MULTI – CRITERIA DECISION SUPPORT IN MAINTENANCE OF MACHINE PARK

Ewelina KOSICKA, Dariusz MAZURKIEWICZ, Arkadiusz GOLA

Abstract: The development of maintenance strategies led to the use of modern computer techniques and monitoring systems for control of machine park. In addition to this, actions are taken to analyze the available *big data* sets in order to infer about machine failure frequency. This paper presents maintenance strategies and prediction models used for failure prediction. It also points to problems connected with predicting undesired events and proposes a new prediction and decision model. The model is universal, which makes it suitable for application in many industrial branches.

Keywords: maintenance, failure prediction, prediction models, diagnostics

1. Introduction

Modern production technologies and highly complex production processes pose stringent requirements with respect to reliability of production equipment. As a result, maintenance operations and activities become more and more significant. Production equipment must be kept in constant operational efficiency, which can be ensured by i.a. effective control of technical condition of machines and devices. It is especially required that potential failures of the production system could be predicted and full operational efficiency of the system could be restored in the shortest time possible, without impairing the manufacturing process. This is particularly important given severe competition, which means that a company's success depends on its improvement of manufacturing systems, technological development and production automation.

The objectives of maintenance activities include:

- maintaining specific quality of products/services,
- maximum prolongation of working life of production equipment,
- ensuring conditions that enable safe operation of machines and devices,
- reducing production costs to the minimum by decreasing the number of stoppages during production.

It can therefore be claimed that maintenance is a key problem in the functioning of every company in terms of technological development, automation and pursuit of operational efficiency. The application of adequate maintenance methods, tools and techniques is critical for efficient operation of equipment. Also, it has a significant effect on the economy of every economic subject involved in production. Another significant thing is the search for new more effective and innovative solutions for this particularly important field of production engineering. Consequently, new maintenance solutions (related to good practices as well as equipment and analytical support) should be proposed to companies to help improve their efficiency.

2. Maintenance strategies

According to the definition [1], maintenance strategy is a method for dealing with machines and devices which enables obtaining the desired condition of the operation system. In terms of maintenance, maintenance strategy is executed on two planes [1,2,3]:

- as a decision process related to individual objects of technical infrastructure,
- as a decision process in the context of complex functioning of maintenance.

As far as the first plane is concerned, maintenance strategy is one of the pillars of maintenance policy [1].

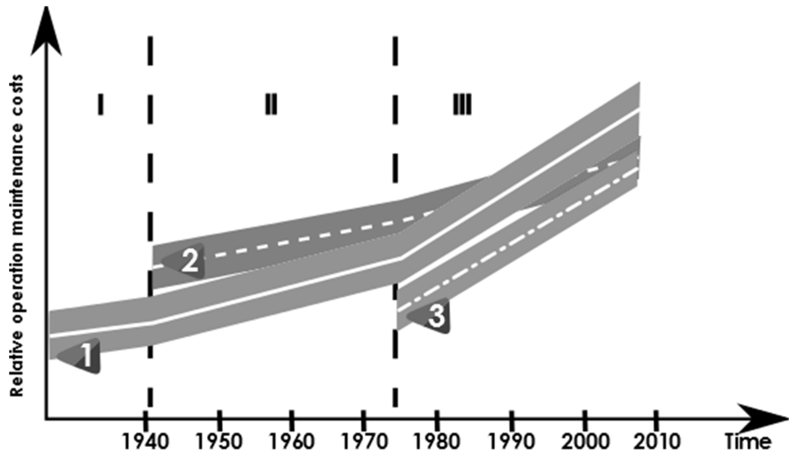

Fig. 1 Three development stages (I, II, III) and three methods (1, 2, 3) in maintenance of devices and machines
I), 1) - reactive maintenance – repairs performed when equipment fails; II), 2) - preventive maintenance – planned, preventive repairs; III), 3) - predictive (proactive) maintenance – preventive inspections, monitoring of technical condition, participation of device and machine operators in maintenance, RCM, TPM, 5S, individual inspections [9]

Analyzing the development of this strategy, one can distinguish three main approaches to maintenance of technical infrastructure (fig. 1) [4, 5, 6,7,8]:

- reactive maintenance,
- preventive maintenance,
- predictive (proactive) maintenance.

