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ECONOMIC PERSPECTIVE ON ALGORITHM SELECTION FOR PREDICTIVE MAINTENANCE

by

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Research paper

Abstract

The increasing availability of data and computing capacity drives optimization potential. In the industrial context, predictive maintenance is particularly promising and various algorithms are available for implementation. For the evaluation and selection of predictive maintenance algorithms, hitherto, statistical measures such as absolute and relative prediction errors are considered. However, algorithm selection from a purely statistical perspective may not necessarily lead to the optimal economic outcome as the two types of prediction errors (i.e., alpha error ignoring system failures versus beta error falsely indicating system failures) are negatively correlated, thus, cannot be jointly optimized and are associated with different costs. Therefore, we compare the prediction performance of three types of algorithms from an economic perspective, namely Artificial Neural Networks, Support Vector Machines, and Hotelling T^2 Control Charts. We show that the translation of statistical measures into a single cost-based objective function allows optimizing the individual algorithm parametrization as well as the un-ambiguous comparison among algorithms. In a real-life scenario of an industrial full-service provider we derive cost advantages of 15% compared to an algorithm selection based on purely statistical measures. This work contributes to the theoretical and practical knowledge on predictive maintenance algorithm selection and supports predictive maintenance investment decisions.

Keywords: Predictive Maintenance, Algorithm Selection, Economic Perspective, Prediction Error.

1 Introduction

More and more digital data are available to mankind and, ultimately, to industry. Over the last three decades, computing capacity, bidirectional telecommunication and digital information stored worldwide grew with an unprecedent pace. Whereas at the turn of the millennium only 25% of the information per capita was stored digitally, in 2007 it was already 94% (Hilbert and López, 2011). Especially computing power has grown exponentially, as the IBM Supercomputer Summit demonstrates where a peak performance of 200,000 trillion calculations per second was reached (McCorkle, 2018). These technological advancements lead to the digitalization of entire industries and do not stop when it comes to physical production (Reyna et al., 2018). New concepts such as the Industrial Internet of Things (IIoT) integrate physical objects into digital networks and offer new opportunities for the optimization of production processes (Sadeghi et al., 2015).

Driven by the availability of data and computing capacity, the IIot now breaks new ground in maintenance strategies that represent one of the largest cost drivers in industrial production (Windmark et al., 2018). Maintenance strategies are traditionally preventive based on expert experience paired with basic information on maintenance cycles and machine run times. Therefore, preventive maintenance (PvM) is also referred to as use-based maintenance and usually complemented by reactive maintenance (RM) efforts in case of unforeseen system breakdowns (Swanson, 2001). Novel data-based predictive maintenance (PdM) approaches leverage collected data to analyse the fluctuation of system and process parameters and provide automatic signals if threshold values are exceeded (Bevilacqua and Braglia, 2000). As a result, upcoming failures and corresponding maintenance needs can be predicted in advance. In turn, maintenance cycles are optimized which leads to savings in maintenance costs as well as the prevention of breakdowns (World Economic Forum, 2015).

Academic and practical literature proved in manifold studies that PdM is economically advantageous compared to PvM and RM (Gu et al., 2017a; Gu et al., 2017b; Xu et al., 2015; Zarte et al., 2017). For example, Gu et al. (2017b) show that significant economic benefits can be achieved in an automotive manufacturing context by relying on PdM algorithms that analyse system reliability states. To implement PdM, various qualitative and quantitative approaches have been examined, e.g., expert systems, statistical methods, and neural networks (Baptista et al., 2018; Li et al., 2014; Venkatasubramanian et al., 2003). For the selection and evaluation of PdM algorithms in specific contexts, hitherto, absolute and relative prediction errors are considered. For example, Baptista et al. (2018) use mean and median absolute as well as percentage prediction errors as PdM selection criteria for their autoregressive-moving-average model. However, it was noted by Li (2014) that an algorithm's prediction errors have an impact on costs and that therefore a cost perspective should be taken into account when selecting algorithms. In other words: Algorithm selection from a purely statistical perspective may not necessarily lead to the optimal economic outcome as the two types of prediction errors (i.e., alpha error ignoring system failures versus beta error falsely indicating system failures) are negatively correlated, thus, cannot be jointly optimized, and are associated with different costs. For example, adjusting a given algorithm to decrease the number of alpha errors, increases the number of beta errors in turn, as reducing ignored failures implies an increased likelihood of false alarms. From a statistical perspective, this trade-off cannot be un-ambiguously solved and cost implications are neglected.

To the best of our knowledge, a holistic economic (i.e., cost) perspective on algorithm performance in the PdM context and its implication on algorithm selection is missing. This is especially relevant in a full-service provider context, where the maintenance supplier bears all costs and risks of maintenance resulting for example in penalty costs in case of non-compliance with service level agreements (SLA). Thus, our research question is as follows: *Does an economic perspective change the selection of PdM algorithms compared to statistical measures in an industrial full-service provider context?*

To answer this question, we compared the prediction performance of three types of algorithms from a statistical as well as an economic (i.e., cost) perspective in a real-life scenario of an industrial full-service provider. The case company was a European machinery company building and operating car wash systems and traditionally pursuing a PvM strategy complemented by RM in case of unforeseen system breakdowns. In this work, we supported the case company in developing a PdM prototype for one selected failure pattern and in identifying the economically most favourable algorithm building on sensor data of 4.9 million car washes. We selected three algorithms for comparison based on Venkatsubramian's et al. (2003) typology, i.e., Artificial Neural Network (ANN), Support Vector Machine (SVM), Hotelling T^2 Control Chart (HT^2). Whereas the first two are so-called 'black-box' approaches, HT^2 allows the adjustment of prediction error sensitivities, i.e., the trade-off between alpha errors and beta errors. The algorithms were trained to correctly assign the case company's sensor data as 'incontrol' indicating that the system was fine or 'outcontrol' indicating that a system failure would ocurr within the following week. For the case data set and the three algorithms under consideration, predictions were simulated, alpha errors and beta errors identified, statistical measures derived, and translated into an economic calculus. Finally, we compared the algorithms according to cost implications and selected the economically most favourable algorithm.

