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Preventive Risk-based Maintenance Scheduling using Discrete-Time Markov Chain Models

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The seemingly exponential increase in technological advances and increased globalization forces companies to optimize their maintenance and production activities to remain competitive. This paper proposes a novel Risk-Based Maintenance (RBM) and production decision-making support methodology for manufacturing assets, emphasizing just-in-time manufacturing. The proposed methodology uses historical machine log data to construct a Discrete-Time Markov Chain model (DTMC). The model is then used to evaluate production risk and consider preventive maintenance during the production setup. Probabilistic model checking is applied for the DTMC evaluation. The applicability of the developed method is demonstrated in a real-life case study, where production logs from the semi-automated cutting- and crimping machine are evaluated.

Keywords: Smart Manufacturing, Industry 4.0, Risk-based Maintenance, Discrete-time Markov Chains, Wire Harness, Crimping Machine.

1. Introduction

From the mid-18th to the early 19th century, companies have been pursuing technological advancements to gain a competitive edge. Eras of significant technological breakthroughs are referred to as industrial revolutions, characterized by the widespread adoption of paradigm-shifting advances. With each revolution, the complexity and variety of physical assets have significantly increased (Poor et al., 2019), necessitating the development of maintenance strategies (Khan and Haddara, 2003), particularly in the context of Just-in-time (JIT) production. In JIT, unexpected stoppages can pose significant threats to profitability, making maintenance strategies critical to minimize disruptions (Rivera-Gómez et al., 2019). This is especially true today, as businesses continue to rely heavily on advanced technologies to drive growth and efficiency.

Maintenance[a] has been influenced by production in three key aspects: avoiding unexpected failures, minimizing maintenance downtime, and maintaining product quality. Maintenance objectives are defined as assigned targets for maintenance activities (EN 13306, 2017). Targets for maintenance activities may include traditional Key Performance Indicators (KPI) such as availability, cost reduction, or asset value retention,

[a] "Combination of all technical, administrative, and managerial actions during the life cycle of an item intended to retain it in or restore it to a state in which it can perform the required function" (EN 13306, 2017)

but increasingly, include safety and environmental factors (Khan and Haddara, 2003). Historically, maintenance actions are carried out to retain or restore the state of an asset and refer to preventive actions, and corrective actions respectively (Wang and Miao, 2021).

However, Maintenance trends are shifting towards predictive maintenance (PdM), which is a key enabler for Industry 4.0 (Bousdekis et al., 2019) and an integral part of Maintenance 4.0 (Cachada et al., 2018). Successful implementation of PdM faces a series of both organizational and technical challenges (Roda et al., 2018). For some assets, significant modifications may be required for a successful PdM implementation and thus be difficult to justify financially. Therefore, a Risk-Based Maintenance (RBM) strategy can be an attractive alternative. This paper introduces a methodology for supporting maintenance and production decision-making for manufacturing assets using observable Risk Indicators (RI) and machine log data to construct Discrete-time Markov Chain models that evaluate risk and prioritize preventive maintenance and production activities.

In the next section, we briefly introduce the concept of risk and RBM. The rest of the paper is structured as follows: Section 3 presents the proposed methodology. Section 4 provides a real-life case study demonstrating the application of the methodology. Finally, Section 5 contains the discussion and summary of the paper's findings.

2. Related works

2.1. *Risk definitions*

Risk is a concept that has no unified definition and has been described across disciplines in various ways. Aven (2012) has classified risk definitions into nine categories and traced the development of six categories that originated from de Moivre's expected value definition of 1711 shown in equation 1, which is still commonly used in decision analysis (Aven, 2012).

$$\text{Risk} = \text{Probability} \times \text{Consequence} \qquad (1)$$

Kaplan and Garrick (1981) argues that one cannot equate a low-probability high-consequence scenario with a high-probability low-consequence scenario and defines risk as the answer to the three questions: "What can happen?", "What is the likelihood of that happening?", "What are the consequences?". Formally, the risk is a set of triples comprising scenario s_i, probability of occurrence p_i, and consequences x_i (Kaplan and Garrick, 1981) as shown in equation 2.

$$R = \{\langle s_i,\, p_i,\, x_i \rangle\}, \qquad i = 1,\, 2,\, \dots,\, N \qquad (2)$$