Reactive maintenance is the oldest approach to the problem of failure frequency of machinery and it consists in taking actions to restore reliability of machines and devices after their failure [1,10,11]. The approach dates back to the times of production and operation of the first machines and devices [10]. At present this approach is less and less popular yet there are companies which take actions that only boil down to ”extinguishing fires.”

This can particularly be observed in the case of piece production or small batch production, where the repair of a machine or a device does not interrupt the production process [11].

This approach to maintenance of a company’s technical infrastructure does not generate costs connected with control of machine/device operation during the failure-free period.

It should also be highlighted that reactive maintenance does not enable planning or scheduling of maintenance services' activities or budget for these activities [11].

The approach to maintenance changed in the second half of the twentieth century [1]. A higher awareness of the role played by reliability of a machine park, machine-invested capital and the dependence of manufacturing processes on infrastructure condition led to the concept of preventive maintenance [10]. Compared to the previously applied system, the new system of scheduled and preventive repairs led to decreasing failure frequency; as a result, the period of failure-free operation increased, so maintenance and repair work could be performed as scheduled [11], usually based on technical documentation recommendations [13]. Although more beneficial than reactive maintenance, preventive maintenance has numerous shortcomings, the most significant being the fact that maintenance activities require involvement of a vast number of staff. In addition to this, the frequency of scheduled activities does not result from real wear of machine/device components; these activities are usually taken at constant time intervals or following a specific number of man-hours, which often leads to redundant inspections and even random damages due tp performing unnecessary actions [11]. In light of the above, maintenance and repair works done in compliance with the principles of preventive maintenance do not enable optimization of machinery operation costs [14].

Information about machinery condition enables performing predictive maintenance. Predictions are based on measurement of factors such as vibrations [15,16,17,18], temperature [18], noise [15,19] or simply on data about a lubrication system (i.a. pressure, chemical composition and physical properties of lubricant/oil) [21,22,11]. Predictive maintenance is nowadays one of the dominant approaches to machinery operation and its effectiveness depends on expertise about stages of prediction system design [20,23]. Despite difficulties resulting from the necessity of devising complicated database queries, this approach enables identification of processes contributing to failure [14].

Prediction in multi-symptom diagnostics can be based either on numerous predictive models to generate a number of independent predictions or on the use of a single model to generate many predictions simultaneously [25]. Schematics of such prediction models are shown in Fig. 2.

For the presented models, a set of input quantities can be made up of an object operation measure or components of the work parameters vector, while the output values are predictions of symptom value [25]. As for the first approach to predictive modeling (fig. 2a), it is possible to use any available prediction methods; however, the other approach (fig. 2b) requires designing an independent model. The prediction of values or changes in endogenous variables can be done by means of developed prediction methods which are selected depending on the nature of a predicted variable [26].

3. Problems connected with failure prediction

Predictive maintenance is nowadays one of the dominant approaches to machinery maintenance, yet its effectiveness is highly dependent on individual stages of designing a prediction system [23, 24, 28]. Given the advancement of prediction models and the number of data collected for analysis (sets of condition parameters can be described as *big data* sets), the development and implementation of a prediction system can be a challenge for companies, particularly when decisions about executing appropriate maintenance and repair works must be taken based on the generated predictions.

