Intelligent Systems of Forecasting the Failure of Machinery Park and Supporting Fulfilment of Orders of Spare Parts

Ewelina Kosicka[1(✉)], Edward Kozłowski[2], and Dariusz Mazurkiewicz[1]

[1] Faculty of Mechanical Engineering, Lublin University of Technology, Lublin, Poland
{e.kosicka,d.mazurkiewicz}@pollub.pl
[2] Faculty of Management, Lublin University of Technology, Lublin, Poland
e.kozlovski@pollub.pl

Abstract. The article presents the possibility of forecasting failures of machinery park using IIOT (Industrial Internet of Things) that supports the range of activities concerning the collection of data using solutions that, by means of time series analysis and dynamic adjustment of the individual models, will allow to generate prognosis for failures of machinery park. Moreover, the use of the generated prognosis to control the storage of replacement parts and to support the area of orders fulfilment was proposed.

Keywords: Predictive modelling · Expert systems · Predictive maintenance

1 Among the Source Development Factors Contributing to the Definition of the Currently Developing Concept of the Industry 4.0 One May Note

Continuous pursuit of the world of technology to create newer and newer solutions to improve the actions that take place in the industry [1], to achieve increased operational efficiency but, above all, to relieve human from his work, has become the cause of ground breaking changes known as industrial revolution. Thus, over the past two centuries, evolution of industrial solutions has taken place, of which the most advanced elements once were water and steam drives, while today, as part of the fourth industrial revolution, cyber-physical systems or the Internet of Things and Services are used.

The target solution formed by the concept of Industry 4.0 is to create smart factories, in which cyber-physical systems for monitoring physical processes will provide relevant information thus enabling decentralized decision-making.

One of the areas that are rapidly developed and supported in the smart factories through the use of modern technology is the Maintenance Department. Among the assumptions about its mode of action, the use of tools containing algorithms predicting failures, remote support systems and integration with machines are indicated. It will be possible for obtaining by [3]:

– implementation of modern manufacturing systems (through visualization and monitoring of the production),

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- the use of cloud computing (through storage and processing of data in the clouds, the use of analytical systems and spreadsheets in the cloud data storage),
- analysis of data coming from production (the use of advanced decision-making algorithms for real-time analysis),
- the use of smart sensors (for obtaining wireless transmission of data),
- the use of cyber-physical systems (ones that link the machines together to form a team with a global reach, as well as those being autonomous decision-making systems).

Despite the risks associated with improper operation of the monitoring systems for machine operation or for the analytical and decision-making systems, as well as the issue of information security, the introduction of automation to the analysis and interpretation of data becomes an unavoidable reality. The entry into realities of the functioning of IIoT enterprises, as well as easier access to the systems for monitoring operation of the machines has significant influence on it. Moreover, management staff becomes aware that the issue of automatic data collection may constitute the historical documentation of the status of the machinery park [4], but having huge data sets at disposal, the excess of which does not allow one to perform the analysis, requires implementation of the solutions for decision-making support.

2 Internet of Things and Cyber-Physical Systems in the Industrial Plants

The Internet of Things (IoT) is a concept according to which every object in the real world can automatically connect to the network and communicate with any other module connected to it [5]. The term was first used in 1999 by Kevin Ashton in his presentation on the transmission of data via the Internet with the use of radio-frequency identification (RFID) to control the supply chain in the enterprise Procter and Gamble [6]. According to the Cisco Internet Business Solutions Group, as the beginning of the Internet of Things one should consider the point at which the number of devices connected to the network exceeded the number of inhabitants of the Earth, which dates back to the turn of 2008 and 2009 [7]. The dynamic development of the IoT associated with increasing technological capabilities contributed to the increase of the range of application of this concept.

According to the classification adopted by O. Vermesan and P. Friess IoT can be used in the areas of smart environment, water management, transport, energy, cities, housing, life, health and industry [8]. Of course, these areas do not limit the potential of the IoT for wider use in other areas, especially taking into account the dynamics of its development.

Although the Internet of Things is a concept which was already discussed in the previous century, the year 2016 can be regarded as the moment of its implementation into industrial solutions. The interconnection of the machines in the production plants gave birth to IIoT (Industry Internet of Things), which is based on the same principles as IoT. Improving communication between the machines, as well as conducting autonomous action based on the exchange of information in real time has become an opportunity to exceed, by the company, the so far achieved level of efficiency and process flexibility.

