{j,p}(\Theta_b + \tau) - y_j(\Theta_b)}, \tag{12}$$

  where r_σ –the radius of the prognosis error range (calculated *a posteriori* appropriately for each method of the prognosis value determination $y_{j,p}(\Theta_b+\tau)$);
- Θ_{d2} via levelling method of the diagnostic parameter boundary value $y_{jg1} = y_{jg}$, $y_{jg1} = y_{jg} + \gamma(y_{jn} - y_{jg})$ for $y_{jn} > y_{jg}$, and $y_{jg1} = y_{jg}$, $y_{jg1} = y_{jg} + \gamma(y_{jg} - y_{jn})$ for $y_{jn} < y_{jg}$, e.g. for $\gamma = 0.1$:

$$\text{for } y_j(\Theta_b) > y_{jg} \quad \therefore \quad \Theta_{jd2} = \Theta_{jb} + \frac{\tau\left[y_j(\Theta_b) - y_{jg1}\right]}{y_j(\Theta_b) - y_{j,p}(\Theta_b + \tau)}, \tag{13}$$

$$\text{for } y_j(\Theta_b) < y_{jg} \quad \therefore \quad \Theta_{jd2} = \Theta_{jb} + \frac{\tau\left[y_{jg1} - y_j(\Theta_b)\right]}{y_{j,p}(\Theta_b + \tau) - y_j(\Theta_b)}, \tag{14}$$

4. Industry application – a case example

In order to demonstrate that the exposed process may be applied effectively in engineering, this work is applied to researches of combustion engines referenced as UTD-20, the laboratory test was made in stationary condition, the engine was subjected to a series of tests obtaining a set of diagnostic parameters Y_1 [13, 16] in the form of time rows whose elements are the values of diagnostic parameters: p_{sil} –engine power [kW], p_{spr} –compression pressure [MPa], p_{wtr} –fuel injection pressure [MPa], p_{ol} –engine oil pressure [MPa]. Examining procedures includes:

- examining the set of diagnostic parameters in the aspect of estimating an optimal set of diagnostic parameters for estimate the diagnostic parameters values according to the above exposed algorithm;
- estimating prognosis methods of diagnostic parameters values and methods of estimating the next diagnosis-observation term according to the above exposed algorithm;
- examining the prognosis value of diagnostic parameters with the prognosis damage, and the manner of estimating the next diagnosis-observation term depending on the following parameters:
  - prognosis value of diagnostic parameters values,
  - the size of the diagnostic parameters set,
  - the prognosis horizon.

4.1. Optimization procedure of diagnostic parameters set

Examining procedure of estimating the optimal diagnostic, the parameters set for the prognosis of diagnostic parameters values are:

- estimating an optimal set of diagnostic parameters according to the above exposed process. For the set of output parameters $Y_{1,}$ the set of diagnostic parameters with appropriate weight values was obtained (Table 1). The result analysis showed that the highest weight values w_{1j} are possessed by the diagnostic parameters p_{wtr} and p_{ol}, and the lowest weight values w_{1j} by the diagnostic parameter p_{sil};
- examining the optimal set of diagnostic parameters in the aspect of the influence of time row size through estimating weight values w_{1j} for the set Y_1 and the set Y_2 in elation to the length of time row. For this purpose, time rows for set sizes: k=10, k=20, k=40, k=50 were considered. The result analysis in it field indicated that there are value changes of the weight w_{j1} in the function of time rows lengths.

Summing up the performed researches for the optimization procedure of diagnostic parameters set, it is concluded that:

- examining diagnostic parameters sets in the aspect of the influence of time row size for the set Y_1 showed a considerable influence of time row length on estimating weight values w_{1j} for the engine type UTD-20;
- in examining the methodology of machine state recognition, it is suggested to accept diagnostic parameters of the highest weight values, e.g. for the combustion engine UTD-20: $w_{1j} \geq (0{,}02–0{,}05)$, in order to obtain a set of at least three (3) elements.

Table 1. Set of an optimal set of diagnostic parameters to UTD-20.