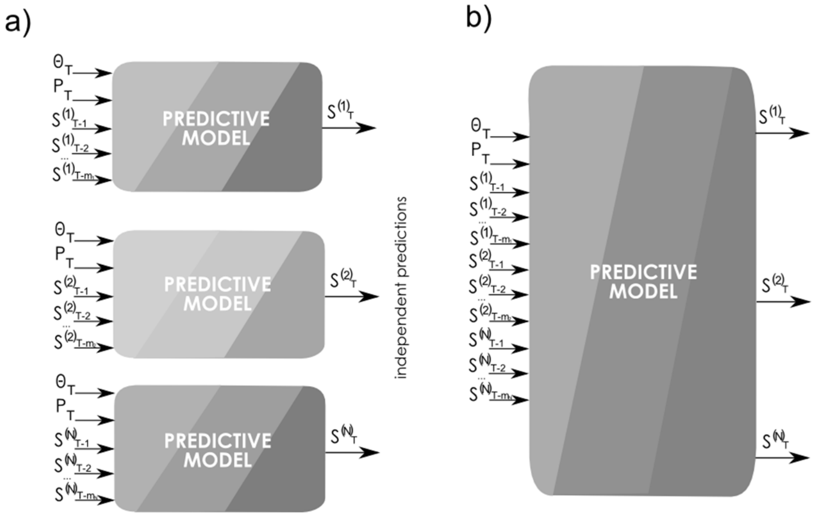

Fig. 2 General schematics of prediction models used for multi-symptom diagnostics The approach based on the use of many models and many independent predictions (a) and the approach based on the use of a single model for generating many simultaneous predictions (b) (Θ_T – a value of maintenance measurement why a forecast is generated, P_T – a vector of control parameters for diagnosed object (for T-moment), S_T –a observation vector of symptoms in T-moment $[S^{(1)}{}_T, S^{(2)}{}_T, \ldots, S^{(m)}{}_T]$) (based on [25])

The difficulty occurring at the beginning of prediction model design concerns reducing dimension of the observation vector to a smaller subspace that will not lead to a loss of information sufficient for correct definition of the machine's condition. This reduction enables designing simpler and more effective models of described phenomena.

Another problem connected with failure prediction pertains to random factors. Some of the previously used prediction models take into account random values; it must however be emphasized that these values come from random-number generators (e.g. as in the case of the Monte Carlo method [27]). The randomness of variables in formal models is one of the main difficulties in practical application of quantitative methods, hence it would seem justified that devising a prediction based on randomness should also include random values from historic values of the observed signals.

Prediction models described in the literature discuss prediction that is only based on technical factors. Although the applied models use reliable data recorded automatically by real-time machine monitoring systems, they do not take into account non-technical aspects or qualitative features which are reported in the literature as factors affecting reliability of a machine park. Non-technical aspects include, among other things, economic issues and seasonal character, while qualitative features are related with such issues at the operator's knowledge of a machine, reliability of performed repair work or audit results concerning implementation of good practices under Total Productive Maintenance (TPM). The above-mentioned factors are ignored in employed failure prediction models, which can result from a lack of standards for expressing them, particularly in light of the fact that - given their nature - most of these factors should be defined in linguistic terms.

Another aspect affecting the accuracy and reliability of predictions is aging of observed objects. A survey of the literature [29,30,31,32,33] reveals that there is a strong relationship between the number of failures and the working time of an object; however, this relationship was not taken into account when predicting failure frequency of machines and devices. For this reason, it seems justified that generating prediction and inferring about failure frequency should also be done in a function of variations in failure frequency due to working time.

With so many factors used for generating predictions and scheduling maintenance work to ensure machinery reliability, it seems justified to create an expert system which will replace men at the stage of selecting prediction method depending on input parameters and deciding about the moment of repair work. An analysis of data from measurement systems monitoring a machine park in real time will enable dynamic response to potentially dangerous values indicating the risk of failure.

Although companies are more and more effective in using data about maintenance resourced, the main task of currently applied systems (computer-based e-maintenance using systems or m-maintenance systems based on the use of mobile devices) is to ensure monitoring of a company's technical infrastructure, contact with production and maintenance systems, as well as data acquisition. In the age of advanced measurement techniques which are connected with database systems registering parameters of machinery operation, it is necessary to consider designing tools for analysis of data in so-called *big data* sets which are more and more often used as a source of implicit knowledge. Owing to its nature and the frequency of measurements, this knowledge can only be acquired from a thorough analysis using IT systems with in-built mathematical models.

