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Process Mining for Dynamic Modeling of Smart Manufacturing Systems: Data Requirements

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Abstract

Modern manufacturing systems can benefit from the use of digital tools to support both short- and long-term decisions. Meanwhile, such systems reached a high level of complexity and are frequently subject to modifications that can quickly make the digital tools obsolete. In this context, the ability to dynamically generate models of production systems is essential to guarantee their exploitation on the shop-floors as decision-support systems. The literature offers approaches for generating digital models based on real-time data streams. These models can represent a system more precisely at any point in time, as they are continuously updated based on the data. However, most approaches consider only isolated aspects of systems (e.g., reliability models) and focus on a specific modeling purpose (e.g., material flow identification). The research challenge is therefore to develop a novel framework that systematically enables the combination of models extracted through different process mining algorithms. To tackle this challenge, it is critical to define the requirements that enable the emergence of automated modeling and simulation tasks. In this paper, we therefore derive and define data requirements for the models that need to be extracted. We include aspects such as the structure of the manufacturing system and the behavior of its machines. The paper aims at guiding practitioners in designing coherent data structures to enable the coupling of model generation techniques within the digital support system of manufacturing companies.

Keywords: Model generation; discrete event simulation; process mining; machine behavior; reliability models

1. Introduction

Modern manufacturing systems are becoming increasingly complex. Several factors influence their complexity, including customer requirements for high product quality, low costs, short lead times and a high degree of customization in a globalized market with demand fluctuations [8]. Thus, understanding and controlling the nonlinear behavior of such systems is critical to making them more productive [14]. This calls for novel approaches on how to design, manage and monitor modern manufacturing systems.

Digital tools that imitate or represent processes, functionalities or dependencies (e.g., digital twins) enable manufacturers to make more accurate decisions [28, 10]. They support long-term decisions during production planning (e.g., shop floor layout) as well as short-term decisions regarding production control and improvement (e.g., quality control, costs, scheduling). However, modern manufacturing systems are subject to frequent modifications that can quickly make static digital tools obsolete [18]. Thus, there is a need to dynamically generate accurate models for manufacturing systems based on real-time data streams to ensure optimal exploitation in the shop-floors.

Several contributions highlight the advantages of exploiting data to enhance planning and execution phases of manufacturing systems [13]. Belhadi et al. have reviewed the most important contributions on big data analytics for manufacturing processes [2]. The authors have classified existing approaches based on the main goals of the reviewed contributions: (1) descriptive analytics, (2) inquisitive analytics (i.e., root cause analysis), (3) predictive analytics, and (4) prescriptive analytics. Process Mining (PM) is a recent research area focusing on the data-driven development and analysis of models based on event logs of a system. PM can be used to generate dynamic models of manufacturing systems. However, existing approaches produce models that focus on specific components of a system and offer a limited choice on the level of detail. Therefore, we aim to mine detailed models of manufacturing systems including several aspects of a system, such as material flow (i.e., the paths that objects follow in the system), machine behavior

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(i.e., operational and degradation state changes of resources) and other aspects such as the availability of resources (Figure 1). The combined models enable the extraction of several performance indicators (e.g., throughput, lead time, reliability indicators) [17].

In this paper, we study the data requirements for a joint mining approach, which enables the retrieval of a detailed and accurate model of a manufacturing system. Our key contributions are as follows: (1) propose data requirements for the extraction of material flow and machine behavior models; (2) present methods to model the material flow in a manufacturing system; (3) present methods to model machine degradation.

The remainder of the paper is structured as follows: in section 2, we provide background on PM methods to identify material flow, additional perspectives and joint approaches. Section 3 covers the data requirements for joint mining of material flow and machines behavior. We provide a summary in section 4 and conclude our work in section 5.

2. Background

In a model generation framework for the manufacturing domain, we may classify the existing contributions depending on the application scope: most of the works regard the material flow identification, which uses PM to retrieve the movement of physical objects, such as work-pieces or tools; other contributions exploit PM to improve existing processes or to analyze process performance [27]. Furthermore, PM is used to retrieve additional perspectives of the plant, such as production policies, maintenance management, incidence management, probabilistic models, as well as all the business processes that surround the production environments [27]. Other common applications of PM are performance evaluation [25] and process monitoring [16].

