ALGORITHM OF A MULTIPLE METHOD FOR PREDICTING VALUES OF RESIDUAL PROCESSES

Ewelina KOSICKA, Dariusz MAZURKIEWICZ, Edward KOZŁOWSKI

Abstract: The increased popularity of Industry 4.0 has led many manufacturers to develop and implement solutions based on automation and data exchange in manufacturing techniques. The progress in automation of manufacturing processes along with new solutions for cyber-physical systems present both challenges and opportunities regarding predictive maintenance. The paper presents the assumptions of an intelligent system of prediction method selection for a zero-integration homoscedastic series, which is part of an original algorithm of multiple-model prediction method. The algorithm comprises an ARMA model, ADF test, AIC and BIC criteria, as well as MAE, MPE and MAPE prediction errors which are indispensable for establishing prediction error indexes.

Keywords: failure prediction, econometric models, maintenance

1. Introduction

Given high competition, companies are forced to introduce changes ensuring higher efficiency and enhanced product quality without additional manufacturing costs. For this reason, manufacturers take numerous actions to implement rationalizations and new technological solutions to eliminate defects which can have a negative impact on maintaining production continuity, machinery availability, reliability and safety, as well as product quality [2,16].

Maintenance in this area must ensure the implementation of activities connected with a new industrial revolution concept, Industry 4.0. According to this concept, it is essential to create a smart factory through [36]:

- implementation of advanced manufacturing systems (via visualization and monitoring of production processes),
- the use of data clouds (via data storing and processing in the clouds, the use of analytical and calculation systems in the cloud),
- analysis of manufacturing process data (the use of advanced decision algorithms for real-time analysis),
- the application of intelligent sensors (to ensure wireless data transmission),
- the use of cyber-physical systems (ones that connect machines into a global unit as well as those which are autonomous decision systems),
- the use of state-of-the-art maintenance (based on failure prediction algorithms, remote support systems and maintenance control systems).

The objective of creating state-of-the-art maintenance can only be met via considerable involvement of maintenance service staff as well as implementation of relevant procedures and advanced, prediction-based maintenance techniques [11]. Previous studies on the use of prediction models in predicting failure of a machine tool stock and other areas, were primarily based on the use of either some imposed model or prediction models defining the time interval when boundary values can be exceeded. None of the models employed in the listed studies was selected depending on varying characteristics of input data (residual processes). In addition to this, inferences were made only based on values obtained from the monitored residual processes, i.e., technological factors, excluding other factors which could lead to failure occurrence. A state of the art survey has revealed that further studies should be conducted to create prediction systems ensuring more accurate forecasts based on the use of new mathematical models (or their hybridisation), multiple-model prediction algorithms, and factors affecting boundary values which were not previously taken into consideration in the prediction process.

Moreover, a prediction system is also expected to provide additional support for the decision area regarding the selection of an optimum moment for maintenance works based on a work schedule of maintenance services. Therefore, steps must be taken to build a cyber-physical system which will, similarly to expert systems, signal scheduled repair or machine part/subassembly replacement based on implemented preventive actions, which could, in turn, prevent additional assembly line stoppages.

This paper presents a general classification of prediction methods, their previous applications in selected engineering problems, primarily those connected with the operation of a stock of machine tools. The paper also describes an original algorithm of multiple-model prediction method developed in response to the demand for further development of systems for predicting failure of technological infrastructure. To illustrate the dynamic selection of a mathematical model depending on variations in the nature of residual processes, the paper presents a piece of algorithm taken from an intelligent system of prediction method selection (part of the algorithm of multiple-model prediction method) for a homoscedastic series with zero-integration.

2. Prediction models in engineering problem

The main objective of prediction methods is to design a model which will enable prediction of further values of the input flux using previous information about the character of a set being observed. There are many methods for predicting the behaviour of physical, technical and economic systems. Such methods are employed to model behaviours or events. A general classification of prediction methods is shown in Fig.1.

To gain more insight about the progression of phenomena and behaviour of objects, the developed prediction methods were used for solving engineering problems. For this reason, the literature on the subject reports only few examples of forecasting applications.