The remainder of the paper is structured as follows. Section 2 provides an overview of current process history-based methods for PdM. Section 3 presents the case study as well as the research method. In Section 4, the model design is elaborated before we present and discuss the results in Section 5 and 6. Section 7 highlights limitations and stimuli to further research.

2 Process History-based Methods for PdM

To set the stage for PdM algorithm selection, this section provides a non-conclusive literature overview of current algorithm classes, their advantages, disadvantages, as well as application for PdM. As shown in Figure 1, a distinction is made between quantitative and qualitative methods for analysing and interpreting process history-based data for predictive insights. Qualitative methods incorporate expert systems and qualitative trend analysis (QTA). In this work, however, we focus on quantitative algorithms for pattern recognition to identify irregularities, respectively wash system failures. Main categories are ANN as well as statistical methods that comprise statistical classifiers (SC) and principal component analysis (PCA)/partial least square (PLS) (Venkatasubramanian et al., 2003).

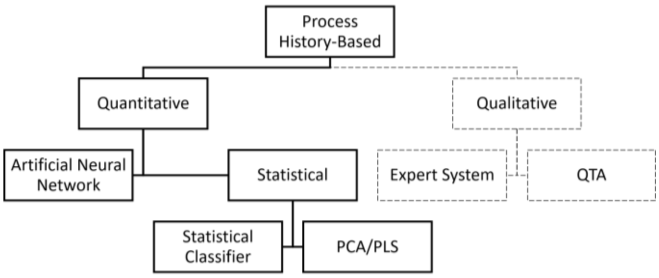

Figure 1. Process history-based methods for PdM following Venkatsubramian et al. (2013)

Artificial Neural Networks are advanced pattern recognition algorithms that can extract complex relationships between variables (Somers and Casal, 2009). ANNs are characterized above all by their ability to cope with nonlinear relationships (Lek et al., 1996). ANNs consist of three different layer types: input, hidden, and output layers. Each layer contains several neurons, which consist of a large number of interconnected processing elements that are associated with weighted connections, analogous to synapses (Haykin, 1995). Dependent variables and predictors represent the input and output layers. Neurons of the hidden layers process incoming information and pass it on to connected neurons in the network. They do not represent variables. Training an ANN aims at minimizing the error metric in the source neuron. For this, a fitting algorithm identifies the optimal number of layers, neurons and connection weights (Haykin, 1995). Advantages of ANNs are computing speed, coverage of nonlinear dependencies, and continuous improvement through additional data (Zhang et al., 1998). These advantages also drive ANN applications for PdM in complex systems. For example, Saxena and Saad (2007) use neural network classifiers for condition monitoring. Lin and Tseng (2005) develop a neural network application for reliability modelling and condition-based PdM. A disadvantage of ANNs is the lack of interpretability of weights due to the parallelism of ANNs and as inner structural knowledge is not accessible.

Therefore, ANN are often referred to as ‘black-box’ approaches (Sjöberg et al., 1995). Black-box algorithms transform the input through an imaginary box into output, without interference from the outside. The backpropagation algorithm, as demonstrated by Chen and Wang (2009) and Dilruba et al. (2006), is ANNs’ most popular supervised learning strategy (Venkatasubramanian et al., 2003). Therefore, we use a multilayer perceptron with the backpropagation algorithm for this study.

Statistical Classifiers utilize pattern vectors with different categories to map solid and disjunct regions in a n-dimensional characteristics space (Jain et al., 2000). SC can be distribution based or distribution free, whereas given by the data set provided we focus on the latter. *Support Vector Machines* are parameter-free statistics and characterized by the fact that the model structure is not defined a priori but based on the input data. By compromising between the number of training errors and the so-called Vapnik-Chervonenkis-Dimension measuring complexity, SVM classifiers optimize the generalization error (Moulin et al., 2004). Therefore, SVMs are used to solve classification and regression problems. SVMs are considered effective models using small sets of training data to solve nonlinear problems with supervised learning (Cristianini and Shawe-Taylor, 2000). Li et al. (2014) show that also in a complex system, SVMs are useful for failure detection and in Baptista et al.’s (2018) work, SVMs score best among the compared methods for PdM. Similar to ANNs, SVMs are black-box algorithms. Therefore the disadvantages of SVMs are the lack of transparency and often reported fitting complexity (Moulin et al., 2004). In this study, SVMs are used to represent SC.

Principal Component Analysis/Principal Least Square is a technique to reduce the dimensionality of a multivariate data set (Jolliffe, 2002). PCA transforms the original raw data into a reduced set of linear data with minimal correlation (Baptista et al., 2018). Like PCA, PLS is useful for reducing the dimensions of variables to be analysed. Systems such as PCA/PLS are ideal for extracting information on relevant trends in data using only a small number of factors (Venkatasubramanian et al., 2003). PCA/PLS is widely discussed as an efficient approach for multivariate statistical process monitoring (Choi and Lee, 2005; Dong and Qin, 2018; MacGregor et al., 1994; Zhao et al., 2010). In particular, the Hotelling T^2 Control Chart (HT^2) is a well-known approach to monitor fluctuations around an average value (Li et al., 2011). As HT^2’s major advantage Montgomery and Klatt (1972) cite the simple parametrization and fast calculation. In contrast to SVMs and ANNs, HT^2 enables accessing internal structural knowledge. The algorithm’s prediction error sensitivity can be adjusted via the parameter alpha, which is negatively correlated to the beta error, namely false negatives. This flexibility enables to proactively balance the trade-off between alpha and beta errors and corresponding costs. Therefore, we select HT^2 as the third algorithm for comparison, applying the most common alpha level of 5% as start configuration (Samuels and Gilchrist, 2018; Wright, 2009).

