Maintenance Budgeting based on Predictive and Prescriptive Strategies

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Abstract: - This paper is concerned with developing an approach for estimating the maintenance costs, budgeting maintenance, and searching for opportunities to reduce maintenance costs. The proposed approach refers to predictive and prescriptive maintenance, and it is dedicated to companies that are interested in creating budgets for improving maintenance performance. Prediction models are based on regression analysis and artificial neural networks. The proposed approach uses the identified relationships to predict maintenance performance, and then to identify ways of improving maintenance performance. Consequently, this approach allows maintenance managers to find such changes in a maintenance system, by which the acceptable maintenance cost can be achieved. A number of inspections of machine components and the duration of maintenance were used as an example of variables that can improve maintenance performance.

Key-Words: - decision support system, maintenance costs, neural networks, regression models, sensitivity analysis, simulation modelling.

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1 Introduction

Today's production engineers, process specialists and managers of industrial companies face a key challenge in ensuring the continuous operation of the machines, which are the foundation of manufacturing operations and the main source of revenue for the company. Preventing the failure, albeit of only one subsystem, in a unit with a large number of assembled components is crucial to maintaining the timeliness of manufactured products and signed contracts with numerous contractors. Moreover, the dependency of manufactured goods on successive production processes puts greater pressure on engineers to maintain control over process reliability. Increasing operational efficiency requires not only the intensification of production by increasing productivity, shortening the production cycle and reducing unit costs, but also the minimization of the labour resources required to realize production processes. To date, the industrial technology development has proven the ability of engineering to respond to growing market needs, offering solutions focused on improving productivity and reliability. In recent years, digital transformation under the concepts of Industry 4.0 and Industry 5.0 has revolutionized the operating models of industrial companies, [1], [2]. Industry 4.0 uses technologies such as the Internet of Things (IoT), artificial intelligence, big data analytics and automation to create intelligent and flexible manufacturing systems, [3], [4], [5]. The integration of these technologies into operational processes leads to increased productivity and enables predictive decision-making. The concept of Industry 4.0 therefore means the unification of the real world of production machines with the virtual world of the internet and information technology. People, machines and IT systems automatically exchange information during production. This happens within the factory and various IT systems existing in the company. Industry 4.0 encompasses the entire value chain: from placing orders and supplying components for ongoing production to shipping goods to customers and after-sales service.

However, the implementation of advanced digital technologies requires a coordinated approach, due to the complexity of system components and their interconnectedness. High-tech production processes often operate on a continuous basis and their failure rate may be due to both design inadequacies and operational errors. As a result, there is a need to implement an appropriate operations management strategy that can minimise the risk of machine failure. In response to these needs, maintenance managers should ensure the ongoing technical performance of machinery and equipment. This includes both preventive and intervention measures in the event of faults, [6]. According to the

literature, the maintenance strategy should be part of a long-term technical asset management policy, considering the operational and strategic goals of the company, [7]. The implementation of an adequate maintenance strategy can provide tangible benefits such as the reduced number of unexpected failures, operational safety, prolonged equipment life, and improved production efficiency, [8].

The goal of this study is to develop an approach based on using parametric models to predict the cost of materials, labour, and additional services in maintenance. The parametric models are identified using regression analysis and artificial neural networks to obtain predictions of maintenance performance metrics. Neural networks are able to identify complex relationships in the dataset. These relationships can be used to the prediction of maintenance performance, and to simulations dedicated to prescriptive maintenance, [9]. The latter allows the maintenance department to obtain information about possibilities for improving maintenance performance. This can be seen from the perspective of a reverse approach, for which such values of input variables are sought, to achieve the acceptable maintenance performance.

The novelty of this study is the use of parametric models to maintenance budgeting, and a reverse approach to obtain variants for obtaining maintenance performance. As a result, the identified parametric models are applied to forecast the maintenance / repair costs (predictive maintenance), and to check a possibility of reducing these costs (prescriptive maintenance).

The remainder of this paper is structured as follows. The Section 2 reviews both theoretical and practical aspects of predictive and prescriptive maintenance, including its significance and benefits. Section 3 presents the proposed approach to predictive and prescriptive maintenance. Section 4 illustrates an example of using the proposed approach. Finally, Section 5 includes discussion, and Section 6 summarizes key points of this paper and provides directions for future research.

2 Literature Review

2.1 The Importance and Benefits of Predictive and Prescriptive Maintenance

The development of sensor technologies, the reduction in the cost of industrial Internet of Things devices and the increase in the availability of communication technologies have made it possible to introduce real-time machine monitoring systems, using Supervisory Control and Data Acquisition (SCADA) infrastructure, Programmable Logic Controllers (PLC) and real-time operating systems, [10]. In parallel, the development of data mining methods and advanced analytics, including machine learning and deep learning methods, has laid the groundwork for the implementation of predictive models that enable the detection of early signs of component degradation and the determination of remaining useful life of a machine, [11].

Predictive maintenance (PdM) is an approach based on the analysis of historical and current data. Its aim is to plan maintenance actions based on the actual technical condition of the equipment. Unlike preventive maintenance, which is based on a schedule, and reactive maintenance, which is undertaken after the fact, PdM only allows action to be taken when it is actually warranted, [12]. Each intervention, even if planned, influences the production rhythm, so optimizing the timing of the intervention translates directly into an improvement in operational indicators. Reducing the number of unplanned downtimes and aligning the maintenance schedule with the actual wear and tear of equipment are now one of the key objectives of reliability management strategies, [13]. In the context of the Industry 4.0 concept, which integrates cyber-physical systems, real-time data processing and decision-making automation, the PdM strategy fits in as one of the fundamental links of maintenance management systems, [14]. The ability to react quickly to symptoms of technical degradation, while reducing the number of unnecessary service interventions, is an important element in improving production logistics and spare parts management. As a result, it is possible not only to increase the operational availability of technical resources, but also to reduce the risk of execution delays, which in many industries has a direct impact on the level of customer satisfaction, [15].