Hand in hand with the enthusiasm about the opportunities created by the implementation of IoT to the industrial plants, goes the prospect of risks associated with the operation of the industry network, among which one may indicate connection failure, failure of devices, improper configuration, breach of security [9].

As a result, enterprises can suffer the consequences arising from the loss of security or from production losses. Thus the prospect of dynamic market development of IIoT creates the need for protection against cybercrime.

Referring to the Internet of Things in the context of Industry 4.0 it is scarcely possible not to mention cyber-physical systems which, together with IoT, forms two essential components of its generation [10]. Cyber-physical systems (CPS) are systems in which by means of sensors and actuators the physical world connects with the virtual one where the information processing, based on a mathematical representation of physical objects known as Digital Twin, takes place [2]. The implemented mathematical model uses data from the sensors installed on the device. CPS, like IoT, has a wide range of usage the example of which may be its use in, among others, medicine (e.g. to monitor patient's vital signs), energy sector (e.g. to control the state of power grids), transport (air, car or rail), the industry (e.g. to monitor the state of the machinery park).

In the case of usage of the CPS solutions in the industry, the name cyber-physical production systems (CPPS) is used. They are defined as extensive production systems, whose purpose is to collect, analyse and store information on processes and technical infrastructure of a company. Information can be exchanged via communication interfaces, and may also be transmitted globally to those responsible for the operation or service. Easier access to data should be guaranteed by BYOD program (Bring Your Own Device), which involves the performance of duties on employees' own devices. As a result there will be a popularization of e-maintenance and m-maintenance class solutions.

3 Algorithm of Prediction of Failure with the Use of CPPS and IIoT

Futuristic technologies, which more and more easily enter the reality of the operation of production plants, [11] encourage the creation of new solutions that can support the human factor in the analytical and decision-making area. The Maintenance Department is the department in which the correct definition and implementation of IIoT and CPPS will increase the effectiveness of these actions.

Disposing of the noted technologies by MD personnel is related to the necessity of a change of realized maintenance strategy into predictive one. Adequately adjusted predictive model or models so that the moment in which failure may occur was indicated as precisely as possible constitutes a challenge. Thanks to this, it will be possible to avoid certain types of failures, as well as incorporating the forecasted failures within the schedule of works of Maintenance Department and adequate management of storage of spare parts. So far, the literature has described predicting failures during the use of various predicting methods, however, none of them was based on intelligent selection of adequate model, depending on the change of character of the monitored parameters.

Carrying out activities in accordance with the Predictive Maintenance requires the application of appropriate mathematical models, which will allow to gain knowledge about the occurring development phenomena or mode of action of objects under study. Analysis of literature allowed to identify mathematical models applied so far, used for predicting failures both of machines and their components.

Huang, Xi, Li, Liu, Qiu and Lee undertook the research on the use of self-organizing map and neural network using an algorithm of back propagation (back propagation neural network methods) to predict failure of ball bearings. The obtained results were significantly better than those obtained so far on the rating life [12]. Also Zhao, Chen and Li were interested in the bearings failure rate and suggested the use of neuro-fuzzy model to predict damage [13]. On the other hand, Lahyani, Venet, Grellet and Viverge focused on predicting the failure of electrolytic capacitors during the operation of switched-mode power supplies [14]. Salfner and Malek in their publications presented the possibility of using hidden semi-Markov models for effective online failure prediction for the telecommunications system [15]. Whereas Tabaszewski and Cempel proposed method of Deng's grey systems for predicting the state of machines using vibration symptoms [16]. Srivastava and Mondal focused on the possibility to use modified failure mode effect and criticality analysis technique (Mod-FMECA) to predict the failure of the coal mill, and the positive predicting results that were achieved encouraged the authors to expand the possibilities of using the developed methods of prediction to other industrial equipment. Legat, Mosna, Ales and Jurca in their work described a method of determining an optimal break time for periodic preventive maintenance, and optimal diagnostic parameter for predictive maintenance. In the study they used the three-parameter Weibull distribution, proposing the use of the method for typical engineered facilities [18]. Sobaszek on the other hand introduced the concept of predicting the failure of the machinery park based on the survival analysis [19].

The indicated examples present only a small part of the conducted research on the use of prediction methods in forecasting the failure and intend to show the comprehensive use of various prediction models. Research results obtained by the authors confirm the benefits of the application of prediction to infer about further development of phenomena and dispose to continue research on the use of other mathematical models for forecasting in accordance with the predictive maintenance strategy [20] according to technical status which will be able to intelligently adjust to the values of monitored residual processes changing in real time. Such an approach is designated to reflect changes taking placed by mathematical modelling and generating the forecast of date of failure which will most likely cover the real-time date. Furthermore, including predicting of failures of both IIoT and CPPS gives a chance of effective elaboration of solutions which might form the basis of intelligent tools as expert systems constituting human support at decision-making level.