3 Case Study Overview and Research Method

We compare the prediction performance of the selected algorithms from a statistical and economic perspective in a real-life scenario of an industrial full-service provider. The case company is a European machinery company and a global market leader for full-service solutions in the field of car wash systems. The case company’s business customers are for example oil companies operating fuel stations or private investors. The case company acts as a full-service provider for about 80% of its car wash systems. In these cases, the customers pay a fixed annual rate to the case company for operating the car wash systems. The case company bears all costs and risks for repairs and maintenance. Therefore, the case company is particularly interested in the cost advantages of PdM for its own profitability, in contrast to other machinery companies which offer PdM as additional service for their customers. Hitherto, the case company has not installed a PdM system yet but uses PvM in the form of two regular maintenance sessions per year. In case of unforeseen system failures, the customer calls and informs the case company which sends a service technician to check and repair the car wash system (RM). The case company aims at identifying failures before the system shuts down through PdM. In addition, PdM promises accelerated maintenance processes as well as more reliable and faster failure detection compared to the current customer-induced notification system. The customer sometimes notices failures only after a considerable time delay, which results in additional costs and more difficult traceability of errors. In conclusion, the case company aims at introducing PdM to reduce time and costs of repairs, prevent penalty costs due to non-compliance with SLA, and increase customer satisfaction.

In this work, we supported the case company in developing a PdM prototype for one selected failure pattern and in identifying the economically most favourable algorithm for implementation. As a starting point we built on an extensive data set the case company has collected to enable PdM as well as information about the distribution network and cost structure. The research approach for comparing algorithms from a statistical and economic perspective is based on the big data analytics guidelines by Müller et al. (2016). We elaborate on the relevant steps in the following along the phases *data collection*, *data preparation*, *data analysis*, and *result interpretation*.

First, *data collection* comprised the collection of available sensor data as input for the PdM prototype which was directly taken from the case companies IT system. After processing and cleaning, the data set contained metered revolutions per minute (rpm) of four brushes for 536 car wash systems from January 2017 to July 2018. For each of the 4.9 million car washes within the considered period, a single snapshot of the sensor data was taken. To identify relevant failures the case company also provided information on event logs which included 14.0 million log entries. These log entries could be mapped to the sensor data providing information on performance critical events like automatically detected failures, manual emergency stops, and service actions. For the PdM prototype we focused on the most promising sensor in terms of delivering a unique detectable failure pattern. Together with the case company, the left side brush sensor was chosen accordingly indicating a motor damage of the car wash system's left side brush.

Second, *data preparation* was necessary, as it was not possible to automatically distinguish between technical failures and man-made event logs (i.e., emergency switch). Hence, we manually categorized all observations of the 536 car wash systems' data into incontrol or outcontrol based on sensor data, event logs, and interviews with the case company's service technicians. Over the course of data preparation, observations that could not be un-ambiguously classified (e.g., noise, missing data) were excluded leading to a final dataset of 1.7 million observations test set after data preparation. A binary variable was introduced being one for an outcontrol observation. In this context, incontrol means that the car wash system was operating as expected at least for the seven following days after the observation. Observations were labelled outcontrol, if a system failure occurred within the following seven days. In total, we found three system failures concerning three of the 536 car wash systems over the period of investigation. We categorized the previous week's observations as outcontrol accordingly.

Next, the algorithm-specific training sets and the overall test set were prepared to develop, train, and evaluate the algorithms with regards to car wash system failure detection. In this context, we defined failure detection as the algorithm detecting at least one outcontrol observation in the week before a failure occured. In other words, the detection of one outcontrol observation by the algorithm was interpreted as alarm – be it a justified or false alarm. First, the training sets were created. This was done simultaneously for ANN and SVM as they have similar requirements and secondely for HT². Both ANN and SVM require a training set that contains incontrol as well as outcontrol observations. As three car wash system failures in the overall data set did not lead to enough outcontrol observations to train ANN and SVM overall, we chose to synthesize and upscale the failures and corresponding outcontrol observations. Following Sun et al. (2007), we therefore, multiplied the original outcontrol variables and added randomly drawn standard normal values. Finally the ANN and SVM training set consisted of 250,000 observations with equally weighted incontrol and synthesized outcontrol observations including 20 failures to avoid an imbalanced training (Longadge and Dongre, 2013). In contrast, for HT², the training data set was built on 250,000 incontrol observations only. Finally, a disjoint test set was determined containing 1.2 million car wash system observations including 100 system failures and respective outcontrol observations. Again, the test set was based on the overall data set including, the three car wash system failures, that were synthesized and upscaled (Sun et al., 2007).

Third, *data analysis* comprised the actual development, training, and evaluation of the three algorithms applying the R (CRAN) packages as listed in Table 1.