Prescriptive maintenance (PsM) represents the next stage in the development of maintenance strategies, [16]. Its main objective is not only to predict failures, but also to recommend specific actions to minimize the effects of component degradation. As an example, while PdM can indicate the probability of bearing failure based on temperature anomalies, PsM can suggest lowering the operating speed of a machine in order to extend the Remaining Useful Life (RUL), [17].

The application of PdM allows companies to achieve the economic, technical and organizational benefits. In the context of modern strategies for managing the operation of technical infrastructure, PdM is a fundamental link to minimizing losses and

optimizing the operational availability of production equipment. The most significant effects of PdM implementation are as follows:

1. **Reduction in repair and maintenance times** through using condition monitoring systems and failure prediction based on historical and current data. As a result, it is possible to plan maintenance activities in advance, to make better preparation of technical assemblies, optimal selection of tools and spare parts, and to reduce the time of inspections and repair interventions, [18].
2. Predictive algorithms support maintenance managers in detecting component degradation that can indicate when a critical failure occurs. Consequently, preventive actions can be earlier taken, **reducing unexpected failures**, and increasing reliability of a maintenance system, [19].
3. PdM facilitates the planning of spare parts based on actual usage needs. As a result, there are **lower costs of spare parts inventory** and more agile supply chain management of spare parts, [20].
4. PdM supports production continuity through minimizing downtime and improving the scheduling of technical operations. In industries where penalties for delivery delays are substantial, this directly **reduces contractual costs of late order fulfilment**, and enhances the company's reputation, [21], [22].
5. Scheduled maintenance based on predictive analytics tends to be shorter and less invasive than emergency repairs. Consequently, machine downtime is reduced, and **production output improved**, [23].
6. Sudden process stoppages can lead to damage or loss of materials currently being processed. PdM mitigates the risk of such events, **reducing material waste due to equipment failure** and improving quality indicators, [24].
7. Unplanned failures often require staff to work beyond regular hours. Early fault detection and timely intervention **reduce the need for overtime hours due to breakdowns** and the associated labour costs, [25].
8. The technical condition of machines directly influences occupational safety. Equipment failures can create hazardous situations, including injuries to operators and maintenance personnel. The use of PdM can **improve workplace safety**, [26].

Prescriptive maintenance also offers a wide range of benefits. It significantly reduces unplanned downtime by using predictive analytics and action-oriented recommendations, enabling failures to be prevented before they occur. Additionally, PsM reduces response times and enables more doctored and targeted interventions compared to traditional predictive maintenance methods, [27]. Moreover, PsM supports efficient decision-making, notably in terms of maintenance scheduling, spare parts availability and resource allocation affecting better management of both technical and cost risks, [28]. As a result, PsM contributes to lower maintenance costs by minimizing unnecessary inspections, excessive preventive repairs and unnecessary maintenance activities. This ensures that assets are maintained in optimal condition at the lowest possible total cost. In addition, PsM reduces unreliability risks as data-driven recommendations increase decision certainty and reduce the likelihood of human errors and critical failures. The core concept of PsM is in line with the philosophy of Industry 4.0, including digital twins, IoT, cloud computing, and artificial intelligence. Prescriptive maintenance works with information systems such as Manufacturing Execution Systems (MES), Computerized Maintenance Management Systems (CMMS), and Enterprise Resource Planning (ERP) systems, [29].

2.2 Stages of Implementing Predictive Maintenance

Effective implementation of a predictive maintenance strategy in the industrial companies requires a well-designed and integrated approach. This process can be divided into several key stages, which complement each other and jointly determine the success of the final solution. However, there is no one-size-fits-all PdM implementation model. This process may vary depending on the industry, the technological maturity of the organization, and the availability of data. The literature review indicates that the many researchers identify six key steps for the incremental implementation of PdM tailored to the realities of Industry 4.0, [22]:

1. **Data collection and integration.** This step focuses on collecting operational data from machines and equipment using maintenance of traffic sensors, SCADA systems, PLCs, etc. The data should be integrated into a unified structure to enable further analysis. There is a need to unify the industrial communication standards with MES/ERP systems.
2. **Data processing and feature selection.** At this step, data is cleaned, completed, normalized and analysed to identify relevant variables. The feature selection refers to a machine's

condition, what is critical to the performance of predictive models.

3. **Modelling and learning.** At this step, machine learning models are developed to enable prediction or component state classification.
4. **Model validation.** Models should be validated using both offline (historical data) and online (real-time production data) methods. There are recommend performance metrics such as mean absolute percentage error (MAPE), mean absolute error (MAE), and root mean square error (RMSE) to assess prediction accuracy.
5. **Implementation.** Once validated, the PdM models are integrated with the plant's operational systems – dashboards, alerts and automatic work order generation through CMMS.
6. **Continuous improvement.** PdM models should be adapted to changes in machine operating conditions, striving to continuous improvement.

The above-presented process of implementing PdM can also be related to proactive planning of maintenance activities based on anticipated RUL, what can significantly reduce costs compared to traditional periodic maintenance, [30].

3 The Proposed Approach to Maintenance Budgeting

The proposed approach is dedicated to companies that are interested in using their databases to improve the prediction of maintenance costs through using parametric models. The relationships between the variables are identified using regression analysis and neural networks. These relationships are further used to search for the prerequisites, by which the acceptable maintenance/repair cost can be achieved.

ERP systems can support asset management, including maintenance planning and scheduling. This functionality is based on indicators such as due maintenance orders and completed work vs. planned work. Predictive maintenance in ERP systems can provide information of the failure curve of equipment based on probabilities of failures. These probabilities are determined using the data of machine failures in the past. However, using only probabilities for predicting potential failures of machines can be insufficient for maintenance managers. Therefore, the proposed approach uses the additional data to determine the cause-and-effect relationships, and to apply them for predicting potential machine failures. Moreover, the cause-and-effect relationships can additionally be used in simulating changes in parameters of the maintenance model that can reduce the maintenance cost.