2.2. *Risk-Based Maintenance*

Risk-Based Maintenance (RBM) has been studied in the literature for over three decades. Chen and Toyoda (1989) has proposed an incremental risk-based strategy for maintenance scheduling, while the American Society of Mechanical Engineers (1991) began the development of Risk-Based Inspection (RBI), and maintenance guidelines in 1991. More recently, Khan and Haddara (2003) suggested a methodology consisting of three components for RBM: risk estimation, evaluation, and maintenance planning. The methodology uses Fault Tree Analysis (FTA) to determine the probability of undesired events and optimizes preventive maintenance to adhere to risk acceptance criteria. Arunraj and Maiti (2007) refined the methodology and several methods to prioritize and optimize the maintenance planning component have been proposed (Arunraj and Maiti, 2010; Wang et al., 2012; Jamshidi et al., 2015).

To address the fundamental deficiency of the previously mentioned method's inability to capture dynamic risk during operations, Bhandari et al. (2016) developed a methodology for Dynamic Risk-Based Maintenance (DRBM) using Bayesian Networks (BN). In this paper, we aim to show that a DRBM methodology using DTMCs may also be used for manufacturing assets and a DRBM methodology allows for decisions made on the basis of observable RI during operations.

3. Methodology

This section outlines a proposed model-based decision-making tool for risk-based maintenance and production scheduling. The methodology considers risks associated with failures, as well as normal and/or degraded states during operation. The methodology allows for consideration of the transient nature of risk and evaluation of cumulative and time-dependent risk. The methodology is demonstrated using machine log data, wherein a tree of DTMCs is created and where each branch corresponds to observable RI during the setup process. The methodology evaluates whether the expected risk during the production process meets or exceeds the risk acceptance criteria. The proposed methodology is outlined in Fig. 1 and detailed in the following subsections.

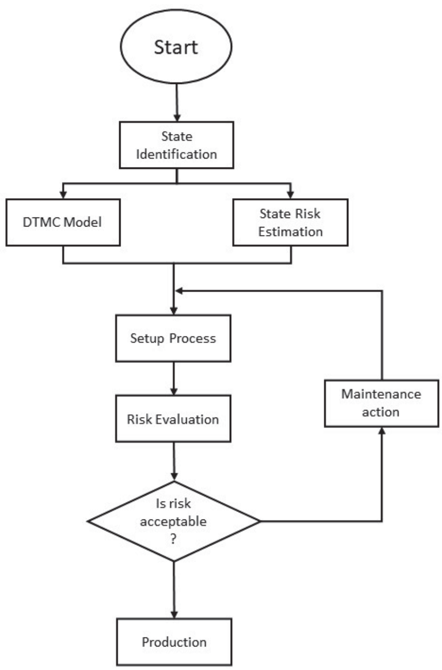

Fig. 1. Workflow of the proposed methodology, adapted from Khan and Haddara (2003); Arunraj and Maiti (2007).

3.1. *State Identification*

To identify the states of a process, the first step is to define the process scope and identify all relevant and non-relevant states, which requires expert knowledge of the real-world process. Non-relevant states can be used to filter out noise from the dataset. The states are classified into Risk Indicator States (RIS), Hazardous States, Reward States, or Safe States.

3.1.1. *Hazardous States*

Hazardous States refer to states that may contain hazards that have the potential to cause harm to assets, the environment, or personnel. This includes states that may appear hazard-free from a technical standpoint. For example, states that involve human-machine interactions are always at risk of human error.

3.1.2. *Risk Indicator States*

Øien (2001) defines Risk Influencing Factors (RIF) as: ”an aspect (event/condition) of a system or activity that affects the risk level of that system/activity” and RI as the measurable or operational quantifiable definition of a RIF (Øien, 2001). Rausand (2011) defines RI as ”A risk indicator presents our knowledge and belief about a specific aspect of the risk of a future activity or a future system operation”. In this paper, a Risk Indicator State (RIS) is a state where the observed frequency of occurrence is used to infer the risk level in the future development of the process, but the state itself has otherwise no discernible hazards.

3.1.3. *Reward States*

In certain processes, particularly those involving financial aspects, certain states may offer a reward. For instance, in a production process, hazardous states may incur a cost, while the end of the production state can be rewarded.

