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SIMULATION-BASED EVALUATION OF IMPERFECT PREDICTIVE MAINTENANCE MODELS IN DISCRETE MANUFACTURING: A PROCEDURE MODEL AND CASE STUDY

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ABSTRACT

The performance and reliability of production systems is greatly affected by sudden breakdowns. In order to avoid these unforeseen interruptions, predictive maintenance (PdM) systems are being widely used to predict failures and prevent outages by maintenance. The performance of PdM systems however depend heavily on precision and recall of prediction results. In the worst case, missing or false alarms can actually worsen the performance of an production system instead of improving it. We present a new procedural model which specifically focus on the imperfection of such PdM systems and estimate the impact of this unwanted property on the performance and economic aspects of a production system. The model is presented in all steps needed for implementation and evaluation and demonstrated in a realistic use case examining an interlinked production system with a simulation-based approach.

1 INTRODUCTION

Manufacturing industry is faced by fluctuating markets and cost pressure of global competition. To remain profitable, a high reliability and availability of the underlying production system (PS) is crucial. Maintenance plays an important role for ensuring reliability, particularly in large interconnected and automated PSs with minimized inventories. Following Matyas (2022), maintenance costs in European and American mid-size companies exceed 4% of the equipment's acquisition value on average. Maintenance expenses can reach up to 70% of total production costs or even exceed annual net profits (Madu 2000). While higher maintenance intensity increases costs, it also enhances reliability and reduces production losses. Hence, the challenge for maintenance and production planning and control is to find the optimal maintenance intensity and strategy mix which allow for a maximum level of reliability and minimizing overall production costs.

Historically, machines, equipment and tools required maintenance due to wear. During the first industrial revolution, corrective maintenance was the primary strategy for addressing breakdowns (BDs) or worn-out equipment. As equipment faced strain and loads, preventive maintenance was introduced to periodically extend the equipment's remaining useful lifetime (RUL) (Sherwin 2000). Nowadays, critical equipment's condition is often monitored by sensors and computerized maintenance management systems. Condition-based maintenance CbM plans and performs maintenance actions based on wear or deterioration, aiming to avoid sudden BDs and increase equipment's availability (Poór et al. 2019). Following Achouch et al. (2022), not only collecting information on the condition, but also predicting an equipment's condition became subject to research and industry during the last two decades. The advent of Industry 4.0 has seen a rapid increase in publications proposing predictive maintenance (PdM) models for industrial applications.

PdM strategies maximize equipment life and prevent unplanned downtime by converting corrective maintenance into planned actions. Following (Achouch et al. 2022), PdM models include condition-based maintenance (CbM), prognostics and health management (PHM) and RUL assessment. CbM gather indicators of equipment's condition, PHM assess deterioration and future condition, and RUL estimation models provide long run information for planning and optimization. As the time horizon may be very long, these models often contain confidence measures representing accuracy and precision. All models rely on sensing or non-sensing technologies, signal processing and monitoring to supply physics- or data-based prediction models (Gutschi et al. 2019). Physics-based models use mathematical principles and expert knowledge, while data-based models employ artificial intelligence (AI) or machine learning (ML) to explore relations between data and RUL (Carvalho et al. 2019). Implementing PdM involves defining the operational model, collecting and processing data, and implementing a decision support system (Florian et al. 2021). However, successful industrial PdM applications face four major challenges (Achouch et al. 2022).

1. Financial and organizational challenges: The implementation cost of a PdM system depends on factors, such as: complexity of the equipment; sensors; knowledge extraction; infrastructure; existing competences and expertise; consulting; etc. Profit oriented companies will assess each new investment extensively while the economic benefit is often hard to evaluate.
2. Data source challenges: The availability and quality of relevant data for predictions is crucial. Sensors and other data sources may provide incorrect data or fail themselves. Human documentation of relevant data may be inaccurate as well. These factors degrade the quality of prediction models and raise the possibility of missed alarms (false negative (FN) predictions) and false alarms (false positive (FP) predictions) (see e.g. Dalzochio et al. (2020)). Both FNs or FPs result in higher costs due to unplanned downtime or wasted RUL and too early investment in spare parts.
3. Machine repair activity challenges: Today, maintenance is mainly performed by humans and the quality and effectiveness of maintenance actions depend on the skills of existing maintenance resources. This proper known problem is unsolved and maintenance actions may result in conditions from as good as new to as bad as broken (see e.g. Pham and Wang (1996)). Research initiatives on self-awareness and self-care already exist, but they are not industrialized today.
4. Challenges of industrial PdM models: For successful long term application of PdM models, they have to be installed, integrated and updated continuously. After PdM models are developed and tested, they can be integrated into industrial applications for monitoring. In industry, the deployment of PdM models is mainly managed by IT-teams, which are usually not involved in R&D, nor know the special requirements of maintenance staff. For continuous retraining and model updating feedback loops must be designed. Compared to traditional software, updating PdM models mean changing the code, models and data simultaneously, which require expert knowledge and high skills.

This paper presents a new procedural model for the implementation of PdM in discrete manufacturing PSs that enables a quantitative evaluation as well as a case study demonstrating its application. First we present criteria when and where PdM should be implemented and secondly a model for evaluating real-world PdM models and assessing their capability to predict all BDs correctly.