The authors of this article propose application of an algorithm that forecasts failure frequency of machinery park and uses time series models, which, due to the possibility of real time processing of residual process values, as well as implemented stationarity tests and forecast errors, will generate information on the date of failure. Additionally, an intelligent algorithm will facilitate inventory controls of replacement parts, and, in case of their absence, it will make an inquiry about the possible delivery time and costs incurred. Such type of solution has not so far been proposed and it fulfils the expectations placed in the context of a strive for obtaining an intelligent company, ensuring dynamic support of predicting and decision-,making process in the scope of ordering spare parts.

Figure 1 presents the concept of the proposed algorithm of decision support in the maintenance system, which is to represent a new approach to forecasting failures, a system of setting the terms of repairs, as well as ordering replacement parts.

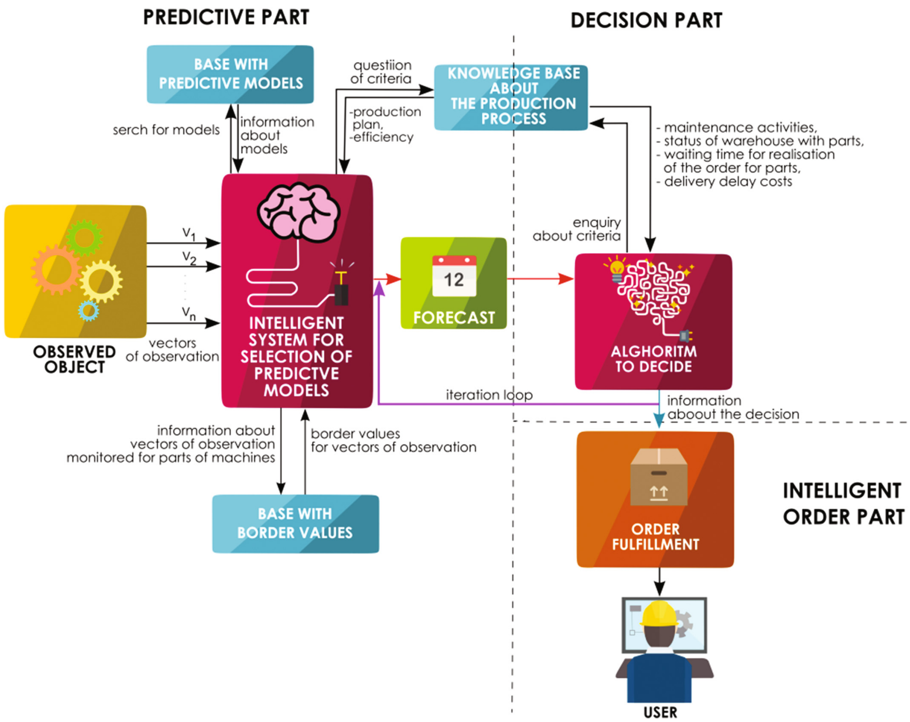

Fig. 1. Concept of the prediction and decision model supporting actions taken by maintenance services [21]

Information from the system that monitors working of the observed object (such as readings of temperature, vibrations, or noise intensity), marked in the drawing as the observation vectors, are received by the *intelligent system of prediction method selection*. On the basis of a set of values for the studied phenomenon (factor) the intelligent system, by using the appropriate information criteria, would select the appropriate mathematical model (Linear Regression, ARMA, ARIMA, ARCH, HARCH, TARCH, GARCH, EGARCH, or RGARCH).

The optimal model is projected in this way, understood as model that enables receiving the most accurate forecast. It is selected with the use of a ranking method as model that receives most of the indications of information and predictive criteria.

Moreover, it is important to link the system with the base of limit values for observation vectors, due to which the safe size level of the observation vectors for the monitored machine parts will be determined, exceeding of which carries the risk of failure. For the conduct of the forecast, in addition to the measurement of key residual processes, information from the database of the production process relating to the plan, schedule, and productivity will be used. This type of approach will help to clarify the forecast by making it dependent on the operating conditions of the machinery. Production stops, as well as planned productivity losses, contribute to delaying the possibility of potential failure, which in turn translates into the extension of the time between maintenance works carried out by Maintenance Service.