Package	Algorithm	Applied methods in R (CRAN)
MSQC (Santos-Fernández, 2013)	HT^2	mult.chart
RSNNS (Bergmeir and Benítez, 2012)	ANN	mlp
e1071 (Meyer, 2018)	SVM	svm

Table 1. R packages used for algorithm development and evaluation

We applied statistical measures as well as the translation into an economic calculus for algorithm comparison. First, we derived and compared statistical prediction errors, i.e., alpha errors referring to system failures that were not indicated by the algorithm and beta errors referring to false alarms by the algorithm when no system failure would occur. Therefore, we applied an algorithm that compared the algorithms' failure detection results with the real historical states of the car wash system for all observations. Next, the statistical prediction errors were translated into an economic calculus by considering the different costs associated with the two different types of prediction errors (i.e., alpha error and beta error). This time, we simultaneously optimized HT^2 with regards to the prediction error sensitivity (i.e., alpha level) targeting the minimization of total costs as objective. Compared to the statistical perspective, this was possible as the negatively correlated statistical error measures were translated into a single cost-based objective function. The following *result interpretation* was supported by R (CRAN) visualizing the results. Further, a sensitivity analysis was provided for the economic perspective to sharpen our findings.

4 Model Setup

In the following, we introduce the model setup for determining statistical error measures for PdM algorithm selection as well as its translation into an economic perspective. For both perspectives we compare the three algorithms' performance with RM. RM serves as a benchmark representing the case company's current maintenance approach combined with PvM. We consider the measures related to RM as lower boundaries. Algorithms performing below this boundary should not be selected and implemented.

4.1 Determining Statistical Error Measures

As described in the previous section, first we evaluated the performance of the three algorithms applying statistical error measures. For this purpose, we considered a standard ratio for classification problems based on four model states resulting from the algorithms' prediction in relation to the actual state of the car wash system. As described above, each observation was classified manually as either incontrol (0) or outcontrol (1) and can therefore be depicted as observation vector $x_i = (x_{i,1}, x_{i,2}) \in \mathbb{R} \times \{0;1\}$. The first entry $x_{i,1}$ represents the actual sensor data (rpm). The second entry $x_{i,2}$ represents the corresponding actual system state, i.e., 0 for incontrol and 1 for outcontrol. The PdM algorithms build on the observation $x_{i,1}$ generating the prediction $f(x_{i,1}) \in \{0;1\}$ where 0 indicates that the algorithm categorizes the observation as incontrol, 1 indicates that the algorithm classifies the observation as outcontrol and, thus, indicates that a failure will occur within the next week. In other words, the detection of one outcontrol observation by the algorithm is interpreted as alarm – be it a justified or false alarm. Further, we define the weekly observation matrix $x = (x_1, \dots, x_D)$, where $D \in \mathbb{N}$ denotes the number of observations within one week and the weekly prediction function

$$F(x) = \begin{cases} 1, & if \sum_{i=1}^{D} f(x_{i,1}) > 0 \\ 0, & else. \end{cases} \quad (1)$$

For example, let the matrix $\tilde{x}$ comprise all observations in the week before a failure occurs, then it must hold that $\tilde{x}_{i,2} = 1, \forall i = 1, \dots, D$. The algorithm correctly detects the failure upfront if $F(\tilde{x}) = 1$ and ignores the failure if $F(\tilde{x}) = 0$. Depending on the actual system states, the algorithms´predictions for each weekly input matrix x are sorted into one of the following four model states, illustrated in Table 2.

Actual system state / **Algorithm prediction**	**No failure** $\exists\ i = 1, \dots, D\colon\ x_{i,2} = 0$	**Failure** $\tilde{x}_{i,2} = 1, \forall i = 1, \dots, D$
Alarm $F(x) = 1$	False negative (FN) - *Beta error*	True positive (TP)
No alarm $F(x) = 0$	True negative (TN)	False positive (FP) - *Alpha error*

Table 2. Four PdM model states, where x denotes the weekly observation matrix

To enhance the understandability of our model, Figure 2 illustrates the mathematical interpretation of all four model states by showing 17 exemplary observations and their actual categorizations in lines 1 and 2. In lines 3 and 4 example predictions of two exemplary algorithms are provided. Before a failure occurs, the algorithm can either detect at least one outcontrol observation within the weekly matrix $\tilde{x}$ (TP) or miss all outcontrol observations in the weekly matrix $\tilde{x}$ (FP/alpha error). If no failure occurs, the algorithm can falsely detect at least one outcontrol observation as a system failure in x (FN/beta error). If no outcontrol observation is detected, in x the algorithm correctly does not indicate a failure (TN).

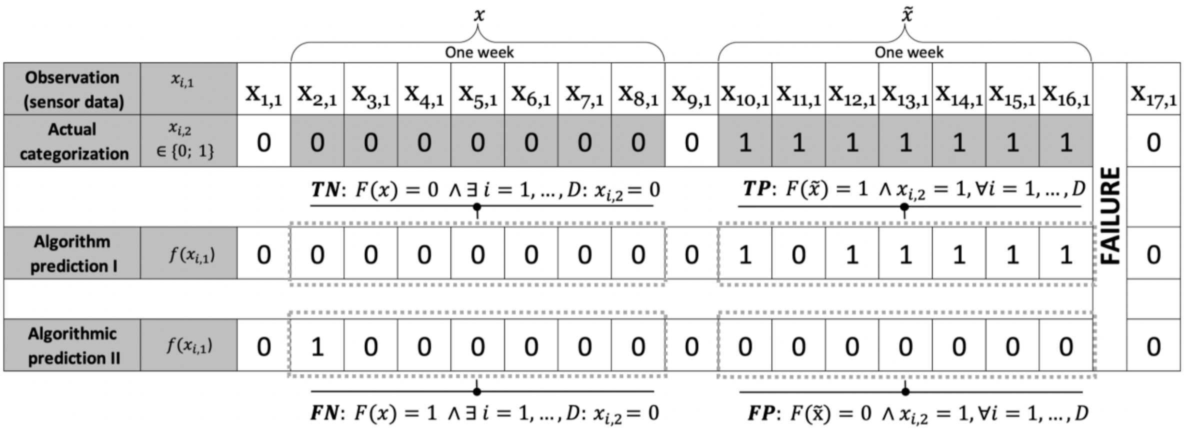

Figure 2. Four PdM model states in an example of 17 observations

To determine and compare the algorithms' performance from a purely statistical perspective, we relied on two error measures: the false positive probability (FPP) and false negative probability (FNP). Regarding HT², the frequencies of the prediction error types also depend on the selected alpha level. The applied evaluation metrics referring to FPP and FNP are defined as follows:

$$FPP = \frac{FP}{FP+TP} \quad (2), \qquad \text{and} \qquad FNP = \frac{FN}{FN+TN} \quad (3)$$