The paper is organized as follows: Section 2 provides background information on PdM such as deterioration modeling and a short review on economics and simulation studies for PdM evaluation. Section 3 presents the procedure model for implementation prioritization and evaluation of PdM in real-world PSs. In section 4 a simulation-based evaluation of a realistic case study applying the procedure model is presented. Finally, we concludes with a discussion and outlook for further research in Section 5.

2 BACKGROUND

This section provides an overview on PdM models, prioritization strategies for interlinked PSs, failure and deterioration models, economic models, and the role of simulation for evaluating imperfect PdM models.

2.1 Predictive Maintenance and Basic Performance Indicators

PdM implementations aim to keep systems in an operational state as well as to increase availability and reliability. These goals are achieved by planning predictive maintenance activities that are performed before sudden BDs occur. Peng et al. (2010) classified prognostic models into four different domains: physical, knowledge-based, data-driven, and hybrid models. While physical models describe health related influences and processes to determine the deterioration of equipment, knowledge-based models are applied when information is lacking and are based on expert knowledge or fuzzy logic. Data-driven models are divided into statistical and AI models. Statistical models are designed by e.g. regression or state space models and can thereby seen as white box models. In contrast, AI approaches rely on ML and often act as grey or black box model. Hybrid models are combinations of different approaches.

Data-driven and especially AI models are considered powerful tools for accurate predictions and have attracted much attention in recent years due to improvements in maintenance and cost savings (Peng et al. 2010; Lee et al. 2013; Achouch et al. 2022). In general AI approaches are very powerful for developing intelligent prognostic algorithms, which are capable to handle multivariate data and extract hidden relationships of given information (Achouch et al. 2022). However, information in real-world is often incomplete, inaccurate, or even erroneous, which is an unsolved problem for industrial applications. This has significant impact on the performance of predictive models.

State-of-the-art performance indicators range from precision and recognition to f-measure and ROC (Powers 2011; Stehman 1997). These indicators rely on a confusion matrix, which consists of real positive (P e.g. a BD) and negative (N e.g. no BD) conditions (Spiegel, Stephan and Mueller, Fabian and Weismann, Dorothea and Bird, John 2018). When predicting these conditions, the result could either be predicted positive (*PP*) or predicted negative (*PN*). If the predicted condition matches reality, the result is classified as true (true positive (TP), true negative (TN)), otherwise as false (FP, FN). With respect to PdM this may be interpreted as follows: TP denotes a prediction of a BD which really occur; TN a prediction of no BD and no BD occur; a FP or type I error predicts a BD but no BD occur; a FN or type II error predicts no BD but a BD occur.

2.2 PdM Implementation Prioritization

Installing PdM systems involves large investments. In order to invest capital such that the desired return on investment (RoI) is maximized, a criticality analysis of the entire PS with all failure-prone subsystems should be considered for prioritizing PdM implementation. Therefore, decision rule matrix, FMECA and bottleneck detection are presented. The selection or combination of methods for prioritization depend on the data availability, interlinkage complexity, and maintenance documentation of the considered use case.

Labib (1998) published a decision rule matrix for suggesting maintenance strategies based on failure frequency and downtime. Following this rules, just BDs with low occurrence probability but high downtime cause should be considered for PdM. This basic rules are excellent for single-station PSs, but when applied to interlinked PSs this approach neglects dependencies between BDs and overall PS performance.

A general approach considering the impact of certain BDs on the PS is failure mode, effects, and criticality analysis (FMECA) (Thoppil et al. 2019). Equipment is split into functional units (FUs) and possible failure modes are analyzed. A risk prioritization number is calculated by assessing and multiplying the severity, occurrence, and detection factors. Although the severity of BDs in interlinked PS is included, the validity of the assessment could be improved in the era of Industry 4.0 by a quantitative approach.

Production data acquisition enable bottleneck detection algorithms, which are powerful tools in detecting bottlenecks limiting the throughput of PSs. These algorithms can be static or dynamic, depending on their applied time horizon. Dynamic algorithms are based on analysis of short time periods representing a prioritization for maintenance task scheduling. Static algorithms analyze long time horizons and represent long term bottlenecks, which indicate a prioritization for the implementation of PdM to increase e.g. the throughput. Common static bottleneck detection methods are average active period (AAP) method (Roser et al. 2001) or blockage and starvation probabilities (BSP) (Kuo et al. 1996). AAP compares the average duration of machines active (work, in repair, changing tools, serviced) and inactive (waiting for part, service, or blocked) states. BSP analyze buffer levels and assume bottlenecks between empty downstream and full upstream buffers. For further details and methods the reader is referred to Roser and Nakano (2015).

2.3 Failure and Deterioration Modeling

For PdM evaluation, production machines can be modeled by FU which are suitable for PdM. All these subsystems deteriorate and cause BDs of the entire machine, if their condition falls below a critical limit. Modeling deterioration is therefore crucial and often represented by failure rates. A failure rate is defined as the probability of a certain system which fails within a specified time interval (Stapelberg 2009). They can be modeled by commonly known distribution functions (e.g. Exponential or Weibull). The Exponential distribution is defined by a single scale parameter (η) and is applicable for systems with constant failure rates. In contrast, the two parametric Weibull distribution is defined by a scale (η) and a shape parameter (β), describing whether the failure rate is decreasing ($\beta < 1$), constant ($\beta \approx 1$), or increasing ($\beta > 1$).