The proposed approach is based on the data related to failure frequency, inspections, maintenance frequency, which is mostly used in ERP systems, and data acquired from other sources such as machine sensors, type of machine, its age, and the quality of used materials. A maintenance manager can use this approach to verify the impact of different factors on the frequency of machine failures. Factors, which have been selected for verifying their significant impact on machine failures, are added to the maintenance model and examined in the context of improving prediction of maintenance performance. The subsequent stages of the proposed approach are presented in Figure 1.

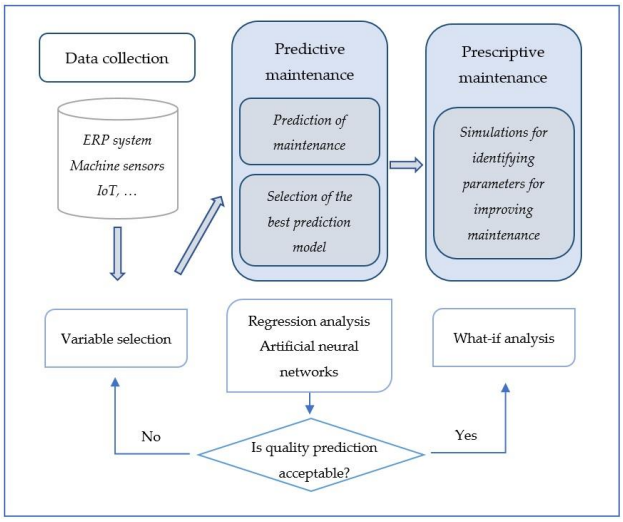


Fig. 1: A framework of the proposed approach
Source: created by the authors

The proposed approach consists of three main stages: 1) collecting the data, 2) identifying the cause-and-effect relationships and using them for predicting the maintenance cost, 3) and searching for opportunities to reduce the maintenance cost.

3.1 Data Collection

Data collection is related to the acquisition of the data from machine sensors, an ERP system and other information systems, which exist in a company. The physical sensors measure machine parameters, for example, temperature, noise, pressure, vibration, and others depending on a kind of a machine. In turn, ERP systems store the data of work hours for machines, times of their failures, inspection and repair time, the amount of materials used to production, including details of suppliers, places for storing materials, and many more.

The stage of data collection also includes data (variable) selection and data preprocessing for using artificial neural networks to determine the cause-and-effect relationships. Data preprocessing is related to cleaning and transforming raw data into a format that is easier for computational intelligence techniques analysis and further modelling. The principal component analysis has been used in this study to transform a dataset in order to simplify data through reducing dimensionality and preserving the most essential information at the same time. All combinations of variable subsets are considered in the process of searching for the best predictive model.

3.2 Prediction of Maintenance Costs

This stage of the proposed approach refers to predictive maintenance, and it includes the use of regression analysis and artificial neural networks (ANNs) to determine a model for predicting the maintenance cost of a machine. The usage of this model is twofold: apart from the prediction of the maintenance cost, it is applied to determine the values of input variables, by which the maintenance cost can be reduced. This second usage is also related to the third stage of the proposed approach – prescriptive maintenance.

The following parametric models have been used in this study: the multiple linear regression (1), polynomial regression (2), and a feedforward architecture of an artificial neural network (3).

$$y = \alpha_0 + \sum_{i=1}^{n} \alpha_i X_i \quad (1)$$

$$y = \alpha_0 + \sum_{i=1}^{n} \alpha_i X_i + \sum_{i=1}^{n} \beta_i X_i^2 \quad (2)$$

where: y is the predicted value of maintenance performance, α_0 is the initial value, α_i refer to regression coefficients, and X_i correspond to n independent variables.

Figure 2 illustrates a feedforward architecture of a three-layer neural network applied in this study. Independent variables are led to the input nodes, and the output provides the prediction of maintenance performance. Hidden nodes are used to processed the data received through the input nodes using nonlinear transfer functions.

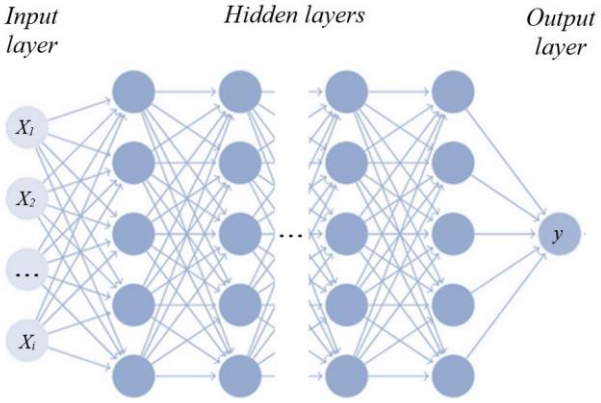


Fig. 2: A feedforward architecture of an ANN
Source: created by the authors

The model of a feedforward neural network is as follows:

$$y = \alpha_0 + \sum_{j=1}^{m} \alpha_j f\left(\sum_{i=1}^{n} \beta_{ij} X_{ij} + \beta_{0j}\right) \quad (3)$$

where: n corresponds to input nodes, m to hidden nodes, α_j to weights related to the hidden and output nodes, β_{ij} to weights related to the input and hidden nodes, and f is a sigmoid transfer function. In this study, the logistic function has been chosen as an activation function for ANNs (4).

$$f(x) = \frac{1}{1+e^{-x}} \quad (4)$$

The most frequently used learning algorithms for a feedforward architecture of an ANN are algorithms based on the concept of error backpropagation. These algorithms belong to supervised learning that consists of a few phases. At first, all weights in a neural network are initialized as small random values. Then, input-output pairs are used to adjust the weights in the network to minimize the sum squared error that corresponds to the difference between the real and desired values among all output neurons and all learning patterns. Finally, the backpropagation algorithm computes the corrections for updating the weights. In this study, a backpropagation algorithm with a gradient descent with momentum and adaptive learning rate was applied (5).

$$\Delta X_k = mc \times \Delta X_{k-1} + \gamma_k \times (1 - mc) \times \frac{\partial E}{\partial X_k} \quad (5)$$

where: ΔX_k corresponds to the update of parameters at the k-th epoch, mc is the momentum coefficient ($0 \leq mc < 1$), γ_k is the adaptive learning rate at the k-th epoch, and $\frac{\partial E}{\partial X_k}$ is the gradient of the error function for the parameters.