Like alpha errors and beta errors, FPP and FNP are also negatively correlated whereby ignoring more failures leads to a higher FPP and implies a lower FNP and vice versa. Hence, for RM there is an FPP of 100 % as no system failure is detected upfront. FNP is 0 as with no alarms there are no false alarms either.

4.2 Translation into an Economic Perspective

As already mentioned, the algorithm selection from a purely statistical perspective focuses on the probabilities of the prediction errors and may not lead to an optimal economic outcome. Therefore, we translated the two types of prediction errors into an economic perspective. This paper is focused on a cost perspective and builds onto a single cost-based objective function that allows for the un-ambiguous optimization within and among the algorithms. It is important to build the cost-based objective function on precise cost factors that suit the given case. The elements of the cost function are listed in Table 3 and refer to the previously introduced model states. The costs for every state were provided from the case company. The cost function is driven by four relevant factors: Travel costs (TC), check costs (CC), repair costs (RC), penalty costs (PC).

Actual system state / **Algorithm prediction**	**No failure** $\exists\ i = 1, \dots, D{:}\ x_{i,2} = 0$	**Failure** $\tilde{x}_{i,2} = 1, \forall i = 1, \dots, D$
Alarm $F(x) = 1$	TC + CC	TC + CC + RC
No alarm $F(x) = 0$	No costs	TC + CC + RC + PC

Table 3. Cost implications of four PdM model states based on the weekly observation matrix x

TC are defined as the costs for the service technician to physically get to the car wash system under consideration (Laporte and Nobert, 1981). For the case company, TC depend on the distance between the service technician's point of departure and the customer, the travel medium, as well as general route planning. TC can be calculated applying a cost factor per kilometre. CC represent personnel and material costs for the service technician's checking activities as well as the use of any special equipment. RC include personnel and material costs depending on the repair time and required components such as spare parts and special equipment. CC and RC on the one hand depend on the failure pattern and failure type. On the other hand, they are driven by local framework conditions and salary structures (Bender and Möll, 2009). For the case company, CC and RC mainly depend on the time required for problem diagnosis and solution by the technician which is driven by the type of problem (i.e. complexity). Lastly, PC consist of a contractual penalty to be paid as compensation for non-compliance with SLA, e.g., in the case of unforeseen system shutdowns (Goo et al., 2009). Further, loss of reputation due to reduced customer satisfaction might be considered as part of PC.

Overall, the four model states and four cost types lead to a total cost function depending on the weekly observation matrix x and the algorithms' predictions $F(x) \in \{0; 1\}$. For HT^2, the algorithm provides only the Upper Control Limit in dependence to the alpha level (UCL_α) and the test statistics T^2. If the test statistics for an observation is greater than the UCL_α HT^2 detects outcontrol ($f(x_{i,1})$ = 1 which implies $F(x) = 1$). If it is lower than the UCL_α, no alarm is given ($f(x)$ = 0). In contrast, ANN and SVM predict the states of an observation $x_{i,1}$ and the costs can be directly associated. The total cost function is depicted in Formula (3) comprising the relevant cost factors as described above. First, if an observation is truly detected as outcontrol, TC, CC for checking the failure and RC for repairing the car wash system occur. Second, if the PdM algorithm does not detect a system failure, PC need to be considered in addition to TC, CC, and RC because SLA are breached. Third, if the PdM algorithm falsely indicates a system failure TC and CC, but no RC, occur. Lastly, no costs occur if the car wash system is running as expected and no alarm is given.

$$Total\ Costs = \begin{cases} TC + CC + RC & if\ F(x) = 1\ \wedge x_{i,2} = 1, \forall i = 1, \dots, D \\ TC + CC + RC + PC & if\ F(x) = 0\ \wedge x_{i,2} = 1, \forall i = 1, \dots, D \\ TC + CC & if\ F(x) = 1\ \wedge \exists\ i = 1, \dots, D{:}\ x_{i,2} = 0 \\ 0 & if\ F(x) = 0\ \wedge \exists\ i = 1, \dots, D{:}\ x_{i,2} = 0 \end{cases} \quad (3)$$

Following Formula (3), total costs are calculated separately for each of the three algorithms' prediction results. While the prediction errors of ANN and SVM cannot be adjusted, HT^2 algorithm is optimized depending on the prediction error sensitivity (i.e. alpha level) as follows:

$$Total\ Costs^{HT^2} = \min_{\alpha \in (0,1)} Total\ Costs_\alpha^{HT^2} \quad (4)$$

This optimization process minimizes the total costs dependent on the alpha level. As the final HT^2 model, the most cost-saving model is selected for comparison and the related alpha level is chosen.