2.1. Material Flow Identification

Real-time data from the shop floor can be used to retrieve part identifiers, activities, and buffer levels, while combining such data with timestamps can allow obtaining more aggregated indicators such as flow or waiting times. Martin et al. [20] improved inter arrival times modeling by including the mining of parts queuing at the entrance of the system. Denno et al. [5] developed a methodology to mine the production system structure and used genetic programming to link colored Petri net states with exceptional system states, such as blocking due to a unexpected machine failure. Martin et al. [21] designed an algorithm to mine how operational activities are batched within a production environment. Popovics and Monostori [26] designed an approach for automatically gathering data from Programmable Logic Controllers (PLCs) with the aim to achieve simulation model generation capabilities. Choueiri et al. [4] proposed a predictive model with the aim to use PM for online prediction of cycle-times in industrial environments.

2.2. Additional Perspectives

Bergmann et al. [3] introduced a methodology for using several data mining methods to recognize which policies are applied in the production system generating the data. Milde and Reinhart [23] worked on the joint material flow discovery, parameter estimation, and control policies identification from manufacturing systems event logs. Ferreira and Vasilyev [9] combined PM with logical decision trees to understand the causes of process delays. Martin et al. [19] used PM to retrieve daily availability records from an event log, by considering a resource availability with both a temporal dimension and the possibility of intermediate interruptions.

Kurscheidt et al. used process mining to feed the probabilistic models of each manufacturing activity using Bayesian networks [15]. Varga et al. [7] used event logs from a coke refinery plant and retrieved the set of actions that operators perform frequently in similar situations. The goal is to infer the causal relationship between the alarms and operator actions, together with the effects of these actions.

2.3. Joint Mining Approaches

More recently, the combination of process mining with other techniques paved the way to the smart exploitation of shop-floor data. Ortmeier et al. [24] discussed on how process mining could support life cycle assessment activities in manufacturing, for instance, to identify process deviations and interruptions. The availability of data records of several instances in a system allows for investigating the quality perspective. In this case, the underlying research question is to find what combination of process steps distinguishes the parts in which a certain production strategy (e.g., parameter setting) is successful from the parts in which the goal is not reached. For instance, Dogan and Gurcan [6] provide a guide to apply lean six sigma together with data-based analyses. The authors insert PM in a Quality Assessment framework, analyzing the role of different process mining algorithms with respect to lean six sigma approaches, such as DMAIC (define-measure-analyze-improve-control) and claim that the combination of process mining with traditional techniques allows to take effective decisions for quality problems. Meyer et al. [22] combined process mining with control theory and proposed an iterative approach to enhance treatment strategies by predicting and preventing failures based on information from electronic records.

Despite the success of the aforementioned approaches, literature is scarce of effective joint mining applications for modeling complex manufacturing systems. For instance, reliability models are used extensively in manufacturing systems. Yet, their recognition is typically not included in model generation procedures. As a result, the generated models miss relevant information that can cause a misalignment with the real system, as well as significant differences in the obtained performances. A comprehensive research on the connection between data types and models is needed. Such research gap covers different aspects: from data types to the capabilities of current approaches to generate models able to correctly estimate different

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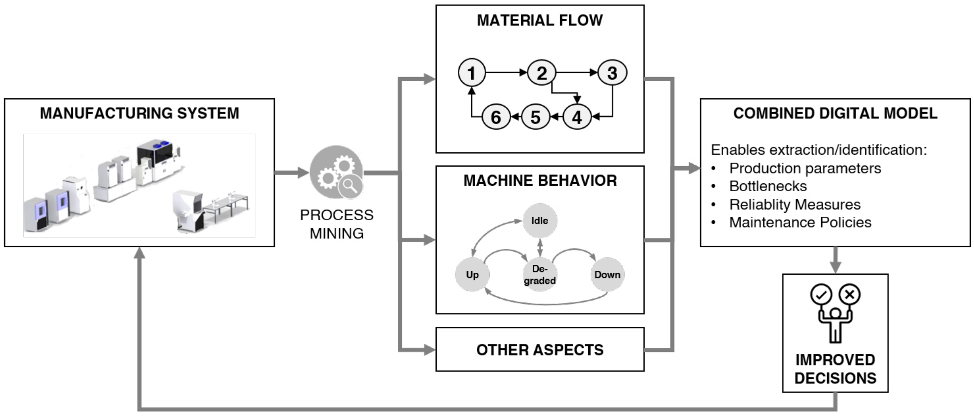