In their work Jui-Sheng Choua, Ngoc-Tri Ngoa and Wai K. Chong [3] report the results of research on predicting the corrosion rate of carbon steel used in the production of reinforcement bars. To this end, a hybrid model was developed based, among others, on an artificial neural network, classification and regression trees and linear regression. According to these authors, the prediction obtained by the combined methods was more accurate than that obtained by a single model (mean absolute percentage error (MAPE) of pitting corrosion was 5.6% while that of sea-water corrosion was 1.26%) [3].

Artificial neural networks have also been investigated by Hashemi and Clarc [9] with respect to their application for predicting Diesel engine exhaust gas emissions. The predictions were made with respect to factors such as the content of nitric oxides (NO_x), carbon dioxide (CO_2), hydrocarbons (HC) and carbon monoxide (CO), while the input data included: axis speed, torque and their derivatives in different time intervals, as well as two new variables defining variations in speed (for over 150 s). The studies helped determine acceptable ANN-based (Artificial Neural Network) predictions; however, it was problematic to model exhaust fume emission beyond the work cycle.

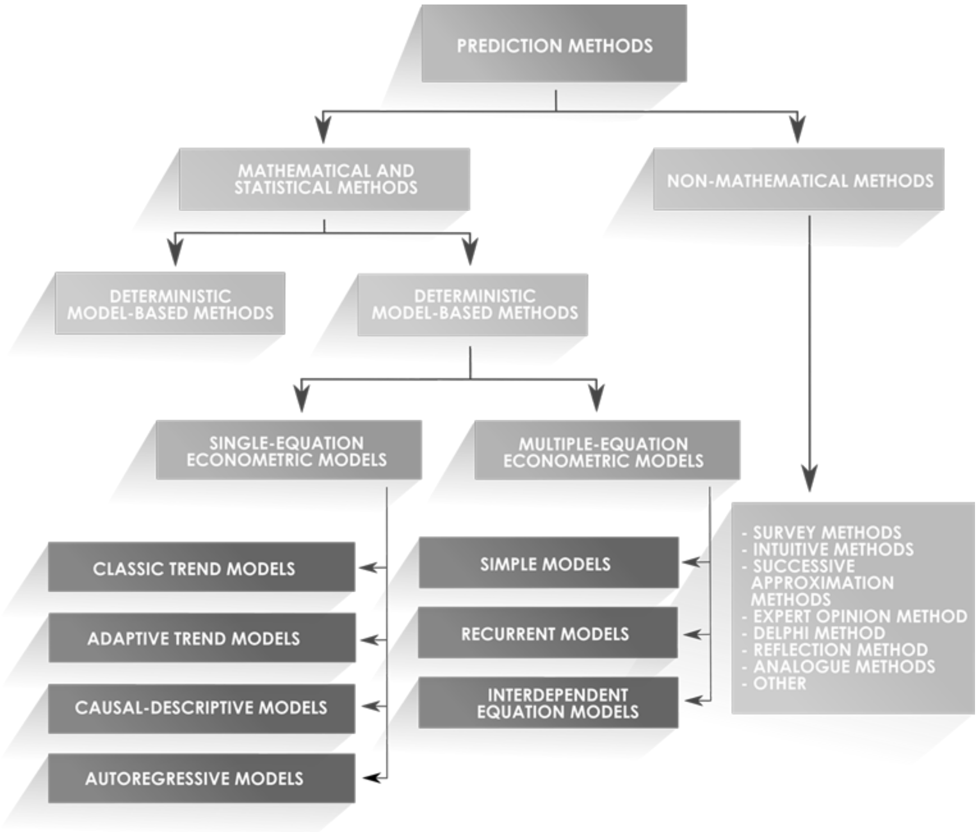

Fig. 1 Classification of prediction methods
Source: Created by the authors based on [34]

Prediction methods can also be used for determining optimum moment of maintenance of bridges [15]. Studies were conducted on the application of a genetic algorithm based on three objective functions: condition and safety indicators as well as accumulated cost of life cycle maintenance.

Negnevitsky and Johnson [21] offer a survey of available techniques for predicting wind energy within a time frame of 30 minutes. Based on a literature survey, these authors indicate that wind energy prediction is done using econometric models such as moving average (MA), autoregressive moving average (ARMA), autoregressive integrated moving average (ARIMA), as well as their modifications enabling the modelling of seasonal effect (SARIMA). Moreover, the authors point to the use of hybrid models created based on fuzzy logic and artificial neural networks.