The vector of parameter update can be written as follows:

$$\Delta X_{k+1} = X_k \times \Delta X_k \quad (6)$$

Noteworthy, the dataset is divided into two sets (training and testing) in order to verify generalization properties of a neural network. The training and testing set consists of input-output pairs that correspond to the data used in a learning algorithm.

The results obtained by applying ANNs are compared to the results obtained by regression analysis in order to select the best prognostic tool. ANNs belong to computational intelligence methods that were inspired by nature structures. ANNs are dedicated to solving complex nonlinear real-world problems, for which using traditional models is often limited. Despite of ANNs are a powerful tool to identifying complex nonlinear relationships, they also have some disadvantages. ANNs require the selection of their structure (the number of hidden layers and neurons in each layer), the shape of an activation function, and learning parameters (e.g., a learning rate and momentum for the above-mentioned backpropagation algorithm). This selection is usually carried out by trial-and-error search. Moreover, the identified relations are stored in the structure of an ANN as a black-box model, what can limit the users' trust for these methods compared to the classical linear regression models. To increase this trust, the prediction errors obtained by ANNs are compared to other prediction models, for example, regression models.

One of ANNs' features is the ability to accurate determination of patterns among a dataset. This ability can be seen as drawback by inputting the additional data to the primary dataset. Therefore, the dataset is divided into two datasets: a training set and a testing set to evaluate the generalization properties of the learnt ANN. Training and testing datasets include input-output pairs (learning cases) that are led to an ANN and procced by its learning algorithm. The quality of a prediction model is measured through the following metrics: (7) the mean absolute percentage error (MAPE), (8) the mean absolute error (MAE), and (9) the root mean square error (RMSE).

$$MAPE(\%) = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{x_t - p_t}{x_t}\right| \quad (7)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|x_t - p_t| \quad (8)$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(x_t - p_t)^2}{n}} \quad (9)$$

where: x_t is the actual value, p_t is the predicted value, and n is the number of learning cases.

Experiments were performed using *k*-fold cross-validation, where the results were averaged for all *k*-folds. Cross-validation is a resampling method, for which parametric models for training and testing datasets are carried out within *k* iterations within the various subsets of data. At the end of this stage, predictions are made using the best parametric model, i.e. the model with the least error in the testing dataset.

Predictions are further used to estimate the cost of material, labour, and related services. Finally, the maintenance budget is determined for each machine separately. Table 1 illustrates a scheme of maintenance budget for machinery and equipment.

Table 1. An example of maintenance budget

Machine	#1	…	#*n*	Total cost
Materials				
Labour				
Services				
Total cost				

Source: created by the authors

The cost of materials is related to exchange the spare parts, lubricants, etc. The labour cost depends on the time devoted to maintain the machine or equipment, including its inspection or repair. Finally, the services are related to support activities within labour and materials used in maintenance, activities such as planning, dispatching, follow-up and quality assurance. The total cost refers to the planned preventive and corrective maintenance.

Predictive maintenance should provide answer to the following question: what is the estimated maintenance cost of materials, labour, and services? The relationships identified for predictive purposes can also be used to prescriptive maintenance.

3.3 Prescriptive Maintenance for Reducing Maintenance Costs

The last step of the proposed method refers to prescriptive maintenance, in which what-if analysis is used to identify the prerequisites for reducing the maintenance costs. The use of what-if analysis may be seen from the perspective of the reverse approach, where such changes in the maintenance process are sought, for which the maintenance cost could be reduced. Prescriptive strategy is often based on the relationships identified in predictive

analytics, [31]. A simulation model consists of variables, domains of these variables, and constraints, by which an objective function is sought. In this study, an objective function refers to the optimization of the total cost of maintenance/ repair a machine through searching for opportunities of anticipatory actions to reduce machine failures.

In this study, the constraints are related to parameters for a specific machine, the technological process (e.g., the optimal material density), limited resources (e.g., the number of maintenance employees), and the cause-and-effect relationships obtained by ANNs. The specification of the considered problem as the reverse approach allows maintenance managers to obtain answers to the questions such as:

- Is it possible to change the values of input variables to obtain the acceptable number of inspections of a machine?
- Is it possible to change the values of input variables to obtain the acceptable maintenance time of a machine?
- Is it possible to change the values of input variables to obtain the acceptable maintenance cost?

4 An Example of using the Proposed Approach

An example is divided into two parts dedicated to predictive maintenance and prescriptive maintenance. In the context of predictive maintenance, the example presents the use of regression models and ANNs to predict the material cost of a machine (10), the labour cost of a machine (11), and the service costs (12). The total cost of machine maintenance / repair (13) consists of these three above-mentioned costs. The identified relationships are used to create maintenance budget, and to carry out simulations within prescriptive maintenance. In the latter, there are sought such changes in input variables, for which the values of output variables can be reduced. This reduction aims to improve overall equipment effectiveness, and finally, manufacturing effectiveness.

4.1 Predictive Maintenance

The presented example refers to a single machine; however, the model can be expanded effortlessly to all machinery. Moreover, the calculations have been done for the time measured in hours per month. The set of variables for specifying the above-described problem is as follows:

V_1 - the number of repairs of the i-th machine in month t-1;
V_2 - the time of repairing the i-th machine in month t-1 (in hours);
V_3 - the age of the i-th machine (in months);
V_4 - the working time of the i-th machine in month t-1 (in hours);
V_5 - the maintenance time of the i-th machine in month t-1 (in hours);
V_6 - the number of inspections of the i-th machine in month t-1;
V_7 - the number of critical components in the i-th machine;
V_8 - the average of daily maximum temperature for the i-th machine in month t-1 (in °C);
V_9 - the material cost of the i-th machine maintenance / repair in month t (in thousand €);
V_{10} - the labour cost of the i-th machine maintenance / repair in month t (in thousand €);
V_{11} - the service cost of the i-th machine maintenance/repair in month t (in thousand €);
V_{12} - the total cost of the i-th machine maintenance / repair in month t (in thousand €).