Y_1	r_j	h_j	d_j	w_{1j}
p_{sil}	0,149	0,022	1,200	0,007
p_{spr}	0,364	0,132	0,740	0,011
p_{wtr}	0,597	0,357	0,01	0,858
p_{ol}	0,578	0,335	0,069	0,122

4.2. Machine condition prognosis methods

Examining the procedures of machine state prognosis in the aspect of determining a prognosis method according to the prognosis error function, examining the influence of prognosis horizon value on the prognosis damage, and examining the influence of diagnostic parameters set size on the prognosis damage, were realized on the basis of: determining the set of prognosis methods of diagnostic parameters values, and estimation method of the next diagnosis-observation term according to the above exposed process. For the set of diagnostic parameters $Y_2=\{p_{wtr}, p_{ol}\}$ (of the highest weight values), the visualization of their prognoses value was obtained (linear model, exponential model, Brown-Mayer model, Holt's model), and two methods of determining the dates of next diagnosis-observation term (Θ_{d1},Θ_{d2}) for three values of the prognosis horizon ($\tau=\Delta\Theta$, $\tau=2\Delta\Theta$, $\tau=3\Delta\Theta$). An example visualization of analyzed values for the parameter p_{wtr} (for Brown–Mayer model) is presented on Fig.5.

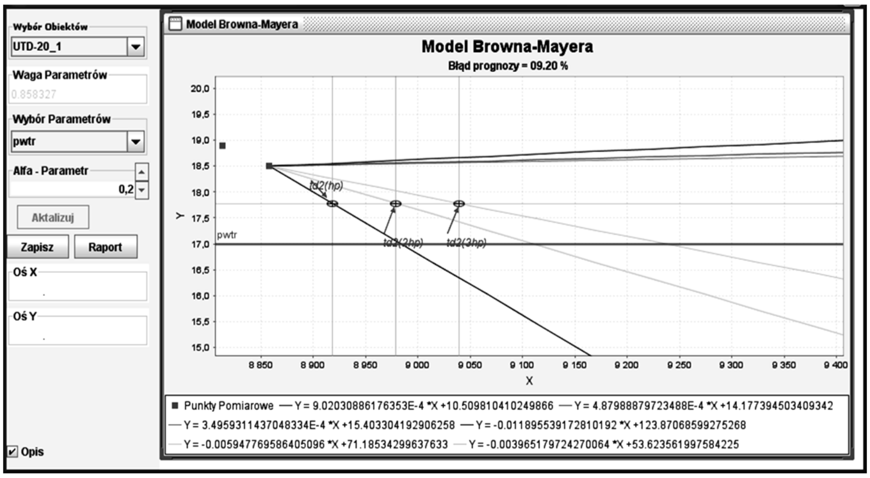

Fig.5. Estimating the prognoses value of the parameter p_{wtr} (weight w_1=0,858) and date Θ_d($\tau=\Delta\Theta$, $\tau=2\Delta\Theta$, $\tau=3\Delta\Theta$) for Brown–Mayer model, type 1 (α=0,2)

The analysis of research results for the combustion engine type UTD-20 showed that:

- different best (according to the minimum value of prognosis damage) prognosis methods of diagnostic parameters values are accepted:
  - for p_{wtr} – Holt method (α=0,1; β=0,1), prognosis error = 3,02%,
  - for p_{ol} – Holt method (α=0,1; β=0,1), prognosis error = 3,39%;
- different values of the next diagnosis-observation term are obtained in relation to the prognosis horizon and the size of the diagnostic parameters set:
  - for p_{wtr} –Holt method (α=0,1;β=0,1), examination dates: $\Theta_d(\tau=\Delta\Theta)$=8775.62; $\Theta_d(\tau=2\Delta\Theta)$=86993.23; $\Theta_d(\tau=3\Delta\Theta)$=8610.85,
  - for p_{spr} – Holt method (α=0,1; β=0,1) and p_{ol} – Holt method (α=0,1; β=0,1) weighed examination dates $\Theta_{dw}(\tau=\Delta\Theta)$=8740.03, $\Theta_{dw}(\tau=2\Delta\Theta)$=8622.07; $\Theta_{dw}(\tau=3\Delta\Theta)$= 8504.11.

