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Expense and revenue factors of Smart Factories: analysis of the economic effects of Condition Monitoring

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Abstract. Numerous approaches for assisting Smart Factory implementations in production companies have been published over the last few years. However, guidelines for calculating the profitability of these efforts have barely been addressed by scientific approaches so far. This paper aims to close this research gap using the Smart Factory application Condition Monitoring as an example. Therefore, a framework of the expense structure, as well as a framework of accompanying effects on business processes and resources, are presented. Based on these frameworks a procedure to support the financial assessment prior to the actual implementation is proposed. This procedure enables decision-makers to follow a deductive approach when identifying the economic relevant factors of smart factory applications. The authors argue that the shift towards a descriptive character of effect assessment simplifies and precises the profitability calculation. The construct validity of the frameworks and the usability of the proposed approach are confirmed in two case studies in separate production plants of ZF Friedrichshafen AG.

Keywords: smart factory, condition monitoring, economic assessment

1 Introduction

Smart Factories are enabled by the evolution of Industry 4.0 and integrate the associated technologies within a production plant. Information and communications technology make it possible for employees, products and assets to exchange information in real-time.[1] Technology is used within the production processes which thereby are enabled to act context-aware and partly autonomous.[2] Production management is supported by enhanced data availability and decision-making assistance tools. The goal is to exploit the capabilities of digitalization in order to generate insights into business processes or to optimize them.[3] Since previous studies already determined purposeful measure identification and implementation approaches [4, 5] this paper addresses their vulnerability. Existing approaches and maturity models were investigated and a lack of assistance tools for performing an economical ex-ante evaluation was identified. The few existing guidelines follow an inductive approach to determine cost-effectiveness.[6, 7] As a basis for a deductive approach, the following research question must be answered: "What are the expense and revenue drivers of Smart Factory applications?" Due to the large scope of this research question, the subject of this paper is reduced to the economic impact factors of one specific Smart Factory application, namely Condition Monitoring (hereafter CM).

In order to implement a Smart Factory, actions can be taken in six consecutive categories. These are Computerization, Connectivity, Visibility, Transparency, Predictability and Adaptability.[8] CM can be assigned to multiple of these categories. Schuh et al. classify the application as a measure to gain transparency [8] whereas Fleischer et. al categorize CM into Computerization, Connectivity or Visibility depending on the setup in the specific use case.[9] Since CM covers a wide range of Smart Factory categories focusing on this application appears to be reasonable. An analysis of the verifiable expenses and revenues might reveal extensive insights into the economic impact factors of Smart Factories.

Choosing CM for the exemplary analysis is also justifiable by a practical approach. Service, maintenance and repair of production machines are essential activities in order to keep a manufacturing business running.[10] As the main goal of CM is to optimize the efficiency of these measures, this Smart Factory application might be beneficial to a brought range of enterprises. Furthermore, CM is a prerequisite for the AI application Predictive Maintenance [11] which is currently researched intensively by computer science studies. Therefore, it is likely that the importance of CM will be maintained in the future. This suggests that from a practical perspective, comprehensive knowledge of the economic impact of CM adds value.

2 Calculation Approaches

One barrier to Smart Factory investments in enterprises is the difficulty in calculating the profitability of single applications.[12] Orzes et al. explain this observation by lack of experience with the upcoming technologies, large sums of initial expenditures and uncertain cash returns.[13]

Existing guidelines for Smart Factory implementation mostly address methodical, technological and chronological aspects. Applicable methods regarding measure identification focus on how to pick suitable applications based on qualitative factors.[6, 11] Quantitative impact determination methods rely on an inductive analysis of the expected effort and benefit.[7] Performing such estimations is hard for inexperienced companies as expertise in smart factory implementation is required.[13] Multiple guidelines recommend using the Net Present Value calculation method [14] without providing further information. It can be stated that the calculation of Smart Factory applications is barely addressed by scientific approaches.

In this paper, a framework of categorized expense and revenue drivers is introduced. The framework represents the cost structure of a CM investment as well as its conceivable effect on business processes and resources. The authors took into account that intended as well as unwanted effects might occur. In contrast to the existing methods, the provided framework enables a deductive approach for effort and benefit determination. Users are guided through the relevant economic factors when considering an investment in CM systems. The explorative character of impact assessments changes towards a descriptive character.