The set of variables includes only one variable related to sensors (V_8) because others (e.g., humidity, noise, vibration) have a low value of the coefficient of variation.

The relationships between input and output variables are as follows:

$$V_9 = f(V_1, V_3, V_4, V_5, V_6, V_8) \quad (10)$$

$$V_{10} = f(V_2, V_3, V_4, V_5, V_6, V_7) \quad (11)$$

$$V_{11} = f(V_9, V_{10}) \quad (12)$$

$$V_{12} = V_9 + V_{10} + V_{11} \quad (13)$$

The dataset consists of the data collected each day during 16 months. For verifying the quality of prediction models, the dataset was divided into two sets: the learning set (80% data) and the testing set (20% data). The quality of prediction models has been measured using the MAPE (7), MAE (8), and RMSE (9). The results of experiments have been averaged for the 5-fold cross validation. The relationships (10), (11), and (12) have been determined using parametric models based on regression analysis and ANNs.

ANNs were trained using a backpropagation algorithm for a gradient descent with the momentum and adaptive learning rate. Parameters of this algorithm were selected in an experimental way, including the logistic function as an activation

function, the momentum as 0.9, and the learning rate as 0.01. Figure 3 illustrates the values of error metrics for varying numbers of hidden neurons. Experiments performed for varying numbers of hidden layers have shown that a neural network with one hidden layer had the best generalization properties for the testing set.

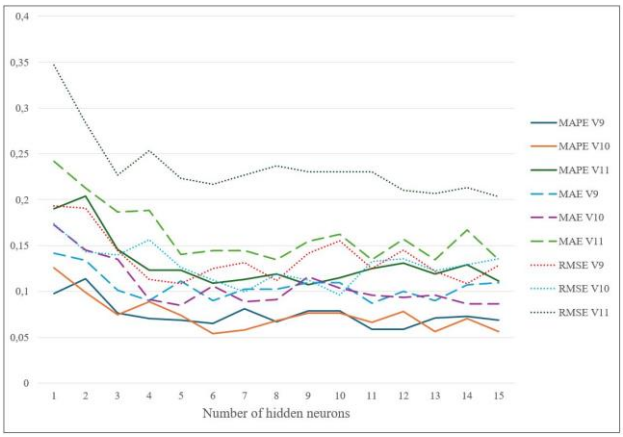


Fig. 3: A number of hidden neurons and error metrics in the testing set
Source: created by the authors

The results of parametric models have been compared to the average (AV) of the above-mentioned costs (10), (11), and (12) for the last 2 months. Regression analysis includes the linear regression (LM, linear model) and nonlinear regression (NM, polynomial model). Table 2 presents the comparison of errors in the testing set for the above-mentioned prediction models.

Table 2. The comparison of error metrics in the testing set for prediction models

Error metrics	Prediction model	V_9	V_{10}	V_{11}
MAPE	AV	0.124	0.107	0.157
	LM	0.079	0.062	0.113
	NM	0.064	0.059	0.104
	ANN	0.059	0.053	0.101
MAE	AV	0.182	0.149	0.236
	LM	0.123	0.103	0.152
	NM	0.090	0.095	0.152
	ANN	0.087	0.085	0.135
RMSE	AV	0.232	0.212	0.288
	LM	0.167	0.106	0.208
	NM	0.132	0.119	0.206
	ANN	0.108	0.096	0.204

Source: created by the authors

The results presented in Table 2 show that prediction models associated with ANNs generates less errors in the testing set compared to regression analysis and the average of the dependent variables. Consequently, these prediction models were used to estimate the cost of material (V_9), labour (V_{10}), and service (V_{11}). The values of these output variables were predicted as the following values: V_9 = 331.9 €, V_{10} = 269.5 €, V_{11} = 41.4 €, and the total cost of machine maintenance/repair V_{12} = 642.8 €.

4.2 Prescriptive Maintenance

An example of prescriptive maintenance is associated with a reverse approach, where such values of input variables are sought, for which an acceptable value of an output variable is achieved. This approach bases on the relationships identified in predictive analytics and domain specification for the selected input variables that can be controllable in the maintenance process. For the problem considered in this study, there are sought values of input variables, for which the total cost of machine maintenance/repair reaches an acceptable level. The parametric model based on (10) indicates the greatest increase of the material cost by increasing the working and maintenance time $(V_4$ and $V_5)$ of the machine and the number of inspections of the machine (V_6). In the case of the parametric model for the labour cost (11), the most important factors are the time of repairing the machine (V_2), its working time (V_4), maintenance time (V_5), and the number of inspections of machine components (V_6). Moreover, the increase of the maintenance time and the number of inspections of the machine affects the decrease of the time of repairing the machine.

Table 3. The cost analysis for changes of the maintenance time and the number of inspections

Variables	V_9	V_{10}	V_{11}	V_{12}
V_5 = 3.1, V_6 = 2	331.9	269.5	41.4	642.8
…	…	…	…	…
V_5 = 5.9, V_6 = 2	323.3	273.6	41.0	637.9
…	…	…	…	…
V_5 = 3.5, V_6 = 11	273.3	288.9	37.9	600.1
V_5 = 3.6, V_6 = 11	273.0	289.1	37.8	599.9
…	…	…	…	…
V_5 = 3.1, V_6 = 15	245.8	301.0	36.4	583.2
…	…	…	…	…
V_5 = 5.9, V_6 = 15	237.3	305.1	36.0	578.4

Source: created by the authors

Table 3 illustrates the results of a few simulations regarding the impact of maintenance time (V_5) and the number of inspections of the machine (V_6) on the different costs of machine maintenance/repair $(V_9$ - $V_{12})$. Noteworthily, the variables V_5 and V_6 can be controllable by maintenance managers. The following domains for these variables were assumed: D_5 = {3.1, 3.2, …,

5.9} and D_6 = {2, 3, …, 15}. The acceptable value of the total cost of machine maintenance has been set at 600 €.