Summing up the performed researches for the state prognosis method, it is stated that:

- considering low values of the curvilinear correlation coefficient (< 0,8) and high values of prognosis damages, and negative values of the next operation dates of the examined objects in analytical models (power model, exponential model and exponential model) for potential applications, it is necessary to use the Brown–Mayer model and Holt model;

- the accepted optimization criteria and the presented algorithm unambiguously identify the prognosis method and the method of estimating the next diagnosis-observation term, which confirms the propriety of the formulated procedure, and will be the basis for examining the methodology of machine state recognition in the field of state prognosis for other objects.

4.3. Summary of result analysis

The analysis of research results of machine state prognosis methodology allows to formulate dedicated conclusion rules of type "IF – THEN" or "IF – THEN – ELSE" in the area of: diagnostic parameters optimization; and state prognosis. In case of the combustion engine UTD-20, the generated rules have form:

- for diagnostic parameters set Y^o:
  - if $w_{1j} \geq 0{,}05$ then $y_j \in Y^o$,
  - or if $w_{1j} = w_{1jmax}$ then $y_j \in Y^o$;
- for state prognosis:
  - if $w_{1j} = w_{1jmax}$ and if $w_{1j} \geq 0{,}9$ then $y_j \in Y^o$ and the set Y^o is a single-element set, $Y^o = Y^{o1}$,
  - if $w_{1j} = w_{1jmax}$ and if $w_{1j} < 0{,}9$ then $y_j \in Y^o$ and the set Y^o is not a single-element set, $Y^o = Y^{oo}$,
  - if the prognosis error of Holt method (with appropriate values of the parameters α, β) for the set Y^{o1}< prognosis error of the Brown–Mayer method (with an appropriate value of the parameter α) for the set Y^{o1}, then the method of value prognosis of the set v is the Holt method (with appropriate values of the parameters α, β), otherwise the prognosis method of the value $Y^{o1}$is the Brown–Mayer method (with an appropriate value of the parameter α),
  - if the value of the next diagnosis-observation term of the engine UTD-20 Θ_{d1} (Y^{o1}) $\leq$ value of the next diagnosis-observation term of the engine Θ_{d2} (Y^{o1}), then the method to estimate the next examination date of the engine is the method of levelling the prognosis error value, otherwise it is the prognosis method of diagnostic parameter boundary value,
  - if the prognosis damages for methods: Holt (with appropriate values of the parameters α, β) or Brown–Mayer (with an appropriate value of the parameter α) for diagnostic parameters of the set Y^{oo} take minimum values, then prognosis methods of values of appropriate diagnostic parameters of the set Y^{oo} are the above methods,
  - if the value of the next examination date of the engine UTD-20 Θ_{d1} (Y^{oo}) $\leq$ value of the next examination date of the engine Θ_{d2} (Y^{oo}) then the method to estimate the next examination date of the engine (for the considered diagnostic parameter) is the method of levelling the prognosis error value, otherwise it is the prognosis method of diagnostic parameter boundary value,
  - if the value of the next examination date of the engine UTD-20 Θ_d is determined for Y^{oo}, then this values is the weighed value of the value Θ_{dw}.

The presented conclusion rules in range of machine state prognosis, after performing appropriate verification researches, could be the basis for dedicated software of a machine state recognition system in an on–line mode (for an on-board system) and off–line (for a stationary system).

5. Concluding remarks and future work

The work has defined a systematic structure of the rules of thumb of machine condition prognosis process based on the technical conditions methods, focused on optimization procedure of diagnostic parameters set; and machine condition prognosis methods.

The presentation of machine state prognosis procedures allows to formulate that presented procedures allow to determine the optimal, as far as the accepted criterion is concerned: diagnostic parameters set; and diagnostic parameters values prognosis and machine operation date estimation.

In order to determine the set of diagnostic parameters and state prognosis, the above presented procedures can be the basis for estimating conclusion rules in the range of: determining an optimal set of diagnostic parameters; and estimating the values of diagnostic parameters in the future, and estimating the date of the next machine operation.

From the concept/principle point of view, the application to the exposed real industrial machine case (combustion engines referenced as type UTD-20) allows to affirm the following technical observations:

- the accepted optimization criteria unambiguously identify sets of parameter values with largest quantity of information on technical state changeable in time of exploitation of the engine UTD-20, which confirms the propriety of formulating optimization procedures of diagnostic parameters set.
- for the combustion engine UTD-20 the order of parameters p_{wtr}, p_{ol}, p_{spr}, P_{sil} are not sustained, which indicates that the accepted criteria for parameter sets of real objects unambiguously identify sets of parameter values changeable in time of machine and having the highest quantity of information on the machines technical state.