Deterioration modeling is based on a PF-curve representing the condition of a system over time (Moubray 1991). The system fails at point (F) and the potential failure is discoverable at point (P) (compare Figure 1 (a)). Due to real world prognostics, predictions may result in too early alarms (P_I) which wastes RUL (F_I) or too late alarms (P_{II}) which results in corrective maintenance at time x instead of the predicted F_{II}. The condition decreases by a deterioration rate, which can be dependent on machine states (e.g. production, idle), the machining process (e.g. rough or fine), or even the raw material (e.g. pores and blow holes in cast material). To deal with this, the deterioration rate can e.g. be modeled by a continuous time Markov chain (CTMC) that allows for dependencies on the machine state and random shocks (Xiang et al. 2012; Zhu et al. 2015). Figure 1 (b) shows a CTMC with deterioration rates for machine states (r_b during BDs; r_i during blocked and starved; r_p during normal production; r_{p_s} during production under shock conditions). Further, transition rates ($q_{p,p_s}, q_{p_s,p}$) allow for shock modeling while the machine is in production state.

2.4 Economics of PdM

Evaluating the economic benefit is crucial to determine whether implementing PdM brings profitability or competitive advantage. Commonly used metrics are RoI, net cash flow, or cost benefit analysis (CBA). All metrics rely on factors which are hard to evaluate such as "savings realized with PdM" or "increased throughput". Furthermore, the influence of prediction errors type I & II adds even more complexity to this analysis. For example, Chang et al. (2013) evaluated RoI by implementing PHM in LED lightning systems with different failure distributions. Goodman et al. (2005) published a methodology for quantifying RoI for prognostics in electronics. They focused on single units (aircrafts) and added FP costs in terms of increased maintenance, req. spare parts and downtime. The PdM literature review of Miller, Kyle and Dubrawski, Artur (2020) categorizes studies by single component machines including several interacting components. They conclude that cost analysis, unlike technological research, is understudied and research focuses mainly on individual components rather than complex systems. In addition, Compare et al. (2019) states, that economics of PdM should be linked to the real performance (e.g. recall ($\frac{TP}{TP+FN}$) and precision ($\frac{TP}{TP+FP}$)) of PdM.

2.5 Simulation

Simulation models are used in maintenance for numerous purposes, including strategy selection, scheduling, staffing, inventory management, reliability, etc. Evaluating the performance of PdM based on its imperfection still seems to be in its infancy and few authors have dealt with it so far. Turan et al. (2020) proposed a simulation-based optimization for maintenance planning, including workforce capacity, spare part stocks and scheduling priorities. Meissner et al. (2021) published an evaluation approach for prescriptive maintenance on aircraft tyres, focusing on reducing average waiting times of an aircraft fleet, limited ground resources

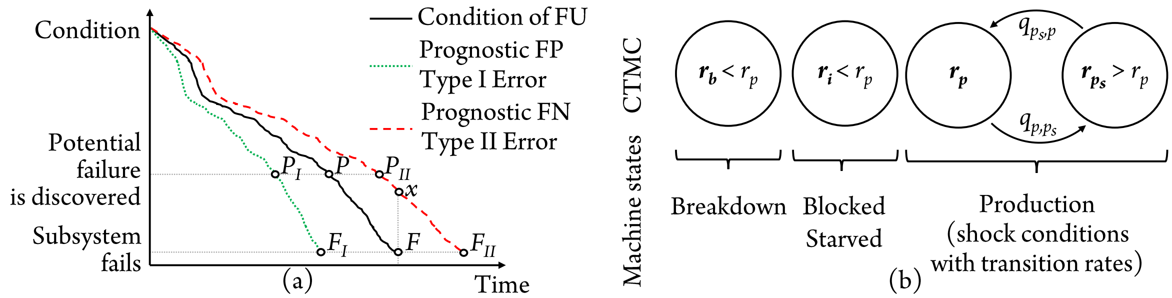

Figure 1: (a) PF-curve including type I and II errors; (b) machine state dependent CTMC.

and conclude for future work to include technological maturity parameters (e.g. missed alarm rate or accuracy), imperfect execution, or staff travel times. Busse et al. (2019) presented a CBA on different PdM maturity levels applied on a single component machine model. While they included FN and FP predictions via accuracy and precision, they modeled only downtime which can be covered by PdM and neglected implementation cost. A ML-based cost-oriented model for PdM implementation was published by Florian et al. (2021). They included FN and FP as imperfection of PdM in their cost model and tested their approach in the process industry. There is research dealing with performance dependent evaluation of imperfect PdM but mainly on individual machine models. In discrete manufacturing PSs the problem of interlinked machines with intermediate buffers arises. Therefore, performance evaluation of PdM must be applied on the entire PS rather than on individual machines to assess significant impacts on e.g. throughput.

3 PROCEDURE MODEL

In this section, we present an approach for prioritization of implementation, modeling and simulation-based evaluation of the performance of imperfect PdM in discrete manufacturing. First, we define the problem and objectives for which the procedure model is intended before describing all steps in detail.