Fig. 1. Digital model generation with joint process mining techniques for manufacturing systems.

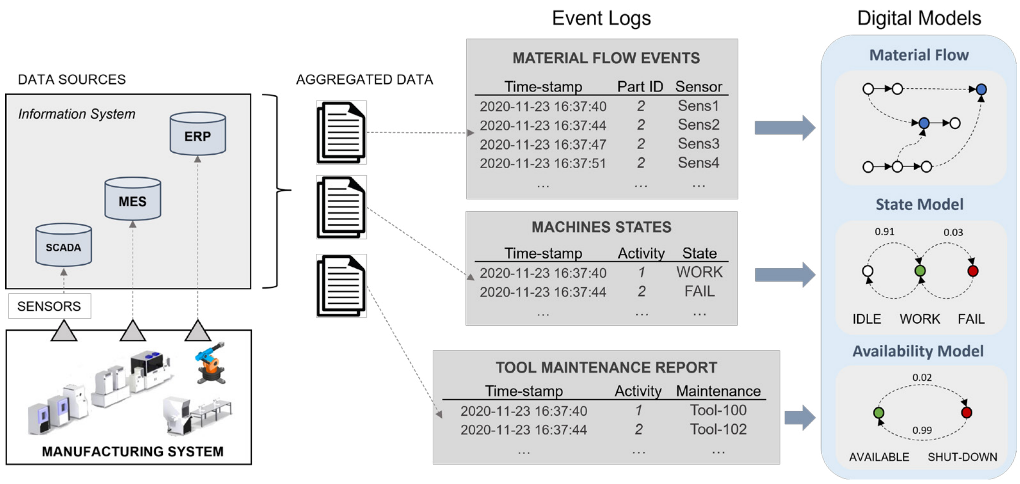

Fig. 2. Overview of the data requirements framework.

properties of manufacturing systems. In this paper, we focus on defining the data requirements, which is the first step that enables the automated model building. We concentrate on the modeling of two aspects of a manufacturing system: (1) material flows and (2) resource behaviour.

3. Data Requirements for Joint Mining of Material Flow and Machine Behavior

In this section, we provide a description of the data requirements for achieving capabilities of mining both material flow and additional system properties. The goal is to provide an overview of which data sources must be used to automatically build models with certain attributes. Figure 2 outlines the framework for data requirements we refer to. Starting from a generic manufacturing system, the data from the system are collected by sensors and distributed among the enterprise information system. Several different tools in the company may hold information about the physical system, for instance, Supervisory Control And Data Acquisition (SCADA), Manufacturing Execution System (MES), or Enterprise Resource Planning (ERP). The data held by such tools need to be aggregated and collected in event logs [1]. Further, depending on the final model scope, different event logs may need to be produced. A model focused on the material flow will use event logs with information about the physical movements of parts in the system; a model which represents the state of resources needs to retrieve such records; similarly, the availability of resources (e.g., machines, tools, operators) can be retrieved by records of their deployment in the system.