The dynamical character of changing parameter values and the peculiar nature of a company operation requires a specific approach to design of a prediction and decision model, one that should also dynamically react to changing conditions of the production process. This means that predictions and resulting decisions must be made immediately after the system received measurement results.

The acquired input values about non-technical aspects and qualitative features are necessary for generating a prediction. This prediction will only provide information about a potential moment of machine failure. To schedule the time of maintenance work, the decision process should include information about a production plan, a schedule of activities taken by maintenance services as well as information about ordered spare parts. This way of multi-criteria support of decision taking excludes human factor which is often based on intuition, and not on data obtained from the process.

Despite the difficulties connected with designing complicated prediction and decision models (fig. 3), it seems justified to adopt an approach that involves taking action with respect to the above-mentioned factors for creating failure frequency predictions of a machine park. As a result, the generated predictions can be more accurate, whereas decisions taken on their basis will undoubtedly bring real benefits for companies operating in the field of production engineering.

4. Concept of multi-criteria decision support in maintenance of a machine park

The currently used solutions for predicting failure are based on predictions which do not take into account qualitative features or non-technical aspects. Moreover, prediction systems communicate the possibility of failure after the expected time with no support in deciding about a suggested moment of taking maintenance or repair actions based on the production schedule and on the schedule of actions to be taken by maintenance services. For this reason, it is necessary to devise a solution supporting prediction and decision. A schematic design of such a solution is shown in fig. 4.

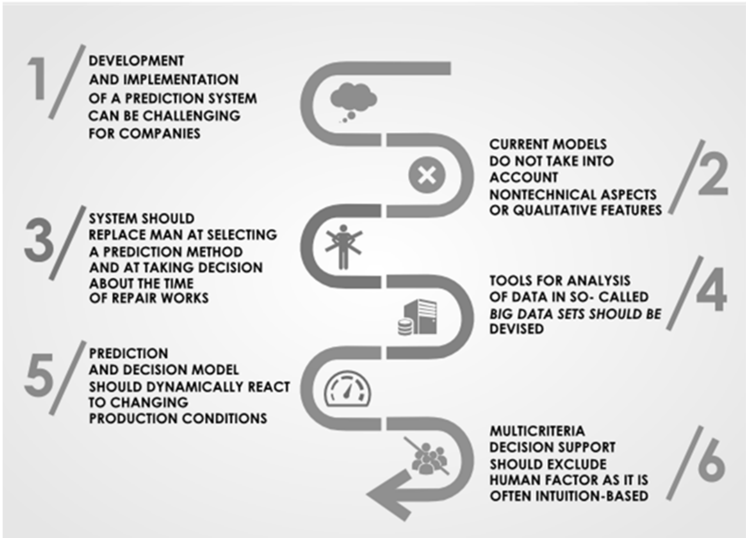

Fig. 3 Problems connected with failure prediction in a company
(prepared by the authors)