Production systems consist of interlinked operating sequences (OSs) with buffers in between. Each OS performs a certain production process and they should have almost equal cycle times c_t in order to enable balanced production. To obtain similar c_t, each OS consists of either a single machine or several in parallel working machines. Conveyor belts or automated guided vehicles create the material flow between OSs and buffers (on belt or dedicated) compensate for minor fluctuations caused by short-term interruptions or BDs. BDs may have several reasons, interrupt a certain function and force a standstill of a machine. In real world PSs, a certain PdM system is implemented at a functional unit (FU) of a machine and is capable to cover some, but not all, causes for BDs. The impact of PdM on the PS additionally depends on the machine applied and its bottleneck behavior. Here, the benefit to the performance and reliability of the overall PS can range from little to significant, depending on where PdM is applied. Understanding the behavior of a PS is already a complicated task, but the imperfection of PdM models adds to the complexity. On the one hand, a perfect PdM would enable maintenance scheduling to transform unplanned BDs to planned maintenance tasks of shorter duration. On the other hand, prognostics are not 100% accurate and when applied in real-world conditions where, for example, data quality is poor or documentation is lacking, further deductions must be considered. Poor prognostics performance result in FP or FN predictions. A FP means that maintenance work is carried out too early and too often, thus wasting RUL and operating and work time. FNs predictions may be even worse because PdM is implemented but BDs are not predicted. They result in reactive tasks of longer duration and unplanned downtime blocking the entire PS in the worst case. Concluding, imperfect prognostics mean that money is spent on a system and, in the worst case, it performs poorly without any benefit for the performance of the overall PS. Therefore, a detailed evaluation of the impact of PdM on the overall PS, including imperfect prognostics, is essential for investment decisions.

The objective of the presented procedure model is to evaluate the impact of imperfect PdM models on the performance of overall PSs quantitatively. The simulation-based evaluation allows to define and

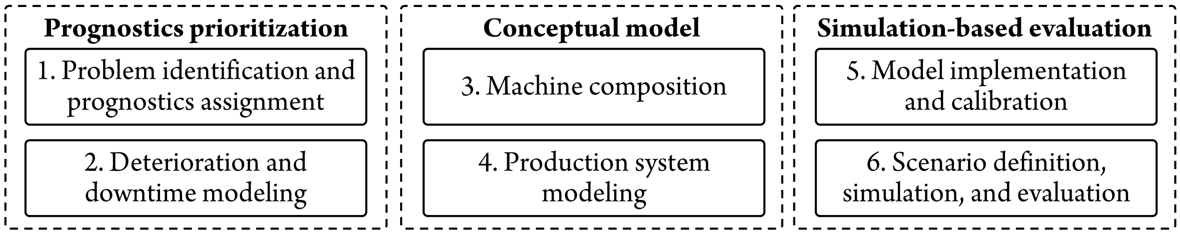

Figure 2: Procedure model for performance evaluation of PdM implementations.

measure all relevant indicators that serve as a basis for further economic assessment of investments in real-world PdM-systems under the risk of type I and II errors. Therefore, it guides through the processes of prognostics prioritization, conceptual modeling, and simulation-based evaluation (compare Figure 2).

The goal of prognostics prioritization is to select appropriate machines and FUs to implement PdM (step 1) and to model deterioration and downtime allowing for imperfect prognostics assessment (step 2). In step 1, system boundaries (e.g. a production line) are drawn and critical elements are identified (compare Section 2.2). Bottlenecks can be determined by static bottleneck analysis and by investigating their downtime, major causes for BDs are identified. BDs are split into minor and major, where the cause of major BDs is suitable for PdM (compare Section 2.2 and Labib (1998): low occurrence probability and high downtime) and machines are split into FUs according to causes of major BDs. Step 2 deals with deterioration and downtime modeling. For creating a deterioration process of a FU, at first a state model of the machines has to be defined for state dependent deterioration. For example, Figure 1 (b) shows a CTMC as the deterioration model mapped on several states.Further, shock conditions may lead to worst deterioration and may be triggered by the simulated part or a transition rate $q_{i,j}$. The resulting condition $c_{real_i}(t)$ represents the real condition of the FU and the deterioration rates r_s can be calculated by the total duration of all states, the transition rates $q_{p,p_s}, q_{p_s,p}$ and the mean time to failure of the FU. To represent the monitoring system, a second condition $c_{mon_i}(t)$ is introduced which triggers maintenance tasks. To model imperfection $c_{mon_i}(t) = c \cdot c_{real_i}(t)$ and can lead to three different outcomes at point F, where $c_{real_i}(t)$ force the machine to break down:

1. $c \approx 1$: the monitored and real condition are equal and a prediction result in a TP.
2. $c < 1$: the monitored condition is worse than real and a prediction result in a FP.
3. $c > 1$: the monitored condition is better than real and a prediction result in a FN.

c controls the imperfection and the outcome of a PdM system. Further, it is assumed that possible BDs can be detected at point P and consequently the downtime of the machine is depending on the PdM outcome. The entire maintenance process consists of a preparation process (PreP) and effective repair process (RepP). During the PreP, (1.) a BD has to be detected, (2.) maintenance staff has to be notified and their appearance must be waited for, (3.) the failure cause has to be diagnosed, and (4.) required spare parts have to be procured. During the RepP, (5.) the maintenance task is executed and (6.) the machine must be tested and set up to fulfill its role in the PS again. Thereby the downtime of TP and FP will just include the RepP while downtime for FN will result in a corrective task and include both, PreP and RepP. Duration for PreP and RepP can, for example, be modeled using a triangular distribution $tri(t_{min}, t_{mode}, t_{max})$. These steps are repeated for all FUs and the remaining minor time between failure TBF_{minor} can be fit to an e.g. Exponential distribution $exp(\eta)$. The duration of the maintenance process for minor BD TTR_{minor} can be fit to e.g. $exp(\eta)$. In addition, all defined major and minor repair processes can require entities (staff, skills, equipment, tools, spare parts).