Rogalska [24] presents a method for predicting duration of building processes based on factors which may affect them. She designed a method combining several prediction methods: multiple regression, multivariate adaptive regression by spline functions, generalized additive models, artificial neural networks, support vectors and integrated autoregression. The final decision concerning the selection of a prediction model is made based on the calculated prediction error (a model with the smallest prediction error is selected). The author claims that prediction can be made based on many factors affecting duration of the process. She also stresses the method's universality, as it can be applied to all building processes.

The above examples illustrate merely some of the studies conducted on the use of prediction methods, demonstrating a wide range of applications for different prediction models in solving engineering problems. The results confirm the benefits of using forecasting to make inferences about further developments of phenomena or object behaviour. Moreover, they prove the need for conducting research on the use of prediction in other areas (including machinery operation).

3. Econometric models in an adaptive decision and prediction algorithm

The furnishing of machine tool stocks with state-of-the-art monitoring systems which keep track of residual processes (along with the current trend for equipping machines with such systems already at the stage of their design and production) led to acquisition of huge databases about the condition of machine tool stock. The introduction of automation at the stage of data acquisition is a significant source of information about reliability, serving as a basis for making inferences about condition of machinery and devices. This can, however, be done only after an analysis of the acquired entries. These entries are only a set of *big data* [10,18,33]; without the use of relevant inference rules, they do not provide information enabling taking actions with respect to maintenance [27].

Previous research on forecasting in technical infrastructure operation involved attempts to apply the existing prediction methods or their modifications in order to generate predictions about the technical condition of a stock of machine tools. Studies were conducted on the use of multiple regression for predicting failure duration in wheel excavators [25], as well as failure frequency of a water power plant [17]. In addition, Lucifredi, Mazzieri and Rossi [17] verified failure frequency predictions by a modified kriging method as well as its combination with neural networks. Artificial intelligence has also been used for designing a system for monitoring the condition of a wind turbine gearbox [8] or mine belt joints [19]. In the work [4] Chuang, Luqing, Liu, Ren, Benoît and Yuanchu propose the use of a genetic algorithm for predicting failure of telecommunications devices. It has also been proposed to use trees and random forests [31]. The application of residual process values to predict failure frequency of a stock of machine tools using ARMA/ARIMA models was investigated by Kaźmierczak [12]. Sobaszek [28] proposed using survival analysis for predicting machine failure frequency.

The implementation of predictive maintenance actions in the above examples enabled prolonging operation time of the monitored machine parts / subassemblies and taking maintenance and repair actions based on their real condition. Another step in the development of prediction systems should be to enhance the existing prediction methods by tailoring prediction models to the nature of monitored values of residual processes and by taking account of factors previously omitted in failure frequency predictions yet which have a real impact on failure occurrence. It would also be significant to combine predicting with an expert system which could support maintenance services with respect to decision about optimal date of maintenance works, and would also comply with the assumptions of Industry 4.0 with respect to maintenance.

Given the lack of a prediction and decision system which could ensure both dynamic prediction model selection and maintenance services support in determining optimal date of maintenance works, the authors propose an adaptive algorithm which is shown schematically in Fig. 2.