3.1.4. *Safe States*

The safe states are the states with no discernible hazards and that possess no risk-indicative or reward properties.

3.2. *State Risk Estimation*

After identifying a process state as a hazardous state, the associated risk is quantified through a quantitative risk analysis, typically comprising scenario development, consequence analysis, and likelihood estimation.

3.2.1. *Scenario Development*

To quantify the risk associated with a specific hazard, scenarios are developed for each identified hazard, which may involve several initiating and hazardous events that can lead to different undesired consequences. A scenario is essentially a description of a specific sequence of events from an initiating event to an undesired consequence Rausand (2011).

3.2.2. *Consequence Estimation*

Consequence estimation is conducted for each undesired event to identify and quantify potential harm to assets, the environment, or personnel. Various models, including dispersion, explosion, and fire models, can be used for consequence estimation and quantification. Khan and Haddara (2003) propose a formula that combines four major categories to calculate the total consequences: system performance losses, financial losses, human health losses, and environmental/ecological losses. However, it is debatable to suggest that human health losses can be quantified and compared to financial or system performance losses. Therefore, this paper suggests evaluating risk concerning the different damage categories separately with acceptance criteria.

3.2.3. *Likelihood Estimation*

Traditional risk methods, such as risk registries, Computerized Maintenance Management Systems (CMMS), FMEA, FMECA, Hazop, or FTA, can be used to evaluate the likelihood of hazardous consequences associated with a state. However, this should not be confused with the probability of encountering the state during the process, which will be calculated using the DTMC models.

3.3. *DTMC Model*

3.3.1. *Model Tree*

Markov chains are stochastic models with the ”memoryless” Markov property, meaning that the future state is only dependent on the current state, not the past. To consider RIS, our methodology uses a tree of DTMC models, with each RIS treatment corresponding to a branch and each leaf representing a specific DTMC model. ANOVA can simplify trees with multiple RISs by determining the most significant RISs and combinations, allowing for adapted RI definitions and treatments. See Fig. 2 for an example model tree.

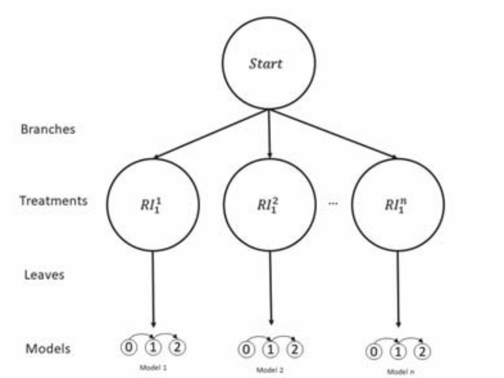

Fig. 2. Example of a model tree.

3.3.2. *DTMC Models*

After the model tree structure is determined, each production cycle is assigned to the correct model to build the transition matrix **A**. The distribution of transition times is checked, if they are all exponentially distributed, the process can be modeled as a Continuous-Time Markov Chain (CTMC). For DTMC models, matrix A contains the transitional probabilities for each step, n. Production processes are assigned to the model corresponding to the observed RIs, and transitions are added to a matrix to calculate probabilities expressed as **A**.

3.4. *Risk Evaluation*

The goal of this step is to assess if observed RIs during setup indicate if the process may meet or exceed acceptance criteria. The appropriate model is chosen and solved with a probabilistic model checking tool. This methodology accommodates two types of risk acceptance criteria: 1) the cumulative risk of the process, representing the total risk accepted for the entire process, and 2) the nth-step or time-dependent risk, which represents the slope of the cumulative risk at a specific time, t or at the nth-step. This allows for consideration of both cumulative risk and risks during certain intervals, leading to the allocation of risk mitigation resources accordingly. If observed RIs indicate unacceptable risk, production is not initiated, and preventive maintenance or other mitigation measures are taken.

4. Case Study

The proposed methodology is demonstrated on a semi-automatic multi-product crimping machine in the automotive industry. After an operator configures the specific product parameters, a sample is produced, measured, and validated repeatedly until accepted. Then, automated production begins, with short stops between batches for packaging. Occasionally, micro stoppages occur, and important parameters are logged. The focus is on production failures and the effects on the production line. The machine log used is from one location over two weeks, with about 14500 production orders. The methodology may be applied to investigate any type of risk.