The result of the working of the cyber-physical system reflecting the work of the machine park will be a time interval in which there is a risk of failure. This information will be passed to decisive part, that consists of the decision-making algorithm and database of production process providing information about the activities carried out by MS (i.e. scheduling maintenance and repair works). In this way, on the basis on indications of cyber-physical system and taking additionally into account non-technical aspects, the narrowed optimal time period will be generated, in which it becomes necessary to perform maintenance works. The attained forecast will be used at a later stage to support the decision-making process from the scope of the ordering machine parts. The role that is played by the decision-making system implementing orders of spare parts was described more extensively by Wang, Zhao, Cheng, and Yang [22].

Information about the forecast date of failure is passed on to the order processing system. If the number of days to failure is equal to the number of days exceeding of which makes it necessary to collect offers for the purchase of replacement parts, then in the first instance the inquiry about the availability of a particular part is directed to the storehouse. In case it is not available there, a demand for it is sent automatically to companies that provide parts, information of which is collected in the system. Within a specified period of time offers containing information about prices, discounts, delivery time of a part, or the proposed warranty period are gathered. On the basis of specific criteria the optimal offer is selected, the selection is authorized by the operator of the system, who is entitled to make decisions about purchasing. After the acceptance, a part is ordered.

4 Example Application of an Algorithm

In fashioning trends occurring in physical, technical, and economic phenomena, the class of the examined time series Trend Stationary or Difference Stationary must be first designated. Using the ADF test (Augmented Dickey-Fuller test [23]) it is possible to designate the degree of integration of time series $\{x_t\}_{1 \leq t \leq N}$ or the polynomial degree that approximates the deterministic part of this series. When the elements of the series are integrated in degree $r \geq 0$, then the time series $\{\Delta^r x_t\}_{r+1 \leq t \leq N}$ is identified with models of the ARMA class $ARMA(p, q)$,where Δ is the difference operator $\Delta^{k+1} x_t = \Delta^k x_t - \Delta^k x_{t-1}$

for $k \in \mathrm{N}$. The elements of the series $\{x_t\}_{1 \leq t \leq N}$ are modelled by $ARIMA(p, r, q)$ model, $p, r, q \in \mathrm{N}$ and fulfil the equation

$$\Delta^r x_t = \alpha_0 + \alpha_1 \Delta^r x_{t-1} + \ldots + \alpha_p \Delta^r x_{t-p} + \omega_t - \theta_1 \omega_{t-1} - \ldots \theta_q \omega_{t-q}, \tag{1}$$

where $\{\omega_t\}_{t \in \mathrm{N}}$ is a sequence of independent identically random variables with normal distribution $N(0, \sigma^2)$, where $\alpha_0, \alpha_1, \ldots, \alpha_p, \theta_1, \ldots, \theta_q$ are the model parameters. The identification of a sequence with model $ARIMA(p, r, q), p, r, q \in \mathrm{N}$ is based both on the choice of autoregressive order $0 \leq p \leq p_{\max}$ and moving average order $0 \leq q \leq q_{\max}$ further to being based on the estimation of parameters of model (1). The highest values of the autoregressive orders $p_{\max}$ and of moving average $q_{\max}$ are determined by analysing the behaviour of PACF (Partial Auto Correlation Function) and ACF (Auto Correlation Function). For the final selection of the model Akaike information criterion (AIC) or Schwarz's Bayesian information criterion (BIC) are used most often.

The example of a DS series was presented below. The results come from a research station that implements accelerated process of pitting of steel rollers. Tests were conducted on a cylindrical sample of ŁH15 (PN) heat-treated steel. The roller was compressed by two discs – one of them was driven by electric motor and transmission belt. The speed of the sample was 27,000 RPM. The vibration acceleration was recorded on the body in which the roller was mounted [24].

In Fig. 2a the black curve represents realization of series $\{x_t\}_{1 \leq t \leq 30}$. The red straight line presents the value of critical level peak acceleration. Below, critical value was accepted $v_{crit} = 6.5$ m/s^2. Using the ADF test the integration degree $r = 1$ was determined.