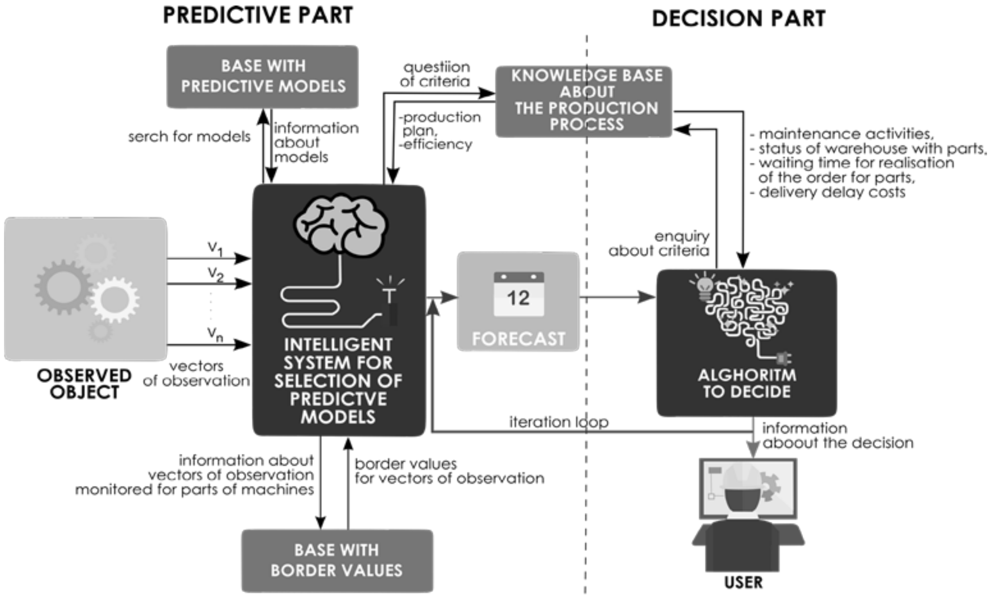

Fig. 2 Algorithm of multiple-model prediction method
Source: created by the authors [13]

Comprised in the PREDICTION PART of the multiple-model prediction method algorithm, the intelligent system for prediction model selection receives input information about the monitored parameters of machine condition (e.g. temperature or vibration). Based on the set of values relating to the studied phenomenon (factor), using proper informational criteria, the intelligent system would select the appropriate mathematical model. The prediction is done by econometric models used for time series analysis due to time-varying characteristics of residual processes. Stationary process phenomena are identified using the following mathematical models:

- for stationary series [12, 5, 29, 35]:
  - AR- autoregressive models,
  - MA- moving average models,
  - ARMA- autoregressive moving average models,
- for non-stationary series [12, 23, 26, 7, 1, 32, 22, 30, 20]:
  - ARIMA- autoregressive integrated moving average models,
  - SARIMA- *seasonal ARIMA*,
  - ARCH- *Autoregressive Conditional Heteroscedasticity*,
  - GARCH- *Generalized ARCH*,
  - RGARCH- *Randomized GARCH*,
  - EGARCH- *Exponential GARCH*,

– TARCH- *Threshold ARCH,*
– HARCH- *Heterogeneous interval ARCH.*

After selection of a suitable model, the system sends an inquiry to the database with boundary values of specified monitored observation vectors of machine parts/subassemblies. The reply as well as a piece of information from the production process database concerning production schedule and production line efficiency is used to predict the time after which a given machine part/subassembly will fail. The generated prediction should be then send to the decision algorithm which, based on an inquiry sent to the production process database with a schedule of maintenance and repair works, stock of spare parts and delivery delay penalties, indicates an optimal date of repair works. A significant feature of such a model is the use of iterative techniques which enable prediction update and generate messages of various rank depending on the time left before the undesired event occurs.

It should be mentioned that such a model for generating predictions and recommendations concerning the method and time of taking preventive actions should also take into consideration qualitative features and non-technical aspects. Consequently, it is necessary to determine criteria for expressing these factors and to determine their effect on failure frequency of a machine tools stock.

Given the extensive structure of the algorithm in the intelligent system for prediction method selection, the subsequent part of the paper will describe only a fragment of this algorithm. By means of ADF test (augumented Dickey–Fuller test [5]), we can determine the degree of integration of a time series $\{x_t\}_{1\le t\le N}$ or order of polynomial approximating the deterministic part of this series. Let Δ be an differential operator of form $\Delta^{k+1}x_t = \Delta^k x_t - \Delta^k x_{t-1}$. In case of elements of the time series being integrated in $r \ge 0$ degree, the time series $\{\Delta^r x_t\}_{r+1\le t\le N}$ is identified using by means of ARMA models. If the elements of the series $\{x_t\}_{1\le t\le N}$ are presented by an equation

$$x_t = f(t) + \varepsilon_t \text{ for } 1 \le t \le N , \tag{1}$$

where $f(t)$ is a polynomial of $r \ge 0$ degree, then the residual series $\{\varepsilon_t\}_{1\le t\le N}$ is also identified by means of ARMA models.