5 Empirical Results

For the development of the PdM prototype and the selection of algorithms we focused on the most promising sensor that indicates a motor damage of the left side brush. As elaborated, the tested dataset consisted of 1.2 million car wash system observations containing 100 failures to be detected. Discussions with the case company revealed that this represents a realistic failure rate with regards to this failure type. Before we present the results of the statistical error measures, their translation into an economic perspective, as well as the sensitivity analysis, we elaborate first on the specification of the cost function as well as second on the training of the algorithms below.

First, Table 4 depicts an overview of the case company's specific costs with regards to the introduced cost factors. For all costs German price levels are assumed following the case company's insights. Interviews with the service technicians of the case company revealed that a service technician usually travels by car from one assignment to the other and does not return to the point of departure until the end of the working day. The average distance for service technicians in Germany is 45 km associated with 0.3 Euro per kilometre. Personnel costs are included in CC (from journey to diagnosis) mainly depending on the time for problem diagnosis driven by the type and complexity of the problem at hand. The failure considered in this case refers to the motor damage of the left side brush, which a technician can diagnose in several minutes. Hence, CC are assumed to be comparably low accounting for 50 Euro. RC include the disassembling and replacing of parts of the car wash system which might take up to several hours. Thus, RC consist of the average costs of working hours related to repair and spare parts accounting for around 5,000 Euro. Finally, PC refer to an average contractual penalty of 6,000 Euro based on the case company's existing SLA in case of an unforeseen system breakdown. For reasons of simplicity we do not consider reputation costs beyond contractual penalties. Further, we only consider one specific failure pattern and, thus, the CC and the RC costs are assumed to be constants.

Cost factor	**TC**	**CC**	**RC**	**PC**
Costs in Euro	0.3*45=12.5	50	5,000	6,000

Table 4. Overview of case-specific cost factors

Second, to train ANN, we used a multi-layer perceptron with the classical backpropagation algorithm which was specified with three neurons per hidden layer. The number of hidden layers was one and it was automatically chosen by ANN. With regards to SVM only the type of classification ('C-classification') was specified (Meyer, 2018). Further, with regards to HT^2 the parameter alpha was optimized for the economic perspective according to Formula (4).

5.1 Statistical Error Measures

In this section, we present the statistical perspective on the algorithms' prediction performance. HT^2's alpha level is set at the most common level of 5%, as the negatively correlated alpha and beta errors cannot be jointly optimized. This is in line with the case company's general statistical approach. The resulting performance of the algorithms is depicted in Table 5 outlining RM measures for comparison.

Algorithm	**FPP**	**FNP**
ANN	0	40.20 %
SVM	40.00 %	0.06 %
HT^2	0	7.61 %
RM	100.00 %	0

Table 5. Results: Statistical error measures

As shown in Table 5, the statistical error measures do not allow for an un-ambiguous selection of algorithms. Both ANN and HT^2 identify all failures and have a FPP of zero, however, both algorithms generate false alarms. In contrast, SVM does not detect 40% of all failures, however, only generates a small percentage of false alarms compared to the other two algorithms. RM, for comparison, does not provide any predictions and therefore no false alarms either which leads to an FNP of zero. In conclusion, a decision maker would have to decide whether it is more favourable to detect all failures and generate a high share of false alarms, as with HT², or to generate less false alarms but also overlooking some failures, which would favour SVM. Hence, algorithm selection remains ambiguous and depends on the decision maker's preferences with regards to balancing statistical error measures.

5.2 Economic Perspective

In this section, we translate the statistical error measures into an economic calculus. Showing that a single cost-based objective function allows the optimization of individual algorithm parametrization as well as the un-ambiguous comparison among algorithms. Thus, we translate the error measures FPP and FNP into total costs. The results from the economic perspective are shown in Table 6. On this basis, the algorithms are compared, evaluated, and total costs depending on the alpha level are presented.

Algorithm	FPP	FNP	Total (calculatory) costs
ANN	0	40.20 %	32 282 385 €
SVM	40.00 %	0.06 %	756 347 €
HT²	0	7.61 %	663 775 €
RM	100.00 %	0	1 106 350 €

Table 6. Results: Statistical error measures and translation into costs

First, ANN detects all 100 failures. However, at the same time ANN generates a large rate of false alarms that are associated with unnecessary TC and CC. 40.20 % FNP referring to 1.2 million observations in the test data set implies that more than 450,000 false alarms would be given. Assuming that a full-service provider would actually follow all of these false alarms causing full TC and CC, more than 32 million Euro would accrue for the observed period of time. However, the comparison against RM costs shows on the one hand that a rationale decision maker would not implement ANN due to the inordinate number of false alarms. On the other hand, a rationale decision maker would neither send a technician to check on the car wash system almost every second car wash when a (false) alarm is given. Therefore, in the following we exclude ANN from further analyses as the implied economic results are obviously disadvantageous and even outperformed by the RM status quo. Second, SVM ignores 40 % of the failures and has a FNP of 0.06 %. This reflects the trade-off between the number of alpha and beta errors as not all failures are detected, however also much less false alarms are given compared to ANN. This leads to an economically advantageous result compared to RM with total costs of 756,347 Euro. During the simulation with HT², alpha levels between above 0 and 1 are tested as described above and corresponding costs are derived. In the following optimization phase, the optimal alpha levels ranging between 0.045 % and 0.06 % are determined. For this alpha level, the algorithm gives a false alarm in 7.61 % of the cases and ignores none of the actual failures. At the optimum alpha level range, total costs of 663,775 Euro accrue, which is un-ambiguously the best economic result.