3.1. Material Flow

Figure 3 summarizes the main steps of an automated modeling procedure. The events recorded on the material flow are collected in the event log. Three data types are required for such scope: (1) a *timestamp* indicating the moment at which an activity has been done, (2) an identifier of the physical part, and (3) an identifier of the activity. Note that the activity ID may correspond to the location of sensors in the manufacturing system (e.g., presence sensor in a station). Once data is retrieved, the activity relationships may be retrieved from the traces. A trace is the list of sequential activities performed by each part. From the collection of traces, the precedence relationships can be retrieved (example: *"activity S2 followed activity S1"*). Such information can be represented in a graph model: each node

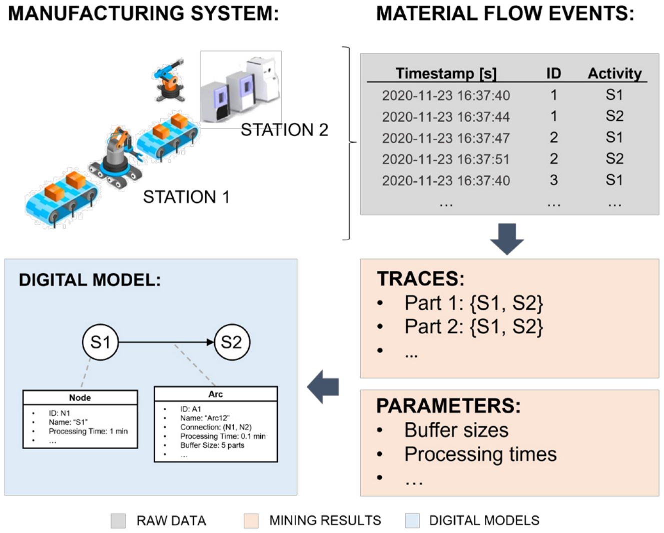

Fig. 3. Automated development of a material flow model.

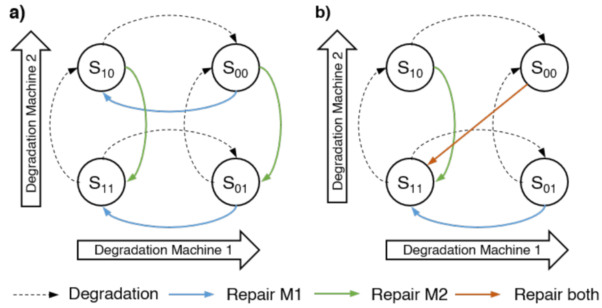

Fig. 4. State transition diagrams for joint machine degradation and maintenance policy modeling.

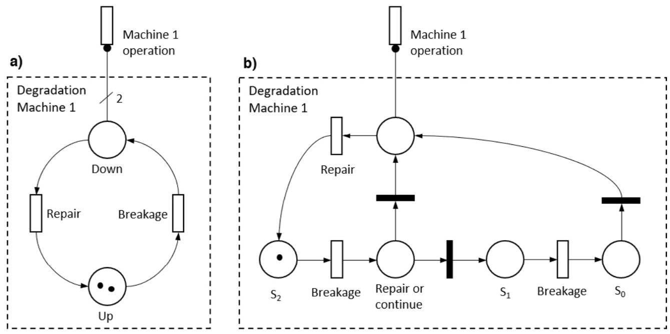

Fig. 5. Two exemplary Petri nets for machine degradation modeling.

represents an activity, while each arc indicates the relationships among activities. This way, most manufacturing system types can be identified: among others, flow lines, flow shops, and closed loop systems. Processing times can be estimated from the event log, provided the availability of timestamps indicating respectively the instant an activity is started and finished. Also, buffer sizes can be estimated by retrieving the number of parts that have been observed waiting before a certain station. Such information can be added to the model as properties of nodes and arcs: processing times are a property of the nodes, while buffer size is an attribute of the arcs [18]. Further, if additional information is available in the log, it can be used to enrich the model. For instance, if each row in the event log contains information about the operator that performed the activity, the utilization of different operators may be inferred from the data. This capability can be used to assess the balancing of operations in a flow line.

3.2. Additional System Properties

Mining of additional system properties includes aspects such as their availability and reliability as well as their operating and degradation states (Figure 2).