$ARMA(p,q)$, $p,q \in \mathrm{N}$ models are linear models, in which the time-delayed elements of time series $\{\varepsilon_t\}_{t\in N}$ are used as explanatory variables [13]. It is assumed that value of variable which is predicted in period t is dependent upon past values $\varepsilon_{t-1},...\varepsilon_{t-p}$ and upon mistakes of past realizations $\omega_{t-q},...,\omega_{t-1}$ Elements of $ARMA(p,q)$, $p,q \in \mathrm{N}$ model are presented by a formula:

$$\varepsilon_t = \alpha_1\varepsilon_{t-1} + \alpha_2\varepsilon_{t-2} + ... + \alpha_p\varepsilon_{t-p} + \omega_t - \theta_1\omega_{t-1} - \theta_2\omega_{t-2} - ...\theta_q\omega_{t-q} \text{, t>max(p,q)} \tag{2}$$

where $\{\omega_t\}_{t\in \mathrm{N}}$ is a sequence of identically independent random variables from normal distribution N(0,1), while $\alpha_1,...,\alpha_p,\theta_1,...,\theta_q$ - are parameters of the model. Utilising above model enables the inclusion of simultaneously autoregressive properties $\{\varepsilon_t\}_{t\in N}$ and moving average properties [13] in the series of residuals or of $\{\Delta^r x_t\}_{r+1\le t\le N}$. The paper presents way of determining autoregressive model AR and moving average MA, enabling dynamic adjustment of model ARMA to the changing values of residual processes.

4. Proposed algorithm of multiple prediction method for a zero integration homoscedastic series

In inferencing based on values of residual process it is vital to determine sampling frequency and the number of entries which are required to restart the algorithm in order to select a suitable prediction model. It is also essential to perform analysis of the deterministic part, which has been deliberately omitted in Fig. 3.

First, the degree of integration of a time series is determined using the ADF test

$$r = \min\{k \in \mathrm{N} : \{\Delta^k x_t\}_{k\le t\le N} \in \mathrm{I}(0)\},$$

i.e., it is the smallest natural number $r \in \mathrm{N}$ for which the series $\{\Delta^r x_t\}_{r+1\le t\le N}$ has zero integration, while $\mathrm{I}(0)$ is a set of stationary series. At the significance level of $\alpha > 0$ for the series $\{x_t\}_{1\le t\le N}$, $\{\Delta\, x_t\}_{2\le t\le N}$, ..., $\{\Delta^{r-1} x_t\}_{r+1\le t\le N}$ there is no ground for rejecting the working hypothesis H_0 (the series is non-stationary), while in the case of the series $\{\Delta^r x_t\}_{r+1\le t\le N}$ the working hypothesis is rejected in favour of the alternative hypothesis H_1 (the series is stationary).

The next step is to identify the series $\{\Delta^r x_t\}_{r+1\le t\le N}$ or the series $\{\varepsilon_t\}_{1\le t\le N}$ (see (1)) using the $ARMA(p,q)$ models, where $p,q \in \mathrm{N}$. This is done only in the class of stationary models $ARMA(p,q)$ for $0 \le p \le p_{\max}$ and $0 \le q \le q_{\max}$. The highest values of the autoregressive orders $p_{\max}$ and moving average $q_{\max}$ are determined by Partial Auto Correlation Function (PACF) and Auto Correlation Function (ACF). The PACF indicates the highest $p_{\max}$ of autoregression (AR), while the ACF points to the highest order $q_{\max}$ of moving average (MA). The ultimate selection of a suitable $ARMA(p,q)$ model for $0 \le p \le p_{\max}$, $0 \le q \le q_{\max}$ is made using the Akaike information criterion (AIC) and Schawartz's Bayesian information criterion (BIC).

Out of the $ARMA(p,q)$ models for $0 \le p \le p_{\max}$ and $0 \le q \le q_{\max}$, a model with the smallest Akaike information criterion (AIC value) is selected and is denoted as $ARMA(p_{AIC}, q_{AIC})$. Out of the $ARMA(p,q)$ models for $0 \le p \le p_{\max}$ and $0 \le q \le q_{\max}$ a model with the smallest Schwarz's Bayesian information criterion (BIC value) is selected and is denoted as $ARMA(p_{BIC}, q_{BIC})$. When $p_{AIC} = p_{BIC}$ and $q_{AIC} = q_{BIC}$, the series $\{\Delta^r x_t\}_{r+1\le t\le N}$ or the series $\{\varepsilon_t\}_{1\le t\le N}$ is modelled by