Figure 2 shows, that HT² leads to the best economic result for a range of alpha levels between 0.002 % and 0.2 %. However, for an alpha level between 0 and 0.0002 % and for alpha levels greater than 0.2 % SVM performs better and for alpha levels greater than 0.5 % even RM is better. However, at the optimum alpha level between 0.045 % and 0.06 % HT² leads to cost-savings of more than 17 % compared to SVM as the second-best algorithm and more than 40% compared to RM. The jumps in the graph between 0 and 0.005% can be explained by local minima occurring when the number of beta errors increases, but the number of alpha errors does not decrease in equal terms. Thus, the increase in costs caused by beta errors outweighs the cost savings from reduced alpha errors.

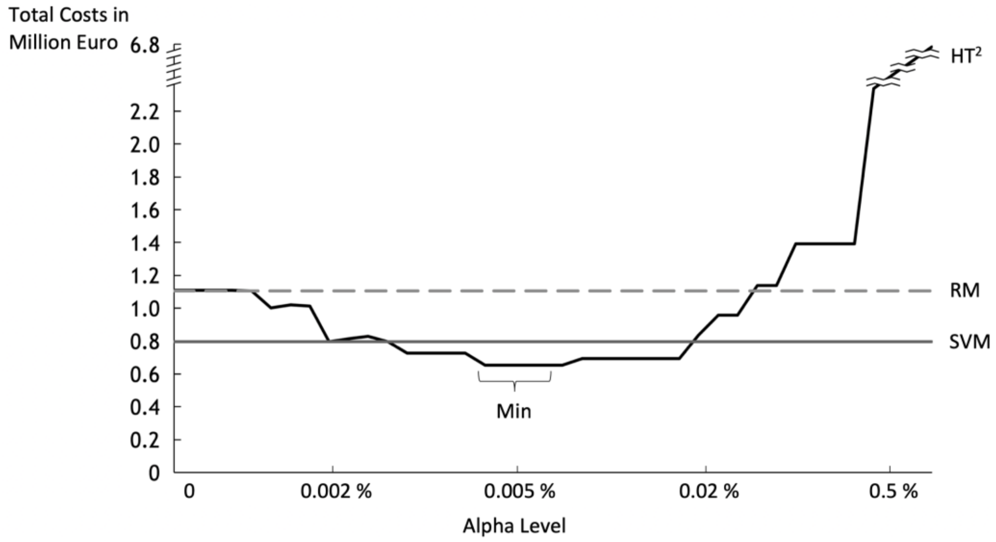

Figure 2. Total costs depending on the alpha level for SVM, HT², and RM

Our results demonstrate that an economic perspective allows for an un-ambiguous selection of PdM algorithms compared to statistical measures in an industrial full-service provider context. Depending on the decision maker's preferences with regards to the balancing of statistical error measures, the economic perspective changes algorithm selection and leads to significant cost savings in our case.

5.3 Sensitivity Analysis

In this section, we test the robustness of the depicted results through a sensitivity analysis. Therefore, we focus on varying levels of TC and PC as the two parameters with the largest deviations according to the case company. TC and PC usually highly depend on contractual negotiations, the customer network, and on country-specific distances between these customers. For example, travel distances in remote countries such as Australia may be much larger and require transportation such as helicopters. Table 7 shows the savings in percent for HT² compared to SVM and the sensitivity analysis with TC on the horizontal in Euro and PC on the vertical in Euro. As it can be seen, HT² outperforms SVM in nearly all cases when the PC are above 0. The two exceptions occur for very high TC (i.e., use of a helicopter instead of a car) as SVM produces less false alarms.

TC/km \ PC	0	6 000	20 000	100 000	1 000 000
0	-12.1%	21.8%	54.1%	86.4%	98.5%
0.3	-15.0%	19.1%	52.2%	85.7%	98.4%
1	-21.2%	13.3%	47.9%	84.1%	98.2%
5	-46.4%	-12.5%	26.9%	75.7%	97.1%
10	-64.7%	-33.8%	6.9%	66.0%	95.8%

Table 7. Savings in percent for HT² compared to SVM depending on TC and PC in Euro

Next, we consider above mentioned assumptions to find the best algorithm for different cost levels. Table 8 shows the best algorithm from an economic perspective for varying values of TC and PC. Again, TC are depicted on the vertical in Euro and PC on the horizontal. As the results in Table 8 show, in selected cases RM can be economically favourable compared to PdM. This is grounded in the fact that RM does not generate false alarms and associated costs. If there is a system failure, the maintenance provider will be notified. When PC are zero, costs associated with TP and FP are the same and therefore FN become disadvantageous compared to FP. Whereas a penalty of 0 and TC of 0 are not realistic, the optimized HT² outperforms the other algorithms for nearly all cases with PC above 0. The exceptions at

(5;6,000) where SVM is best and (10;6,000) where RM is best result from the high number of false alarms from HT² in combination with high TC and low PC. In summary, the results show that the selection of HT² as the most favourable algorithm is comparably robust from an economic perspective.

PC / **TC/km**	**0**	**6 000**	**20 000**	**100 000**	**1 000 000**
0	RM	HT^2	HT^2	HT^2	HT^2
0.3	RM	HT^2	HT^2	HT^2	HT^2
1	RM	HT^2	HT^2	HT^2	HT^2
5	RM	SVM	HT^2	HT^2	HT^2
10	RM	RM	HT^2	HT^2	HT^2