4.1. *State Identification*

This case study focuses on financial and human health loss risks associated with production failures, with micro stoppages during setup identified as possible risk indicators. Fig. 3 demonstrates how the mean number of failures increases with the number of micro stoppages. Table 1 lists five failure states during production and other important states. Additionally, the methodology can be iteratively applied during production, with micro stoppages serving as risk indicators and allowing for the expansion of the model tree and update of appropriate models.

4.2. *State Risk Estimation*

This case study evaluates financial and human health loss risks in a production process, with simplified scenarios and idealized values used for demonstration purposes. The financial risks are shown in Table 3. Human health loss is evaluated using the Lost Time Injury (LTI) metric, which measures non-permanent injuries resulting in loss of productive time. Table 2 shows example LTI values for personnel interacting with the production machine during failed states. Real-world data can be obtained from CMMS, maintenance reports, injury reports, undesired event reports, etc. The values presented in Tables 3 and 2 are examples only and do not represent actual company data.

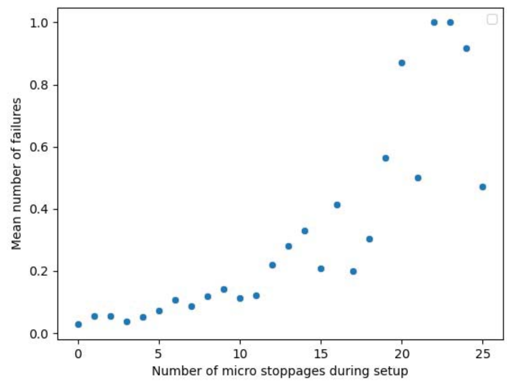

Fig. 3. Scatterplot of the mean number of failures during production and micro stoppages during setup.

4.3. *DTMC Model*

Fig. 4 shows a histogram of the number of orders and the number of risk-indicative micro stoppages in the data. In the interest of keeping the model tree simple, the three treatments of RIS have initially been defined as the set Eq. 3.

$$\mathrm{RI} = \{[0],\ [1,10]\ ,(10,\infty)\} \tag{3}$$

This results in a model tree with three branches with one leaf each. Since it can be shown that the sojourn times are not exponentially distributed, the process is modelled as DTMCs. From the machine logs the orders are processed and the orders are used to build the probability transition matrices $\mathbf{A}_m$ for each model m.

4.4. *Risk Evaluation*

DTMCs were solved with the open-source probabilistic model checking tool Prism, which allocates rewards to states and calculates cumulative and step-dependent rewards for the models. As

Table 1. Process States.

Stage	*State*	*Category*	*Description*
Setup	Changeover	Safe state	Start of the setup process
Setup	Sample	Safe state	A sample is produced
Setup	Short Fault	Risk indicator state	Short micro stoppages during the setup process
Setup	Learning	Safe	Validation of produced sample
Production	Production	Safe state	Automated production of a batch of wires
Production	End	Safe state	End of production
Production	Short Fault	Risk indicator state	Micro stoppages during production
Production	Machine Failure	Hazardous state	Machine failure
Production	Terminal Applicator Failure	Hazardous state	Terminal applicator failure
Production	Rest failure	Hazardous state	Failure
Production	Other failure	Hazardous state	Failure
Production	Maintenance	Hazardous state	Maintenance personnel has been called

Table 2. Example values - Loss Time Injury.

State	*Lost Time Injury*
Machine Failure	0.024
Terminal Applicator Failure	0.028
Seal Applicator Failure	0.033
Rest Failures Hours	0.076
Other Failure Hours	0.064

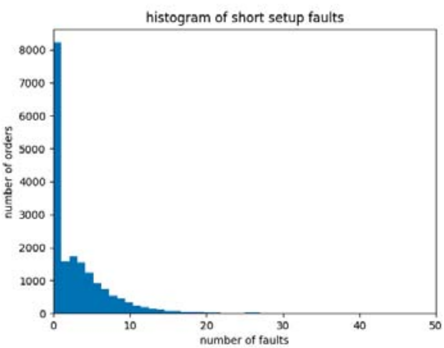

Fig. 4. Histogram of orders and short setup faults.

rewards cannot be set on transitions, the state space was expanded to include expected transition times, creating states with state and expected transition time attributes dependent on the previous state. States were then rewarded based on these attributes using Prism, and the results were exported and calculated using Python. Expected cumulative financial rewards and expected time for RI treatment one are plotted in Fig. 5. By dividing the third RI treatment into smaller treatments, Fig. 6 shows that 11 short faults in the setup phase indicate expected financial loss if the process lasts longer than 850 seconds. Cumulative LTI for n-steps of the process is shown in Fig. 8, and n-step dependent LTI for each n-step is shown in Fig. 7.