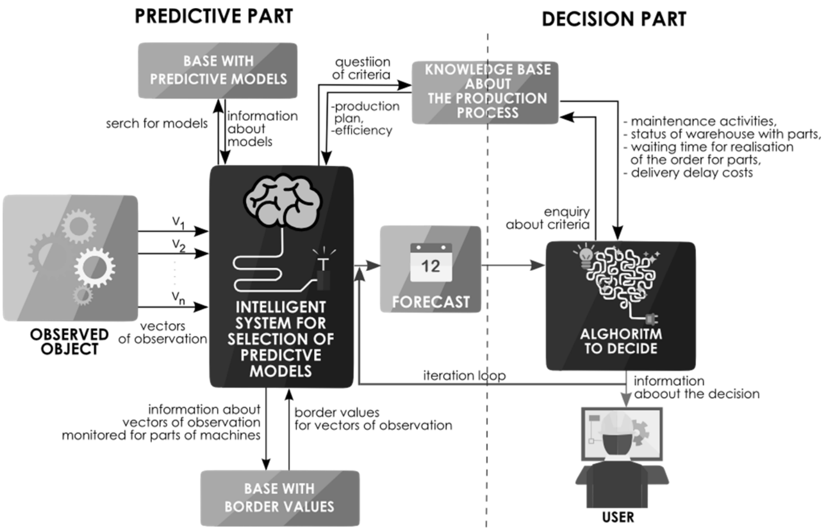

Fig. 4 Concept of the prediction and decision model supporting actions taken by maintenance services
(developed by the authors)

The schematic illustrates a concept of the prediction and decision model which could provide support for the activity of maintenance services. Such a model would be first provided with values of the monitored parameters of a machine condition (e.g. temperature readings). Depending on the character of the provided values, This intelligent system would select based on informative criteria a suitable econometric model from a database with models. Having selected a suitable model, the system would send a query to a database containing boundary values of specific monitored observation vectors for machine/subassembly parts. The return information as well as the information from the production process database about the production plan and production line efficiency could be used to make a prediction, i.e. to determine the time after which the boundary value would be exceeded. The generated prediction should then be processed by a decision algorithm which – based on a query sent to the database about the production process regarding the schedule of maintenance and repair works, a spare parts stock and fines for delivery delay – would indicate an optimal moment of repair work. Importantly, this model would use iterative techniques enabling prediction updates and generation of different status messages depending on a period of time preceding an undesired event.

It should be mentioned that the developed model for generation predictions as well as the recommendations for taking preventive actions should include qualitative features and non-technical aspects, which means that it is necessary to devise standards describing these actions as well as to determine their effect on failure frequency of a machine park (fig. 5).

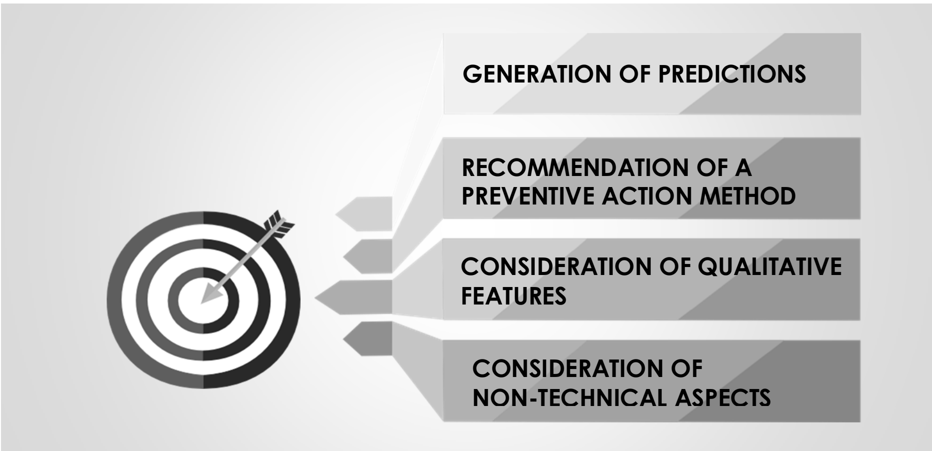

Fig. 5 Objectives of the prediction and decision model
(prepared by the authors)

These objective should therefore be attained in compliance with four stages of prediction model design illustrated in fig. 6**.**

First of all, a system for selecting a mathematical model for values of observation vectors should be designed. The model selection depends on the results of deterministic part of the analysis, on the fact whether we are dealing with a sequence of homoscedastic or heteroscedastic variables, as well as on the results of informative and/or predictive criteria.

Another stage should involve taking actions connected with developing a method for expressing qualitative features and non-technical aspects and for determining their effect on failure frequency of a machine park, as well as developing a method for including them in a prediction-oriented part of the model design process.