The results illustrated in Table 3 indicate that the increase of machine maintenance time and the number of inspections reduces the time of repairing the machine, and consequently, the cost of material, services, and the total maintenance cost. However, the greater machine maintenance time and the number of inspections also increases the cost of labour. The acceptable value of the total cost is obtained by V_5 greater than 3.6 and V_6 greater than 11. The impact of variable V_5 and V_6 is nonlinear affecting the various strengths of changes for the costs. Table 4 presents cost increments for material, labour, service, and the total cost of machine maintenance/repair.

Table 4. Sensitivity analysis for costs (in %)

Variables	V_9	V_{10}	V_{11}	V_{12}
V_5 = 3.1, V_6 = 2 V_5 = 3.2, V_6 = 2	-0.09	0.05	-0.04	-0.027
…	…	…	…	…
V_5 = 5.8, V_6 = 2 V_5 = 5.9, V_6 = 2	-0.1	0.06	-0.04	-0.027
…	…	…	…	…
V_5 = 3.5, V_6 = 11	-0.11	0.05	-0.04	-0.029
V_5 = 3.6, V_6 = 11				
…	…	…	…	…
V_5 = 3.1, V_6 = 14 V_5 = 3.1, V_6 = 15	-2.90	1.14	-1.02	-0.737
…	…	…	…	…
V_5 = 5.9, V_6 = 14 V_5 = 5.9, V_6 = 15	-3.00	1.12	-1.02	-0.743

Source: created by the authors

The results presented in Table 4 indicate the greater impact of the number of inspections (V_6) on the maintenance/repair costs than the maintenance time (V_5). For example, the change of V_6 (from 14 to 15 inspections per month by V_5 = 5.9) results in decreasing the total cost of 0.743%, whereas the change of V_5 (from 3.1 to 3.2 hours per month by V_6 = 2) results in decreasing the total cost of 0.027%. Noteworthily, the longer machine maintenance time and the bigger number of inspections increases the cost of labour (V_{10}). This sensitivity analysis aims to support maintenance managers to identify opportunities of obtaining the optimal cost or the acceptable value of another variable, for example, a number of repairs of a machine.

5 Discussion

The proposed approach supports maintenance managers in obtaining the budget of machinery maintenance using parametric modelling to estimate the material, labour, and service cost of maintenance. Previous studies have used parametric models to identify the mean time to failure and parameters of distribution, [32], the machine setup and human error costs, [33], overhead costs and activity-based costing, [34], to estimate preventive and corrective maintenance performance. Whereas, the proposed approach provides predictions using the data-driven models based on the data related to maintenance/repair machines, for which the material, labour, and service cost of machinery maintenance can be more precisely estimated. The use of the material and labour cost for obtaining maintenance budget is presented in [35], [36], but there the budget is built using analytical models that cannot be applied to prescriptive maintenance. The use of parametric models in the proposed approach enables their usage also to scenario analysis within prescriptive maintenance. Consequently, the presented approach outperforms the previous ones within budgeting maintenance.

Moreover, the proposed approach uses the reverse approach to facilitate maintenance managers obtaining solutions (if there are any) to reduce maintenance costs to an acceptable level. Past research has used the reverse approach in the other areas than budgeting of machinery maintenance, for example, for supply chain operations, [37], for spare parts logistics, [38], and for service parts management, [39]. Noteworthily, the reverse approach is much less used in maintenance than in logistics, [40], [41], [42]. This can result from the fact that more scientific works is dedicated to preventive and condition-based maintenance than to predictive and prescriptive maintenance. The specification of budgeting maintenance from the perspective of the reverse approach facilitates maintenance managers to identify possible opportunities for reducing the maintenance costs.

The proposed approach includes the data acquired from an ERP system (e.g., the time of working, repairing, servicing machines) and machine sensors (e.g., temperature, vibration). A set of variables has been selected considering their usage not only in predictive but also in prescriptive maintenance. This selection aims to obtain the set of controllable variables, i.e., variables that can be changed by maintenance managers, and consequently, that enable the answer to the following question: what values should have input variables to obtain the acceptable value of an output variable? Previous studies have used the data-driven models to specify the machine features (e.g., rotation speed, power absorbed by the machine,

real-to-nominal position in three dimensions), [43], machine class and machine usage intensity, [44], and areas of decision making (e.g., cost estimation, scheduling, and multi-state system optimization), [45], [46]. The detailed classification of the learning task, machine learning methods, data sources, and equipment types was described in [47]. According to this classification, the presented example refers to the regression problem using artificial neural network (multilayer perceptron) learnt with the data related to machine sensors and its faults.

6 Conclusion

Maintenance is one of the most important activities in manufacturing companies. In spite of numerous studies, there is no technology that can guarantee the total reliability in the operation of production equipment. There is a specific risk related to, for example, machine failures or errors in the implementation of production processes. Therefore, the crucial factor in reducing the risk of downtime is maintenance prediction that supports the maintenance staff in scheduling inspections of machines and equipment. Nowadays, the expectations for maintenance are constantly increasing, resulting in developing new concepts such as predictive and prescriptive maintenance.

The leading advantage of predictive maintenance is the ability to identify potential problems that could not be foreseen when using other methods. Both the application of predictive and prescriptive maintenance occurs in real time during normal operation of machinery or equipment. It is worth emphasizing that prescriptive maintenance not only predicts failures, but also recommends specific actions to be taken to prevent them or minimize their effects. This allows the company to increase operational efficiency through reduced downtime and better resource planning, and reduce maintenance costs through avoiding unnecessary interventions and costly break-downs. Moreover, this optimize the supply chain through ordering spare parts earlier, increase safety through minimizing the risk of unexpected failures, and finally, extend the life of equipment.