The holistic listing of economically relevant factors reduces the need for prior experience in Smart Factory implementations. Detailed knowledge about the possible effects of an application is not necessary. Using the framework, it must be determined whether certain effects will have an impact in the specific setting of implementation. The authors state that this procedure simplifies the effect identification and therefore reduces hurdles to implement Smart Factory applications. The evaluation precision might also be optimized since relevant factors will not be disregarded. A reasonable investment calculation can be derived. Following the recommendation of Issa et al., it is suggested that a small heterogenous group of shopfloor employers and management members perform the proposed procedure.[7]

3 Method

The databases ScienceDirect, Web of Science, and EbscoHost are consulted for identifying the expense and revenue structure of CM use cases. The search terms are combinations of the words "Condition Monitoring" and "impact", "cost", "expense", "benefit", "revenue" or "calculation". 30 relevant papers are identified. In addition, documentation of actual use cases and their effects provided by the database of "Plattform Industrie 4.0" are considered. The search term "Condition Monitoring" returns eight listings in the manufacturing industry. Based on the obtained material, expense and revenue drivers of CM are determined. Therefore inductive category formation according to Mayring is carried out.[15] The obtained categories and the assignments have been modified within qualitative, partial-narrative, semi-structured expert interviews and two frameworks were compiled.

Verifying the determined expense and revenue factors as well as the suggested framework usage two case studies have been performed. Elaborating a structured procedure for the case studies the proposed procedure for effect identification was applied. Thereby functionality and applicability of the approach were evaluated. The case studies cover already implemented CM applications in different production departments of ZF Friedrichshafen AG. Accompanying economic effects of the considered CM application are analyzed retrospectively. The internal validity of the frameworks is assessed by the comparison of listed factors and observed effects.

4 Condition Monitoring

4.1 Types of Condition Monitoring

The literature differentiates two relevant types of CM. Solutions based on machine control signals as well as sensor-based signals can be identified. Machine state and processing data are available from the PLC. Further data might also be available on

the machine depending on the initial setup of the control unit. For data gathering, a collaboration with the machine vendor or PLC and communication protocol experts is carried out. Other relevant information can be obtained by attaching appropriate sensors. For this, ready-to-use solutions are available on the market. All incoming signals are getting processed by the CM system. Based on the connected data sources relevant insights can be generated. Feasible evaluations are trend detection, timer and counter implementation and are based on the definition of optimal operating modes deviation detection. Insights can be visualized or responsible employees can be alerted. Condition-based maintenance for the monitored assets is enabled. Typically monitored data points are listed in table 1.[16, 17]

Table 1.	Typical	data	points	of Condi	ion Monitoring
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Signal Source	Data points
PLC	currents, forces, machine states, pressures, positions, process
	parameters, speed, torques
External sensor	acoustic emissions, flow rate, geometries, material alteration,
	material stress, optical alteration vibrations
Possibly both	consumptions, temperatures, timestamps
signal sources	

4.2 Economic effects of Condition Monitoring

One framework lists all identified kinds of potential project expenses while the second framework is dedicated to possible effects on business processes and resources. The authors ensured that the Smart Factory application is considered both a conventional asset investment and an IT project. Both perspectives provide insights about possible expenses and revenues. Depending on the type and environment of the application some of the factors might not be relevant in specific settings. Figure 1 and figure 2 represent the frameworks.

Factor	Туре	Expenses
Asset connection	Hardware	additional sensors, PLC upgrade
	Workload	installation, PLC parameterization, signal interpretation, testing
Infrastructure	Hardware	infrastructure components, network components
	Workload	installation
More one-off		false alarms, licenses, efficiency losses due to the
expenses		learning curve, traveling expenses, training
Project efforts		project management, ramp-up
Recurring		licenses internel surport offerts energy consumption
expenses		licenses, internal support efforts, energy consumption
Software		data integration, programming, testing

Fig. 1. Possible expenses of Condition Monitoring

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Factor	Lever	Effect
Cost	Consumed goods	consumption of air pressure, consumables, energy, equipment, oil, tools, water
	Inventory	need for consumables, equipment, production assets, spare parts, tools
	Manpower	effort in maintenance processes, planning and scheduling, quality processes, operator waiting for machine
	Quality	amount of rework, scrap
	Services	need for external or maintenance services
Leadtime	Operations	availability, duration of documentations
	Quality	grade of automatization, duration of documentation, information availability
Output	Machine capabilities	processing speed, amount of rework and scrap
	Scheduled downtime	amount and duration of planned maintenance
	Unscheduled downtime	amount and duration of breakdowns, waiting / searching for information, waiting / searching for spare parts

Fig. 2. Possible effects of Condition Monitoring on processes and resources

With the established frameworks, the prerequisite for the deductive determination of relevant economic factors of CM is given. The practical relevance of the determined factors as well as the feasibility of the framework usage has to be validated.

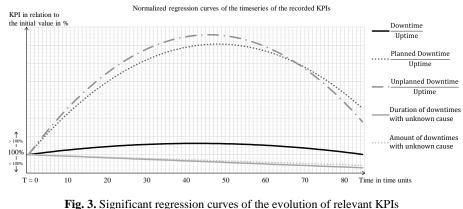
5 Validation and evaluation

Use cases where several signals are monitored, a group of multiple production assets is connected, the responsible employees are amenable and actual measures have already been derived from the gathered information were considered for the case studies. Furthermore, a prerequisite for the quantitative analysis of the profitability is that the required data is available for periods prior to implementation.