In the phase of conceptual modeling, machines are composed due to their failure behavior. The PS is modeled by OSs and material handling as well as buffers in between. For step 3, each machine M_i is composed by n $FU_j(c_j) = FU(c_{real_j}, c_{mon_j}, BD(PreP_j, RepP_j))$ and minor BDs with their according condition or distribution to trigger major and minor BDs: $M_i = \left\{FU_1, \ldots, FU_n, \{TBF_{minor}, TTR_{minor}\}\right\}$. The

PS modeling of step 4 includes the definition of the structure, production planning and control, maintenance planning and control, as well as a list of indicators for evaluation and economic assessment. The definition of the PS's structure includes all OSs with their M_i, material handling and buffer sizes. Production planning & control defines the production input and schedule. Maintenance planning & control includes prioritization rules, resources management and skills, as well as spare part inventories and order policies.

In step 5, the model is implemented and calibrated to match reality. All predictions are disabled to simulate a scenario where all predictions result in corrective actions. With the final calibration, indicators such as the production throughput of the overall PS and technical availability of each machine can be taken into account. Finally the procedure model ends with a scenario definition, multiple simulation runs of each scenario to reach statistical confidence and evaluation.

4 CASE STUDY

This section demonstrates the procedure model from Section 3. Therefore, a simulation-based evaluation of a PS represented by a single production line is assessed. First, the objective and conceptual model including inputs, outputs and all model content is presented in Section 4.1. Then, in Section 4.2 scenarios containing imperfect prognostics are defined and results are presented.

4.1 Simulation Model

In this section, a detailed description of the simulation model based on the Hierarchical Control Conceptual Modeling (HCCM) framework is given (compare Furian et al. (2015)). After defining the problem and objectives, input and output measures are listed in sections 4.1.1 and 4.1.2. Then, the content of the simulation model including all modeled entities, processes, and control structure are presented in 4.1.3.

While the general problem and objective is defined in Section 3, we created an artificial PS with realistic downtime and loss causes to demonstrate the procedure model. Figure 3 shows the PS for PdM evaluation consisting of 15 OSs and 14 buffers in between the OSs as well as their cycle times c_t. The buffer capacities are defined by the length of conveyor belts connecting the OSs and no extra buffers are implemented.

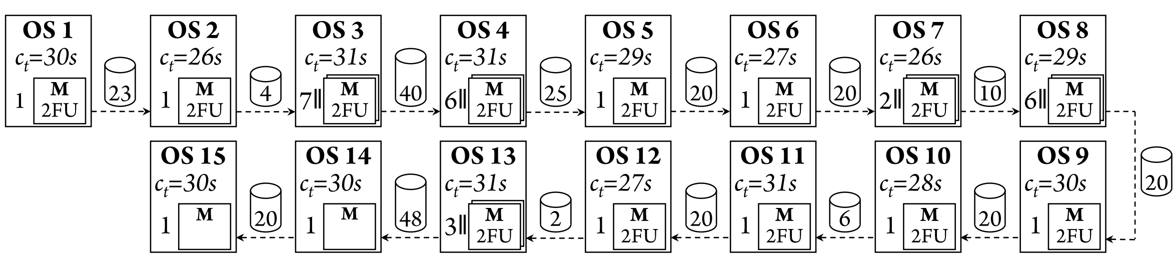

Figure 3: The PS for demonstration purpose consisting of 15 OS and 14 buffers. Each OS has a cycle time c_t and contain at least one machine (M). Machines may further contain FUs, which are suitable for PdM.

Each OS is either constructed of a single or several machines (M) working in parallel (||). Most of them have suitable BD causes for implementing PdM which are given by the number of FUs. They are defined as major BDs and all other BDs are defined as minor BDs. Minor BDs cause production losses and reactive maintenance. Major BDs are suitable for PdM and when perfect PdM is applied to them, they are planable and can be resolved in non-production time. When imperfections occur, impending BDs are resolved in the case of FPs in the non-production time with the loss of RUL or in the case of FNs are not detected and end in reactive maintenance. Thus, minor and reactive major BDs are affecting production throughput.

The objective is to evaluate the overall performance of the PS as a function of different numbers of perfect PdM implementations. Moreover, minimum requirements for PdM system imperfection (ratio of FPs and FNs prediction outcomes) should be identified in order to make investments in PdM profitable.

4.1.1 Inputs and Structure

The input parameters of the simulation model are grouped into fixed and variable parameters. Fixed inputs and structure define the PS and all boundary conditions. Variable inputs are used for scenario definition and therefore allow for applying PdM to FUs and controlling the resulting shares of FP and FN.

The structure of the PS as presented in Figure 3 is defined by OSs and conveyor belts which act as material handling and buffer between the OSs. Each conveyor belt cb_i is defined by the minimum travel time between the OSs $cb_{i,TT}$ and its buffer capacity $cb_{i,c}$. An OS_i consists of a set of machines $M_{i,j}$. Each $M_{i,j}$ of OS_i perform the same task with a cycle time $c_{t,i,M}$ for processing one part without any disturbances. The number of $M_{i,j}$ in OS_i are defining the cycle time $c_{t,i}$ of OS_i. Minor BD occurrences and repair times of $M_{i,j}$ are modeled by $exp()$ using mean time to failure $MTTF_{i,j}$ and mean time to repair $MTTR_{i,j}$.