The main contribution of this research is maintenance budgeting based on parametric models within predictive and prescriptive strategies. The use of neural networks in the predictive strategy improve prediction quality of the maintenance costs. The use of what-if analysis and sensitivity analysis in the prescriptive strategy allows maintenance staff to obtain possible solutions (if there are any) for reducing the maintenance costs.

The identified prescriptive strategies enable the maintenance staff to obtain information of changes in a maintenance model to improve maintenance performance. These changes can be something new and surprising for maintenance managers, revealing new directions of maintenance improvement. On the other hand, the use of artificial neural networks can result in the difficulties of identifying the optimal structure of a neural network. This aspect may be seen as a limitation of the proposed approach.

Future research will be concerned with the integration of maintenance budgeting with a broader company's financial system, and considerations of its impact on quality management. Another direction for future research can be the application of other techniques of machine learning to predictive and prescriptive maintenance.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

References:

[1] Zizic, M., Mladineo, M., Gjeldum, N., Celent, L., From Industry 4.0 towards Industry 5.0: A Review and Analysis of Paradigm Shift for the People, Organization and Technology, *Energies*, Vol.15, 2022, 5221.

[2] Fogaça, D., Grijalvo, M., Sacomano Neto, M., What are Industry 4.0 and Industry 5.0 all about? An Integrative Institutional Model for the New Industrial Paradigms, *Administrative Sciences*, Vol.15, No.4, 2025, 118.

[3] Zhanybek, S., Shaikholla, S., Dikhanbayeva, D., Shehab, E., Turkyilmaz, A., Industry 4.0: Clustering of concepts and characteristics, *Cogent Engineering*, Vol.9, 2022, 2034264.

[4] Bayindir B., Shafighi N., Hajibashi A., Analysis of the Impact of Industry 4.0 Technologies on Service Sector, *Archives of Business Research*, Vol.12, 2024, pp. 127-141.

[5] Jun, J., Kim, T. Y., Lee, J., Jin, T., Park, S., Jeong, J., AI and IoT-based automated camera maintenance system: A study of improving production efficiency and safety through predictive maintenance, *WSEAS Transactions*

on Business and Economics, Vol.22, 2025, pp. 1955-1970.

[6] Ben-Daya M., Duffuaa S., Abdul Raouf A., Knezevic J., Ait-Kadi D., *Handbook of Maintenance Management and Engineering*, Springer, 2009.

[7] Prajapati A., Bechtel J., Ganesan S., Condition based maintenance: A survey, *Journal of Quality in Maintenance Engineering*, Vol.18, 2012, pp. 384-400.

[8] Nunes P., Santos J., Rocha E., Challenges in predictive maintenance - A review, *CIRP Journal of Manufacturing Science and Technology*, Vol.40, 2023, pp. 53-67.

[9] Relich, M., Portfolio selection of new product projects: A product reliability perspective, *Eksploatacja i Niezawodnosc – Maintenance and Reliability*, Vol.18, No.4, 2016, pp. 613-620.

[10] Enemosah A., Ifeanyi O., SCADA in the Era of IoT: Automation, Cloud-Driven Security, and Machine Learning Applications, *International Journal of Science and Research Archive*, Vol.13, 2025, pp. 3417-3435.

[11] Lei Y., Li N., Guo L., Li N., Yan T., Lin J., Machinery Health Prognostics: A Systematic Review from Data Acquisition to RUL Prediction, *Mechanical Systems and Signal Processing*, Vol.104, 2018, pp. 799-834.

[12] Achouch M., Dimitrova M., Ziane K., Karganroudi S., Dhouib R., Ibrahim H., Adda M., On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges, *Applied Sciences*, Vol.12, 2022, 8081.

[13] Yazdi, M., Maintenance strategies and optimization techniques, *Advances in Computational Mathematics for Industrial System Reliability and Maintainability*, Springer, 2024, pp. 43-58.

[14] Lee, J., Bagheri, B., Kao, H., A Cyber-Physical Systems Architecture for Industry 4.0-Based Manufacturing Systems, *Manufacturing Letters*, Vol.3, 2015, pp. 18-23.

[15] Nagy, M., Figura, M., Valaskova, K., Lazăroiu, G., Predictive Maintenance Algorithms, Artificial Intelligence Digital Twin Technologies, and Internet of Robotic Things in Big Data-Driven Industry 4.0 Manufacturing Systems, *Mathematics*, Vol.13, 2025, 981.

[16] Relich, M., Identifying project alternatives with the use of constraint programming, *Proceedings of 37th International Conference on Information Systems Architecture and Technology*, 2016, pp. 3-13.

[17] Ucar, A., Karakosé, M., Kirimça, N., Artificial Intelligence in Predictive Maintenance Applications: Key Components, Trustworthiness, and Future Trends, *Applied Sciences*, Vol.14, 2024, 898.

[18] Pech, M., Vrchota, J., Bednář, J., Predictive Maintenance and Smart Sensors in the Smart Factory: A Review, *Sensors*, Vol.21, 2021, 1470.

[19] Benhanifia, A., Ben Cheikh, Z., Oliveira, P.M., Valente, A., Lima, J., Systematic Review of Predictive Maintenance Practices in the Manufacturing Sector, *Intelligent Systems with Applications*, Vol.26, 2025, 200501.

[20] Wiercioch, J., Hybrid Predictive Maintenance Model - Study and Implementation Example, *Production Engineering Archives*, Vol.30, No.3, 2024, pp. 285-295.

[21] Riccio, C., Menanno, M., Zennaro, I., Savino, M., A New Methodological Framework for Optimizing Predictive Maintenance Using Machine Learning Combined with Product Quality Parameters, *Machines*, Vol.12, 2024, 443.