References

1. Ahmad, R., & S. Kamaruddin (2012). An overview of time -based and condition-based maintenance in industrial application. Computers & Industrial Engineering, 63, 135–149.
2. Batko, W. (1984). Synthesis methods of prediction diagnoses in technical diagnostics (in Polish). Mechanika, 4.
3. Bowerman, B.L., & O'Connel, R.T. (1979). Forecasting and Time Series, Doxbury Press, USA.
4. Box, G., & Jenkins, G. (1970). Time series analysis, forecasting and control, London.
5. Brown, R.G. (1959). Statistical forecasting for invertory control, McGraw-Hill, USA.
6. Cempel, C. (1996). Evolutionary symptom models in machine diagnostics (in Polish). Proceedings of 1st international congress of technical diagnostics, Gdańsk, Poland.
7. Cempel, C., & Tabaszewski, M. (2007). Multidimensional condition monitoring of machines in non - stationary operation. Mechanical Systems and Signal Processing, 21, 1233–1241.
8. Jardine, A.K.S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition- based maintenance. Mechanical Systems and Signal Processing, 20, 1483–1510.
9. Luo, J., Namburu, M., Pattipati, K., Qiao, L., Kawamoto, M., & Chigusa, S. (2003). Model-based prognostic techniques, in: Proceedings of the IEEE Systems Readiness Technology Conference, 22–25 September 2003, pp. 330–340.

10. Qu, J., & Zuo M.J. (2012). An LSSVR- based algorithm for online system condition prognostics. Expert Systems with Applications, 39 (2), 6068–6102.
11. Theil, H. (1971). Applied economic forecasting, Amsterdam.
12. Tran, V.T., Yang, B.S., Oh, M.S., & Chiow, A.C. (2008). Machine condition prognosis based on regression trees and one-step-ahead prediction. Mechanical Systems and Signal Processing, 22, 1179–1193.
13. Tylicki, H. (1994). Conception of the optimization of devices technical condition forecasting process. Machine Dynamics Problems, 9.
14. Tylicki, H. (1998). Optimization of the prognosis method of mechanical vehicles technical state (in Polish), ATR, Bydgoszcz.
15. Tylicki, H., & Żółtowski, B. (2000). The forecasting technical condition of machines. In 16th International Conference on CAD/CAM, Robotics and Factories of the Future (Cars & FoF), Trynidad & Tobago, Port of Spain.
16. Tylicki, H., & Żółtowski, B. (2001). Determination methods of the next diagnosis term of transport vehicle. Archives of Transport, 12.
17. Tylicki, H. (2007). Report on the researches of optimization methodology of machine state recognition. Unpublished materials (in Polish), UTP, Bydgoszcz.
18. Zeliaś, A. (1984). Prognosis theory (in Polish), PWE, Warszawa.
19. Żółtowski, B. (2006). Diagnostic system for the metro train, ICME, Science Press, Chengdu, China (pp.337–344).
20. Żółtowski M. ii (2013): Estimation of combustion engine technical state by multidimensional analysis using SVD method. International Journal of Vehicle Systems Modeling and Testing, Vol.8, No. 2, ISSN 1745-6444, pp.105-118.
21. Żółtowski M. (2014): Redukcja informacji w zagadnieniach opisu dynamiki systemów w ujęciu mechaniki stosowanej. Międzynarodowa Konferencja Naukowa – Komputerowe systemy wspomagania nauki, przemysłu i transportu. Logistyka nr.6/500. ISSN 1231-5478, Zakopane.

Prof. dr hab. inż. Bogdan ŻÓŁTOWSKI
Prof. dr hab. inż. Henryk TYLICKI
Dr inż. Mariusz ŻÓŁTOWSKI
UTP University of Science and Technology
85-796 Bydgoszcz, Kaliskiego 7
tel./fax.: (0-52) 340 82 83
e-mail: bogzol@utp.edu.pl
tylicki@utp.edu.pl
mariusz.zoltowski@utp.edu.pl