For modeling the essential part of BDs suitable for PdM, each machine $M_{i,j}$ may contain FUs $FU_{i,j,k}$ with a state driven CTMC as presented in Figure 1 (b). Each $CTMC_{i,j,k}$ is defined by deterioration rates r_b, r_i, r_p, r_{p_s} and transition rates $q_{p,p_s}, q_{p_s,p}$. The downtime of each major BDs is defined by $Tri()$ distributions of the PreP $t_p = tri(t_{p,min}, t_{p,mode}, t_{p,max})$ and RepP $t_r = tri(t_{r,min}, t_{r,mode}, t_{r,max})$. Also, the number of required staff for maintenance of $FU_{i,j,k}$ is given by $n_{staff_{i,j,k}}$ and the thresholds for point $P\&F$ are defined by $c_P\&c_F$.

Following variable inputs used for scenario definition: (i) $PdM_{i,j,k}$ defines whether PdM is assigned to a $FU_{i,j,k}$ or not and (ii) $s_{FP} \in \{0.0 \dots 1.0\}$ and $s_{FN} \in \{0.0 \dots 1.0\}$ are shares over all major BDs of FP and FN PdM outcomes. Note: $s_{FP} + s_{FN} \leq 1.0$ and the share of TP PdM outcomes results as $s_{TP} = 1 - s_{FP} - s_{FN}$.

4.1.2 Outputs

Output parameters are defined and collected during the run-time of the simulation to answer questions which are defined in the objectives of the simulation study and procedure model.

To allow further economic assessment of imperfect PdM, performance measures of the PS and investment related indicators are gathered. Total parts produced n_{parts}, scrapped parts n_{scrap}, required spare parts n_{spares}, and required maintenance staff hours h_{staff} related to major BDs are accessible for cost assessment. For evaluating the potential of converting reactive into planable proactive maintenance tasks, downtime due to major BDs dt_{major} and the composition of the downtime due to reactive $dt_{major,r}$ and proactive $dt_{major,p}$ tasks are collected. The total downtime dt_{total} further includes downtime of minor BDs dt_{minor}. The downtime on PS level is aggregated over all machines. For bottleneck analysis and PdM prioritization, the state $s_{i,j}(t)$ of each machine over time is collected. Further indicators at machine and buffer levels are accessible at the simulation model and needed for calibration and loss analysis, but not in scope of this publication.

The PdM outcome of $FU_{i,j,k}$ over all its BDs $P_{i,j,k}$ is collected for model evaluation: the share of true predictions $s_{TP_{i,j,k}} = \frac{TP_{i,j,k}}{P_{i,j,k}}$; $s_{FP_{i,j,k}} = \frac{FP_{i,j,k}}{P_{i,j,k}}$ as share of type I; and $s_{FN_{i,j,k}} = \frac{FN_{i,j,k}}{P_{i,j,k}}$ as share of type II errors.

4.1.3 Content

This section provides information about the model content addressing processes and system control. In general, we assume an infinite number of maintenance staff, resources and spare parts on site, without any travel or lead time for maintenance actions. Thus, there are no limitations on these factors and their consumption is part of the model output for comparison reasons.

For modeling BDs and control imperfect PdM outcomes, each machine contain separated processes for minor and all major BDs. Figure 4 presents these processes and the information flow. The time to failure (ttf) is $exp()$ distributed, sampled by $MTTF_{i,j}$ and triggers a minor BD $M_{i,j}$. The machine model is immediately interrupted and change its state to minor BD. The BD is resolved after a certain time to repair (ttr) ($exp()$ distributed and sampled by $MTTR_{i,j}$), the machine returns in the previous production state, and the next minor BD is defined. Maintenance resources, spare parts or scrap are neglected for minor BDs. If any major BD occur during ttf, ttf is prolonged by the maintenance duration of the major BD.

For each FU i,j,k, the outcome of PdM is sampled with a discrete distribution with probabilities s_{FP}, s_{FN}, and $1 - s_{FP} - s_{FN}$ for TP outcome. To control the imperfect PdM outcome, the parameter c is sampled

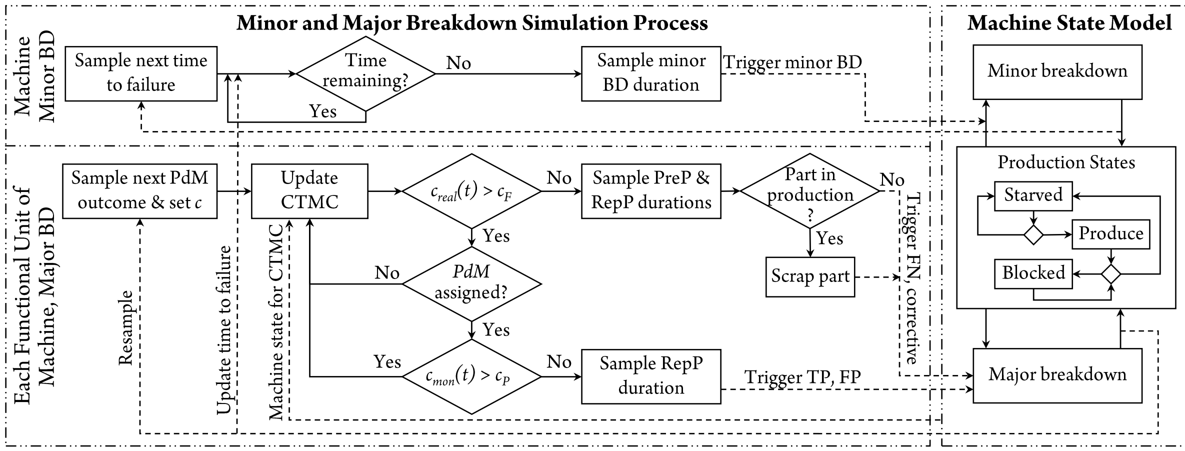

Figure 4: Minor and major breakdown processes and machine state model.