Next, an algorithm of the decision process based on current prediction should be designed. Here it would be important to rank iteration-caused predictions; the model could still communicate failure risk as a piece of information resulting in no subsequent action or as an alert which cannot be ignored as this would shortly cause production line stoppage due to failure.

The developed prediction model should also be verified on two levels. On the first level, the model should be verified based on numerical data, which would enable consideration of potential improvements and *ex post* determination of prediction error. The second level of verification should involve testing solutions under industrial conditions. The recommendation from maintenance services due to their satisfaction with the implemented tool as well as a lower frequency of unexpected failures of monitored components will definitely make the proposed solution successful.

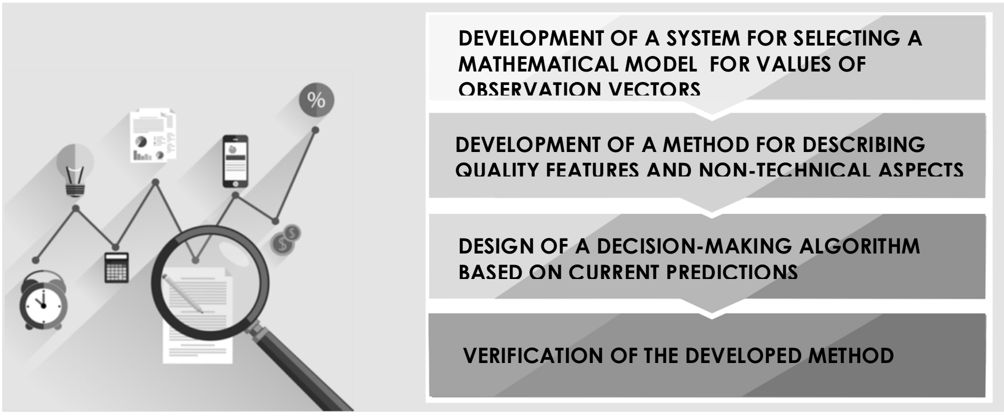

Fig. 6 Main stages of prediction and decision model design
(prepared by the authors)

5. Conclusions

All types of activity taken by maintenance services are aimed at ensuring reliability of a machine park or at identifying and eliminating all ensuing failures as fastest as possible. The increased significance of actions taken by these services stems from a higher awareness of the executive level of the fact that failure-free operation leads to higher machine park efficiency, higher product quality, lower production costs as well as effective brand building, which is vital in light of competition between companies. Maintenance services can be supported by providing them with support tools such as Computerized Maintenance Management Systems (CMMS) [34]. As a result, repair works specified in technical documentation can be done as scheduled**.**

Apart from this, more and more activities are taken resulting from examining changeable values of the monitored parameters of condition of machine components and failures predicted on this basis. Such an approach is known as predictive maintenance and it enables conscious preparation for situations could occur unexpectedly due to a lack of systems for monitoring machine park condition or due to a lack of analysis of the collected data.

The development of a system that enables collection of different types of data (e.g. vibration and temperature measurements, linguistic messages concerning suitability of undertaken maintenance actions) and selection of a suitable prediction model depending on data type as well as provides support for the decision process based on information about the production process is an innovative approach, one that has not been described in the literature before. By taking into account expectations of maintenance services regarding failure prediction and by supporting the decision process, we can significantly improve actions based on intuitive knowledge. It should however be emphasized that the application of prediction models does not guarantee full reliability owing to the risk of sudden catastrophic failures.

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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
e-mail: e.kosicka@pollub.pl,
d.mazurkiewicz@pollub.pl

Dr inż. Arkadiusz GOLA
Katedra Organizacji Przedsiębiorstwa
Politechnika Lubelska
20-618 Lublin, ul. Nadbystrzycka 38
tel.: (0-81) 538 44 83
e-mail: a.gola@pollub.pl