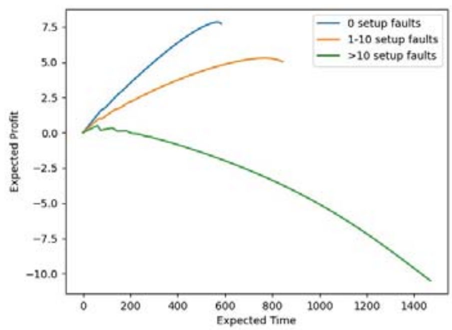

Fig. 5. Shows the expected financial reward for the three treatments.

5. Discussion

We proposed a novel RBM and production decision-making support methodology for manufacturing assets that assesses risk by observing certain indicators during setup. The methodology evaluates cumulative and n-step dependent risk, allowing for two types of risk acceptance criteria and identification of when risk is greatest. However, many RBM techniques today do not consider transient risk during operations. Our methodology

Table 3. Example values.

State	*Description*	*Consequence*	*Likelihood*
Machine Failure	Production Losses	150	0.3
Machine Failure	Replacement of component A	250	0.1
Machine Failure	Replacement of component B	3000	0.01
Terminal Applicator Failure	Production Losses	200	0.2
Terminal Applicator Failure	Production Waste	300	0.1
Terminal Applicator Failure	Replacement of component A	3000	0.01
Seal Applicator Failure	Production Losses	200	0.4
Seal Applicator Failure	Production Waste	400	0.1
Seal Applicator Failure	Replacement of component A	3000	0.01
Rest Failures Hours	Replacement of component B	4000	0.1
Other Failure Hours	Replacement of component B	5000	0.05
Production End	Production completed – value created	10	1.0

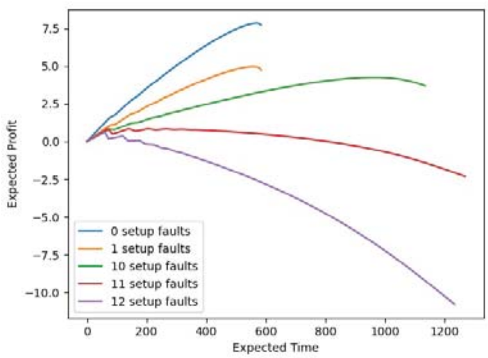

Fig. 6. Expected profit for a number of treatments to RIs.

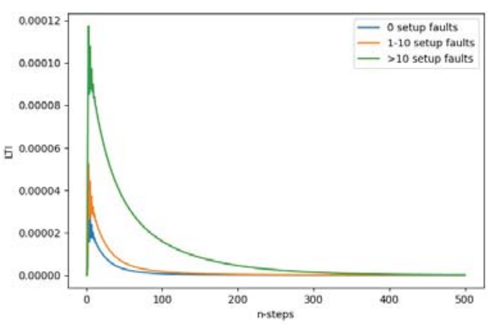

Fig. 7. The n-step dependant LTI.

adheres to de Moivre's expected loss definition of risk and can accommodate uncertainties through

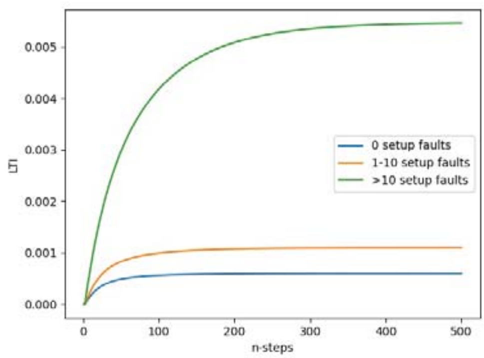

Fig. 8. The cumulative LTI.

confidence intervals in Prism. The methodology is demonstrated on a semi-automatic multi-product crimping machine, where cumulative risk may be acceptable, but n-step or time-dependent risk may exceed acceptable criteria at specific times.

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