from a uniform distribution $c \sim \mathscr{U}(0.7, 0.8)$ for FP, $c \sim \mathscr{U}(0.95, 1.05)$ for TP and $c \sim \mathscr{U}(1.25, 1.42)$ for FN (remark $c_{mon_{i,j,k}} = c \cdot c_{real_{i,j,k}}$, see Section 3). The CTMC is updated each time step and degrades the real condition c_{real} of a FU. It is concatenated to the machine states with a transition probability for shock deterioration rates within the production (compare Figure 1 (b)). First, an instant BD is detected if the real condition is equal or below the condition of point F $c_{real}(t) \leq c_F$. The duration for the PreP and RepP each are sampled by their $tri()$ distributions and a part being processed in the machine while the failure was raised is scrapped. The machine changes its state to major BD due to corrective ($PdM = 0$) or FN ($PdM = 1$) and return to the state starved after the BD is resolved. The reactive outcome is counted as FN if PdM was active and as major corrective otherwise. Then the next PdM outcome is sampled and the process restart. If the condition was $c_{real}(t) > c_F$ and PdM is assigned, a proactive repair action is triggered if the monitored condition is below the condition of point P $c_{mon}(t) \leq c_P$. To meet the assumption of planable repairs, the machine changes its state to major BD immediately but parts cannot be scrapped. The duration of the repair is just sampled by the $tri()$ distribution of the RepP. After the repair is finished, the machine continues at its last productive state. The proactive outcome is counted as TP if $0.95 \leq c \leq 1.05$ and as FP otherwise. Then the next PdM outcome is sampled and the process restarts. In both, reactive and proactive PdM outcomes, maintenance staff and spare parts are added to the statistics.

The machine state model initializes as starved and ask the upstream cb_{i-1} for an available part. When received, it stays in state production during $c_{t,i,M}$. After finishing, available capacity at the downstream cb_i is requested and the part is handed over if available. When buffer capacity is reached, $M_{i,j}$ changes to state blocked and remains until capacity is released. All states are interruptible by minor or major BDs.

Buffers act like conveyor belts with a given transportation time tt a part needs to travel from an up- to a downstream OS. To avoid parallel working machines take parts at the same time, the tt is split into sections according to buffers capacities, and a part can just be handed over, if it had past all sections.

Another system control applies to the machines of an OS: if several machines try to take a part of the same buffer, the machine with the lower index gets the part first. If several machines trying to hand parts over to a downstream buffer, the machine with the highest index is prioritized. To avoid machines having a major BD during minor repair, or FU failing during major repairs, there is no deterioration during BDs ($r_b = 0$). Major BDs are maintained before minor ones. If several FUs of a machine fail at the same time, they are processed simultaneously, but the machine stay in major BD until the longer one is finished.

4.2 Scenarios and Results

For demonstrating the procedure model, we define two main scenarios: First, we investigate the throughput in dependence of the level of perfect PdM installations (SI) and secondly evaluate the impact of imperfection on a certain level of PdM installation (SII). In SI FUs will be equipped by perfect ($s_{FP}+S_{FN}=0$) PdM and the number of active PdM installations is raised from 0 to 100% in steps of $\sim 10\%$. For SII we assume 70% active PdM installations and simulate $s_{FP} \in \{0.0, 0.2, \cdots, 1.0\}$ and $s_{FP} \in \{0.0, 0.2, \cdots, 1.0\}$ with $s_{FP}+s_{FN} \leq 1.0$ to demonstrate the dependence of the PS on the level of imperfection.

For SI & SII the PS given in Figure 3 with following data, assumptions and boundary conditions is used: each $M_{i,j}$ containing FUs has a spindle $FU_{i,j,1}$ and feed axis $FU_{i,j,2}$ assigned. For BD of a spindle, two maintainers are needed, for a feed axis three. Every major BD need one spare part. Due to page restrictions, just a few deterioration and downtime data is listed. The entire data will be available at research gate. The $\{min, average, max\}$ for $MTTF_{i,j}$ and $MTTR_{i,j}$ of minor BDs are $\{1.45,\ 6.30,\ 31.85\}$ and $\{0.04, 0.14, 0.47\}$ hours. The $\{min, average, max\}$ for $tri()$ distributed PreP and RepP of FUs are $\{\{1.1, 2.5, 4.6\}, \{2.2, 4.4, 6.9\}, \{5.0, 8.8, 11.5\}\}$ and $\{\{0.6, 1.4, 2.3\}, \{1.7, 4.0, 6.9\}, \{5.0, 7.7, 11.5\}\}$ hours. The MTTF of FUs is about $\{0.19, 0.42, 0.64\}$ years resulting from following CTMCs: $r_p = \{0.99, 2.22, 3.35\} \cdot 10^{-8}$, $q_{p,p_s} = \{7.12, 7.38, 8.15\} \cdot 10^{-3}$, and these dependent factors for all FUs $q_{p,p_s} = 0.95$, $r_{p_s} = 100 \cdot r_p$, $r_i = 0.001 \cdot r_p$. The conditions at points P and F are defined by $c_P = 0.02$ and $c_F = 0.01$. The transportation time of buffers is between $2s$ and $490s$ and the capacity of the initial and final buffer is infinite.