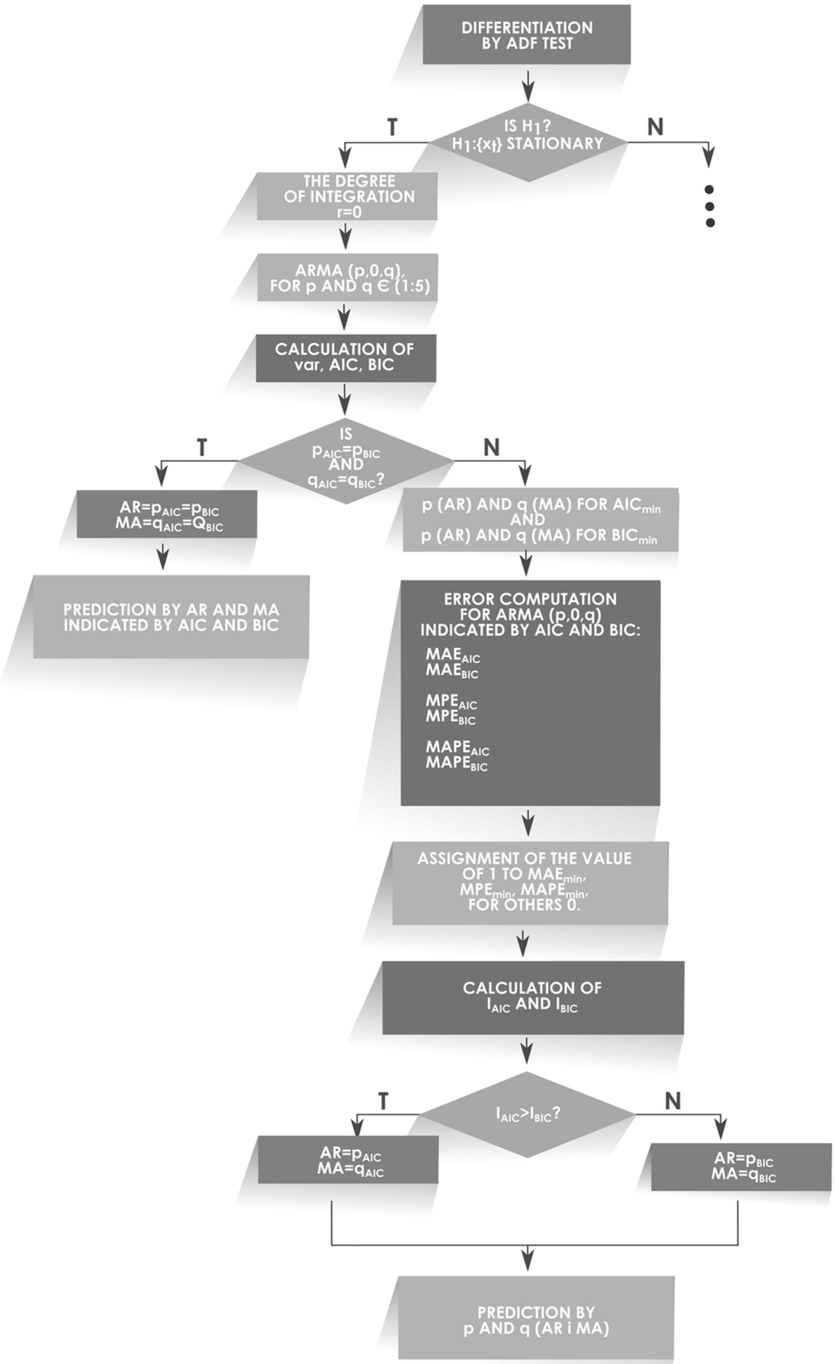

Fig. 3 Fragment of an algorithm of intelligent system for prediction method selection for a zero integration homoscedastic series
Source: created by the authors