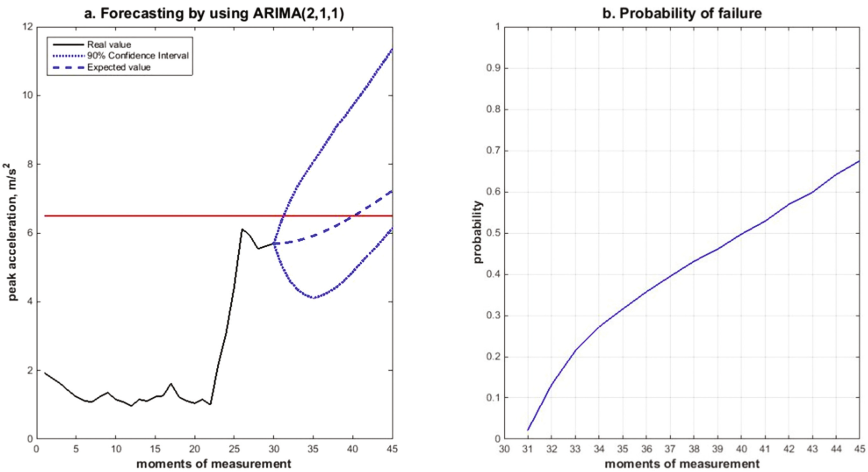

Fig. 2. Forecasting values of vibration acceleration in the band of approx. 16 kHz using (a) ARIMA model, (b) probability of reaching critical level.

As the series $\{x_t\}_{1 \leq t \leq 30}$ belongs to the DS class, models $ARIMA(p, 1, q)$ were identified. While analysing AIC indicator, the elements of series $\{x_t\}_{1 \leq t \leq 30}$ should be shown by the model $ARIMA(2, 1, 1)$ (AIC = 39.5478), i.e. the elements satisfy the equation

$$\Delta x_t = 0.0115 + 1.4027\Delta x_{t-1} - 0.4647\Delta x_{t-2} + \omega_t - 0.96\omega_{t-1}, \tag{2}$$

where $\{\omega_t\}_{t\in\mathrm{N}}$ is a sequence of independent identically random variables with normal distribution $N(0, 0.1602)$. In Fig. 2a the blue dashed curve represents the expected value the elements of this series by formula (2) for 15 consecutive periods. Using the Monte Carlo method also 90% confidence interval which on Fig. 2a is indicated by the blue dotted curves. Figure 2b presents probability of exceeding critical level $P(x_t > v_{crit})$ for moments $t = 31, 32,\ldots, 45$. Figure 2a shows that for moment $t = 40$ expected values of peak acceleration will exceed critical level, that is. $Ex_{40} > v_{crit}$. Also Fig. 2b shows that $P(x_{40} > v_{crit}) > 0.5$, thus with probability of at least 50% critical value will be exceeded in the moment $t = 40$. Combining prognostic part with supportive part of realization of orders for spare parts requires establishing values of probability of exceeding critical value, after reaching of which having a spare part by storehouse is required. Assuming that it amounts to 50% and falls on the 40th day of observation, then it would be advisable until then with adequate advance to start an algorithm supporting the order of spare parts. Date of launching of the algorithm ought to be set based on the so far deliveries of parts and estimated time for formalities related to gathering offers and realization of purchase. Assuming that normally waiting time for a given part amounts to approx. 7 days, then launching of algorithm would occur on the 33rd day of observation when this probability of occurrence of failure amounted to only 22%.

5 Summary and Conclusions

Due to the development of cyber-physical systems, as well as IIoT and deploying them to the enterprise it becomes necessary to consider improving the decision-making process through the development of expert systems. They are designed to support human decision-making based on information generated on the basis of the monitored parameters. Their functioning, in conjunction with the use of intelligent tools that respond dynamically to changes in the reliability of machinery, may become a guarantee of increased operational efficiency. It should however be emphasized that it should not be a stand-alone tool that excludes man from the final stage of decision-making. Instead, it should be a part of a developed CMMS system, the design of which should take into account the possibility of remote access of system end-users of laptops, tablets, fablets or smartphones (in line with e-maintenance [25] and m-maintenance concept [20]). The pursuit of Industry 4.0 to implement predictive maintenance solutions places additional requirements of appropriate selection of a mathematical model. The analysis of the literature has not shown previously developed solutions for the dynamic selection of the model, depending on the changing nature of the collected and processed data. Innovative recognition is therefore a failure prediction based on econometric models selected and determined based on the information criteria, as well as the forecast errors and error rates forecasts. Combining the predictive part with the part responsible for carrying out the orders of replacement parts of machines can replace men at the investigative stage in the case of the determination of stock in connection with the forecasted failure and at the stage of collecting information about the availability of parts from suppliers, as well as the proposed conditions of their purchase. Eliminating the risks of implementing such a solution could be made by carrying out a risk analysis to determine the degree of impact of individual risk factors.

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