The simulation period is set to 1+10 years, with the first year used for simulation warm up. A year is defined by 220 production days with 24/7 production. To achieve statistical confidence, each step of SI and combination of s_{FP} and s_{FN} is replicated 50 times.

The results for SI and SII are presented in Figure 5 (a) and (b). SI starts at a baseline without any PdM installations and two different bottleneck analysis strategies were chosen for installing PdM. The analysis is based on the average buffer level of upstream buffers and the 80% quantile is evaluated for prioritizing PdM. While the results of Q80 static follow the initial prioritization, Q80 reprio refresh the prioritization after each level of PdM installations. The advantage of reprioritization can be seen at the level of 60% and 80% of PdM installations. There was a shift in the PdM prioritization which lead to an earlier increase of the throughput. Q80 static catches up at the respective higher level of PdM installation. Further, the results show major increases of the throughput at 40% and 70% as well as major decreases of required maintenance staff hours at 20%, 50%, and 70% levels. When optimizing a PS through PdM, the respective values should be achieved, depending on if the focus is on increasing throughput or saving labor costs.

For SII, a level of 70% with reprioritization was chosen which raised the annually throughput from $477{,}533$ to $502{,}551$ parts and reduced the required staff hours from $6{,}360$ to $3{,}735$ hours. The shares of type I and II errors representing the proportion of too early (s_{FP}) or too late (s_{FN}) predictions, where the latter results in corrective maintenance actions with PreP and RepP. This correlates with longer downtime and compared to s_{FP} with a higher impact of s_{FN} on throughput and req. staff hours (compare Figure 5 (b)). Perfect PdM means $s_{FP} = 0$ and $s_{FN} = 0$ and is given in the lower left corner. Imperfectness is represented by $s_{FP}+s_{FN} > 0.0$ and for this data, the impact of type II errors is higher than for type I errors. These data do not include, for example, the loss of RUL from type I errors, and the impact can be enormous if spare parts are very expensive. To sum up, the presented data give insights on the impact of imperfect prognostics on an entire PS and allow for further economic analysis or defining technical requirements.

5 CONCLUSION AND FURTHER RESEARCH

This paper presents a procedure model for evaluating the impact of imperfect predictive maintenance (PdM) on production systems in discrete parts manufacturing. It guides through the implementation process of PdM including (i) problem identification and prognostics assignment; (ii) deterioration modeling; (iii) production system definition; and (iv) model implementation and scenario evaluation. Imperfection is modeled via type I & II errors (missed & false alarms). The resulting simulation acts as a sandbox for generating input data for economic analysis or defining technical requirements depending on the performance of PdM.

Although the proposed model provides quantitative support for decision makers, the evaluation process is very time consuming and limited by some major reasons: (i) The output is hardly dependent on the

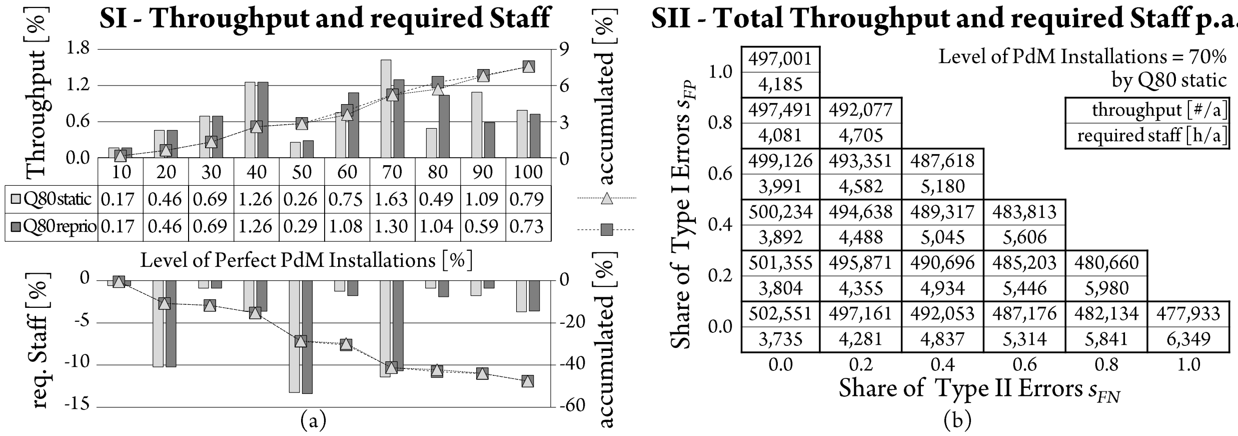

Figure 5: (a) Results SI: incremental increase of throughput and decrease of required maintenance staff hours; (b) Results SII: annual throughput and maintenance staff hours in dependence of imperfect PdM.

occurrence of false alarms (wasted RUL) and (ii) the condition at which failures are are potentially detectable. Both reasons are definitely dependent on different failure modes, but research covering the relationship of monitored conditions with false alarm outcome and real conditions as well as conditions at which potential failures are detectable is lacking. Filling these gap could help industry significantly in evaluating PdM and risk analysis on investments. In future, the procedure model will be extended by suggestions for economic analysis and we are going to generalize it for application in other industries.

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