Table 8. Overview of best economic alternative depending on TC and PC in Euro

6 Discussion

Although PdM is recognised as one of the biggest cost levers to reduce maintenance efforts in the industrial context, the selection of appropriate PdM algorithms is hardly covered in theoretical literature and practical guidance is missing. The contribution of our work is the translation of statistical prediction errors of PdM algorithms into an economic perspective, thus enabling the cost optimization of PdM. To the best of our knowledge, this is the first economic perspective on algorithm performance in the PdM context and its implications on algorithm selection. From a theoretical standpoint, we found that algorithm selection from a purely statistical perspective may not necessarily lead to the optimal economic outcome as the two types of prediction errors (i.e., alpha error ignoring system failures versus beta error falsely indicating system failures) are negatively correlated, thus, cannot be jointly optimized, and are associated with different costs. In other words, a purely statistical perspective as suggested by Baptista et al. (2018) may not facilitate un-ambiguous algorithm selection and may not necessarily lead to the optimal economic outcome. Therefore, the economic perspective we propose translates the two statistical error measures into a single cost-based target function. This allows, on the one hand, optimizing algorithm parametrization for PCA/PCL algorithms (i.e., HT²) with regards to error sensitivities. On the other hand, cost implications of different PdM algorithms can be compared and the economically most favourable algorithm can be selected. Further, we demonstrated the disadvantages of the black-box PdM algorithms ANN and SVM that do not allow for the adjustment of prediction error sensitivities. HT^2, in contrast, provides access to internal structural knowledge and the algorithm's prediction error sensitivity can be adjusted via the parameter alpha, which negatively affects the beta error in return. In our case, this led to the maximum cost saving through an optimized trade-off between the costs associated with alpha and beta errors. This flexibility represents a relevant lever for economic optimization that black-box approaches do not provide. Therefore, the initially set alpha parameter was reduced from 5% to 0.005% to achieve minimum total costs. In this vein, HT^2 leads to cost-savings of more than 17 % compared to SVM as the second-best algorithm. This was found in a real-life case study, where we supported a European machinery company that builds car wash systems.

Further, our study provides practically relevant insights for the implementation and selection of PdM algorithms in an industrial full-service provider context. Although literature shows in manifold studies that PdM is economically advantageous (Gu et al., 2017; Xu et al., 2015), practitioners should be aware that PdM can be implemented through a range of different algorithms that are not only associated with varying prediction performances but as well with different costs. Our study shows that the selection of PdM algorithms from an economic perspective offers significant potential for cost savings that practitioners should consider. Therefore, practitioners should apply an economic perspective to select PdM algorithms ex-ante as well as to optimize PdM algorithms ex-post implementation while taking their business model and corresponding cost structure into account. Further, when considering PCA/PLS algorithms, such as HT², practitioners should be aware that the often-applied standard sensitivity (i.e., alpha level) of 5% might not lead to the economic optimum and therefore suboptimal parametrization of the algorithm or algorithm selection might give away cost saving potential. Hence, practitioners should optimize sensitivity with regards to cost implications when considering PCA/PLS algorithms. In addition, the comparison of different algorithms creates transparency in the introduction of PdM and can thus support investment decisions and increase acceptance. A PdM algorithm should only be implemented if investment and operating costs are over-compensated by cost-savings of PdM compared to PvM and RM. If a PdM algorithm already exists, practitioners should regularly rethink and potentially optimize algorithm specifications ex-post. In this vein, HT^2 leads to over 40 % of savings compared to RM. A growing database or new sensors can also change the data input and single cost-based objective function and, thus, the best selection of algorithm. It is therefore important that companies regularly check and question their algorithm selection and the respective parametrizations. This possibility of cost savings is transferable to other companies acting as full-service providers as well as to companies that bear the costs and risks for repairs and maintenance of their internal systems.

7 Limitation and Outlook to Further Research

In this work, we supported an European machinery company that builds car wash systems in developing a PdM prototype for one selected failure pattern. We leveraged the case company's sensor data of 4.9 million car washes to train, calibrate, and evaluate three types of algorithms (i.e., ANN, SVM, HT^2). By first applying a purely statistical perspective we demonstrated that an un-ambiguous selection among the three types of algorithms was not possible, where SVM and HT^2 looked comparably favourable. When applying an economic calculus, in contrast, HT^2 un-ambiguously led to the best economic outcome saving more than 40% of cost compared to RM and more than 15% compared to SVM. Therefore, we propose an economic perspective that translates the two negatively correlated statistical error measures into one single cost-based target function. This offers two-fold advantages: Optimizing algorithm parametrization on an individual level, for example with regards to HT^2 error detection sensitivity, as well as the comparison and un-ambiguous selection of PdM algorithms from an economic perspective.

As any research endeavour, our work is beset with limitations. First, the focus of our case study and PdM prototype is on one specific failure pattern with regards to the left side brush sensor delivering a unique detectable failure pattern. Further research should also consider more sensor data as well as the interaction between sensors. Second, this work evaluates three PdM algorithms exemplarily for three process history-based methods for PdM. In the future, a broader range of algorithms – including more sophisticated variants such as evolutionary algorithms – should be taken into account. Third, the case study was limited to a single machinery company acting as a full-service provider. Next, PdM algorithm selection should be examined for companies in other industries as well as beyond a full-service provider context. Fourth, an economic perspective is not only relevant for PdM algorithm selection but also for other predictive algorithms for example related to production planning or energy consumption. Hence, algorithm selection from an economic perspective should be investigated in other contexts as well.

In addition, our research also stimulates further research around algorithmic decision making and corresponding cost implications in general. For example, the influence of data accessibility, structure, and quality on prediction performance and costs should be investigated. Also, data security and potential risks within a company as well as between companies should be considered as a next step. Last, cultural aspects with regards to employee acceptance in relation to PdM and algorithmic decision making in general should not be neglected.

In conclusion, an economic perspective on PdM and algorithmic decision making in general will gain importance due to growing data availability and cost pressure. PdM reduces downtimes, optimizes maintenance efforts, and enhances customer satisfaction. We believe that this work is theoretically and practically relevant, and hope it provides fellow researchers with a foundation for continuing their research on maintenance decisions and algorithm selection for PdM.

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