In order to show the construct validity two use cases have been chosen. Both types of CM applications are represented. While the sensor-based solution is analyzed in the heat treatment department of a European site, a manufacturing plant in Asia provides a PLC-based solution. The solutions have been fully integrated into the business processes. A total of nineteen production assets are part of the observation.

The case studies started with a narrative interview with the respective project leads. The authors determined the initial cause of the CM implementation, the organizational and technical realization, the integration into daily business processes and the achieved effects. Factors known to affect the economic viability of CM have been recorded and quantified as far as data was available. A second interview was structured based on the introduced frameworks. The appearance of the listings was assessed by the project leads and one production manager. The qualitative validation was completed by a process chain analysis based on data logs and documentation.

The quantification of the expenses was carried out based on statements from the interviews, archival materials and additional documentation. For the quantification of the effects on business processes and resources, a time series analysis of descriptive KPIs was performed. The impact on the retrievals and the lifecycle of spare parts, the uptime of production machines and the occurrence of maintenance tasks were observed. Significant results ($\alpha \le 0.06$) are shown in the following figure.



(Axes are unlabeled for reasons of confidentiality)

A correlation between the implementation of the CM application and the observed KPIs is evident. The analysis reveals that after the completion of the CM implementation downtime in relation to the uptime rises at first. As the usage of the system is established, a decline in downtime due to maintenance reasons is determined. After 85 time units, the initial ratio of down- to uptime is restored. The extrapolation of the regression curve shows for future time units that further optimization is likely.

At the beginning of the CM usage more planned stoppages occur due to misinterpretations of the gathered data and wrong intervention limits. Unplanned stoppages rise due to the same reasons. Not having all the relevant information to derive proper actions also leads to unplanned stoppages. False-positive and false-negative alarms can be observed. A high trust level in the system operationalizes these false alarms into downtimes. Knowing the characteristics of the monitored asset and the CM system itself, the usage is adjusted. From a certain date on, a decrease in downtimes results. In contrast, the amount and duration of machine stops with unknown causes decrease from the beginning on. The derived measures act preventively. Additionally, the causes can now be determined by the available data and are not unknown.¹

The obtained results from the quantitative analysis can be comprehended relying on the experts' statements. Although other optimization measures took place at the same time, none of them were focusing on key maintenance performance indicators as CM did. The observed KPI evolution can at least partly be led back to the implementation of CM. Based on the consistent observations the authors consider their methodological approach to identify the relevant expense and revenue factors and the derived frameworks as justified.

¹ The given explanations for the KPI evolution are derived from the expert interviews.

6 Conclusion

The performed approach allows the following conclusions to be drawn. It was determined that the initial decisions to introduce CM were made based on quantitative, qualitative and strategic considerations. Neither of the two use cases were calculated with the inclusion of all relevant economic factors. Incomplete consideration of effects can lead to biased decisions. The need for well-founded calculation guidelines has been confirmed. Based on the shown evidence in Chapter 5, it is reasonable to integrate the concept of experience curves [18] in the calculations.

The economic factors identified in the considered case studies can be fully described by the presented frameworks. The internal validity of the frameworks was strengthened. The chosen conceptual approach for determining the expense and revenue factors appears to be appropriate. Factors that were derived from the literature and which were not evident in the cases have not been discarded from the frameworks. These factors may be relevant for other settings of CM implementations.

In the case studies, the proposed approach was applied for the ex-post identification of economic effects originating from CM applications. The applicability as well as the functionality of the approach were shown. According to the authors, this conclusion is transferable to ex-ante analyses.

Expenses and payment arrangements for the most common variants of the considered Smart Factory application have been recorded. The authors conclude that the supposed approach based on the presented frameworks is suitable for supporting an analysis of CM applications. According to the provided justification, CM is considered a representative of Smart Factory applications in this paper. Nevertheless, the external validity of the approach cannot be fully argued. The constraints are determined based on the categorization of Smart Factory applications according to Fleischer et. al. [8]. Due to the similar purpose of applications within one Smart Factory category, the validity of the framework for other applications associated with Computerization, Connectivity Visibility or Transparency is likely. Limitations regarding the transferability to other Smart Factory categories cannot be specified.

The observed effects also depend on the business environment. Liebrecht argues that a correct classification of the observations is achieved by considering production type and level of automation.[11] The provided results were generated in production processes which can be assigned to a small-batch production of industrial gear units. Compared to the KPIs of the automotive industry the cycle time of the products is large, the number of produced units and the number of produced variants is low. The production type can be identified as balanced between quantities and variants. The production is organized with a balanced level of automatization. The transferability of the frameworks to other business environments is not readily possible.

The frameworks focus on monetizable factors of a Smart Factory application. According to Hoitsch, the goal of productions might also include social or environmental goals.[8] Exclusively qualitative determinable effects of CM have not been analyzed in the case studies and are not yet included in the frameworks.

Further research is necessary to meet the identified constraints and extend the applicability of the frameworks.

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