$ARMA(p_{AIC}, q_{AIC})$. A problem arises when $p_{AIC} \neq p_{BIC}$ or $q_{AIC} \neq q_{BIC}$, because it is not clear in which model: $ARMA(p_{AIC}, q_{AIC})$ or $ARMA(p_{BIC}, q_{BIC})$, the series being analysed should be identified. To solve the above problem, a ranking of these models is established based on the calculated values of MAE (Mean Absolute Error), MPE (Mean Percentage Error) and MAPE (Mean Absolute Percentage Error). Next, for each $ARMA(p_{AIC}, q_{AIC})$ and $ARMA(p_{BIC}, q_{BIC})$ models, the values of MAE_{AIC}, MPE_{AIC}, $MAPE_{AIC}$, MAE_{BIC}, MPE_{BIC} and $MAPE_{BIC}$ are calculated, and error indexes, I_{AIC} and I_{BIC}, are created in the following way:

$$I_{AIC}^{MAE} = \begin{cases} 1, & for \quad MAE_{AIC} < MAE_{BIC}, \\ 0, & for \quad MAE_{AIC} \geq MAE_{BIC}, \end{cases} \tag{3}$$

$$I_{AIC}^{MPE} = \begin{cases} 1, & for \quad MPE_{AIC} < MPE_{BIC}, \\ 0, & for \quad MPE_{AIC} \geq MPE_{BIC}, \end{cases} \tag{4}$$

$$I_{AIC}^{MAPE} = \begin{cases} 1, & for \quad MAPE_{AIC} < MAPE_{BIC}, \\ 0, & for \quad MAPE_{AIC} \geq MAPE_{BIC}, \end{cases} \tag{5}$$

and

$$I_{AIC} = I_{AIC}^{MAE} + I_{AIC}^{MPE} + I_{AIC}^{MAPE}. \tag{6}$$

Obviously

$$I_{BIC}^{MAE} = 1 - I_{AIC}^{MAE}, \; I_{BIC}^{MPE} = 1 - I_{AIC}^{MPE}, \; I_{BIC}^{MAPE} = 1 - I_{AIC}^{MAPE} \tag{7}$$

and

$$I_{BIC} = 3 - I_{AIC}. \tag{8}$$

If $I_{AIC} > I_{BIC}$, then the behaviour of the series $\{\Delta^r x_t\}_{r+1 \leq t \leq N}$ or the series $\{\varepsilon_t\}_{1 \leq t \leq N}$ is predicted by $ARMA(p_{AIC}, q_{AIC})$, otherwise the prediction is made using $ARMA(p_{BIC}, q_{BIC})$.

Such an approach enables dynamic tailoring of a prediction model to the nature of real-time determined values of residual processes. The multiple prediction algorithm makes the prediction system resistant to variations in time series, something which cannot be ensured by the use of an imposed mathematical model.

5. Conclusions

Nowadays manufacturing companies have access to vast databases with recorded machinery operational parameters and residual processes due to the availability of systems for the real-time recording of various parameters, conditions or statuses connected with machinery operation. The main challenge these days is to use these databases to obtain information which could help eliminate undesired phenomena or behaviour occurring at different stages of production, which – in turn – would lead to financial benefits. The expectations of production companies with respect to ways of increasing reliability indexes spurred the development of maintenance.

The current developments of Industry 4.0 aimed at the creation of a smart factory comply with the predictive maintenance strategy.

Previous predictive systems did not enable dynamic selection of a mathematical model depending on variations in stored and processed data. The solution proposing the use of econometric models based on the use of previous deterministic part analysis, ADF test, information criteria as well as prediction error and error indexes is an innovative approach to selecting failure frequency prediction models. A predictive system based on such a solution will be characterized by both transferability (it can be employed on different production lines) and resistance to variations in data characteristics.

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Mgr inż. Ewelina KOSICKA
Dr hab. inż. Dariusz MAZURKIEWICZ, prof. PL
Katedra Podstaw Inżynierii Produkcji
Politechnika Lubelska
20-618 Lublin, ul. Nadbystrzycka 36
tel.: (0-81) 538 42 29
(0-81) 538 44 83
e-mail: e.kosicka@pollub.pl,
d.mazurkiewicz@pollub.pl

Dr Edward KOZŁOWSKI
Katedra Metod Ilościowych w Zarządzaniu
Politechnika Lubelska
20-618 Lublin, ul. Nadbystrzycka 36
tel.: (0-81) 538 46 28
e-mail: e.kozlovski@pollub.pl