[22] Zonta, T., da Costa, C.A., Righi, R.R., de Lima, M.J., Trindade, E.S., Li, G.P., Predictive Maintenance in the Industry 4.0: A Systematic Literature Review, *Computers & industrial engineering*, Vol.150, 2020, 106889.

[23] Shah, S.S., Daoliang, T., Kumar, S.C., RUL Forecasting for Wind Turbine Predictive Maintenance Based on Deep Learning, *Heliyon*, Vol.10, 2024, 20.

[24] Ucar, A., Karakose, M., Kirimça, N., Artificial Intelligence in Predictive Maintenance Applications: Key Components, Reliability and Future Trends, *Applied Sciences*, Vol.14, 2024, 898.

[25] Molęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., Mrozek, D., From Corrective to Predictive Maintenance—A Review of Maintenance Approaches for the Power Industry, *Sensors*, 23, 2023, 5970.

[26] Malioris, P., Aivazidou, E., Bechtsis, D., Predictive Maintenance in Industry 4.0: A Multi-Sector Systematic Mapping, *CIRP Journal of Manufacturing Science and Technology*, Vol.50, 2024, pp. 80-103.

[27] Giacotto, A., Marques, H.C., Martinetti, A., Prescriptive Maintenance: A Comprehensive Review of Current Research and Future Directions, *Journal of Quality in Maintenance Engineering*, Vol.31, 2025, pp. 129-173.

[28] Wesendrup, K., Hellingrath, B., Nikolarakis, Z., A Framework for Conceptualizing

Integrated Prescriptive Maintenance and Production Planning and Control Models, *Brazilian Journal of Operations & Production Management*, Vol.21, 2024, 2172.

[29] Mao, H., Liu, Z., Qiu, C., Huang, Y., Tan, J., Prescriptive Maintenance for Complex Products with Digital Twin Considering Production Planning and Resource Constraints, *Measurement Science and Technology*, Vol.34, No.12, 2023, 125903.

[30] Lv, H., Zheng, H., Yuan, Z., Cao, Y., A Predictive Maintenance Strategy for Multi-Component Systems Based on Components' Remaining Useful Life Prediction, *Mathematics*, Vol.11, 2023, 3884.

[31] Relich, M., Renewable Energy in the European Union: The State of the Art and Directions of Development, *WSEAS Transactions on Business and Economics*, Vol.21, 2024, pp. 630-637.

[32] Florian, E., Sgarbossa, F., Zennaro, I., Machine learning-based predictive maintenance: A cost-oriented model for implementation, *International Journal of Production Economics*, Vol.236, 2021, 108114.

[33] Emroozi, V.B., Kazemi, M., Doostparast, M., Enhancing industrial maintenance planning: Optimization of human error reduction and spare parts management, *Operations Research Perspectives*, Vol.14, 2025, pp. 1-24.

[34] Haroun, A.E., Maintenance cost estimation: Application of activity-based costing as a fair estimate method, *Journal of Quality in Maintenance Engineering*, Vol.21, No.3, 2015, pp. 258-270.

[35] Swart, P.D., Vlok, P.J., Failure statistics: Budgeting preventative maintenance activities using forecasted work orders, *Proceedings of the 9th World Congress on Engineering Asset Management*. Springer, 2016, pp. 321-337.

[36] Galar, D., Sandborn, P., Kumar, U., *Maintenance costs and life cycle cost analysis*, CRC Press, 2017.

[37] Gayialis, S.P., Kechagias, E.P., Konstantakopoulos, G.D., Papadopoulos, G.A., A predictive maintenance system for reverse supply chain operations, *Logistics*, Vol.6, No.1, 2022, 4.

[38] Makarova, I., Shubenkova, K., Buyvol, P., Shepelev, V., Gritsenko, A., The role of reverse logistics in the transition to a circular economy: case study of automotive spare parts logistics, *FME Transactions*, Vol.49, No.1, 2021, 173.

[39] Mo, D.Y., Ma, C.Y., Ho, D.C., Wang, Y., Design of a reverse logistics system with internet of things for service parts management, *Sustainability*, Vol.14, No.19, 2022, 12013.

[40] Govindan, K., Bouzon, M., From a literature review to a multi-perspective framework for reverse logistics barriers and drivers, *Journal of Cleaner Production*, Vol.187, 2018, pp. 318-337.

[41] Cannella, S., Bruccoleri, M., Framinan, J.M., Closed-loop supply chains: What reverse logistics factors influence performance?, *International Journal of Production Economics*, Vol.175, 2016, pp. 35-49.

[42] Wilson, M., Goffnett, S., Reverse logistics: Understanding end-of-life product management, *Business Horizons*, Vol.65, No.5, 2022, pp. 643-655.

[43] Paolanti, M., Romeo, L., Felicetti, A., Mancini, A., Frontoni, E., Loncarski, J., Machine learning approach for predictive maintenance in industry 4.0, *Proceedings of the 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications*, 2018, pp. 1-6.

[44] Van Staden, H.E., Deprez, L., Boute, R.N., A dynamic "predict, then optimize" preventive maintenance approach using operational intervention data, *European Journal of Operational Research*, Vol.302, No.3, 2022, pp. 1079-1096.

[45] Bousdekis, A., Lepenioti, K., Apostolou, D., Mentzas, G., A review of data-driven decision-making methods for industry 4.0 maintenance applications, *Electronics*, Vol.10, No.7, 2021, 828.

[46] Bouhalouan, D., Nachet, B., Adla, A., A Knowledge-Intensive Decision Support System for Industrial Machines Maintenance, *WSEAS Transactions on Information Science and Applications*, Vol.17, 2020, pp. 41-52.

[47] Davari, N., Veloso, B., Costa, G.D., Pereira, P.M., Ribeiro, R.P., Gama, J. A survey on data-driven predictive maintenance for the railway industry, *Sensors*, Vol.21, No.17, 2021, 5739.

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