To extract machine operating states three data types are required: (1) a *timestamp* indicating the moment at which an operating state change is happening, (2) an *identifier* of the machine and (3) the *state* it transitioned to [11]. Such information can be modeled using state transition diagrams. A state transition diagram can be formally defined as a tuple $D = (\mathbb{S}, \mathbb{T})$ where $\mathbb{S}$ is a finite set of states, $\mathbb{T}$ a finite set of transitions from one state to another and $S_0 \in \mathbb{S}$ the initial state. Each transition $t \in \mathbb{T}$ is related to its occurrence probability $P(t)$. States are represented by circles, transitions by arrows from the current state to the next state, and the initial state is a node indicated by an arrow with no origin.

Mining degradation states of machines requires a log of discrete state changes. For instance, a machining center typically has a certain number of tools to be used for production. The breakage of a tool may determine the need to use a substitute for production until replacement. In this condition, the station may produce at a lower rate. Hence, the reduction of production rate can be linked to the number of tools available. To mine machine degradation states a log capturing degradation state changes or a log capturing the maintenance actions is required, as indicated in Figure 2. A degradation log includes the following three variables: (1) a *timestamp* indicating the moment of the degradation state change, (2) an *identifier* for the machine and (3) a *state* reflecting the new degradation state. Similarly, a maintenance log includes the following three variables: (1) a *timestamp* indicating the moment at which a maintenance is performed, (2) an *identifier* for the machine on which the maintenance is carried out and (3) a *state* reflecting the new maintenance level.

In the following, we show two possible modeling formalism that can be used to include degradation in a digital model: (1) state transition diagrams and (2) Petri nets [12].

Figure 4 illustrates **state transition diagrams** for the degradation of two machines $M1$ and $M2$. Each state $S_{ij} \in \mathbb{S}$ represents the current state i of $M1$ and j of $M2$ whereas S_{11} means, that both machines are fully operational and S_{00} means that both machines are fully degraded. Transitions either mark the degradation of a machine or the repair of either one or both of the machines. In Figure 4a , the state transition diagram is built assuming that only one machine will be repaired at a time, while the state transition diagram in Figure 4b represents a situation in which both machines can be repaired at the same time.

Petri nets can be formally defined as a tuple $N = (\mathbb{P}, \mathbb{T}, \mathbb{A}, m_0)$ where $\mathbb{P}$ and $\mathbb{T}$ are a finite set of places and transitions, $\mathbb{A}$ is a set of directed arcs and m_0 the initial marking. Arcs connect places with transitions and vice versa. Places in a Petri net may contain a discrete number of tokens. The dynamics of a Petri net results from the activation of transitions: if a transition is activated, it removes tokens from previous places and adds it to subsequent places. Places are represented as circles, transitions as rectangles and arcs as unidirectional arrows.

Figure 5 shows two exemplary Petri nets for modeling the degradation of a machine with three degradation states. The position of the tokens in the net is useful to identify a particular system state. In the model of Figure 5a, the initial marking of the two tokens in the *Up* place correspond to a fully operational system. A timed transition represents a breakage after a random amount of time. Once a token is created in the *Down* place the machine will either be repaired after some time or another breakage will occur. In case two breakages occur in a row the machine is defect and needs to be repaired. By using an inhibitor arc to block the operation of a machine during the repair, the degradation model can be integrated into an existing Petri net of the material flow.

The Petri Net model in Figure 5b explicitly includes three degradation states (S_2: fully operational, S_1: partly degraded, S_0: fully degraded). Starting from S_2, a timed transition represents the breakage after a random amount of time. After the breakage, the machine is either repaired or will continue to operate based on specific probabilities which is indicated by two immediate transitions (i.e., transitions that represent events without associated activities). In case the machine continues to operate and another breakage occurs, a repair is the only logical next step. While the machine is being repaired, it blocks the operation transition of the machine indicated by an inhibitor arc. In case there is more than one machine degradation to be modeled, the previously described models can be applied in the same way.

4. Summary

Table 1 summarizes the data requirements provided in this paper, along with the expected sources within an information system and the specific model components. The minimum data requirements (i.e., timestamps, activity IDs and workpiece/order IDs) enable the extraction of the material flow and queuing policies, as explained in section 3.1. Additional data enables the representation of other features of manufacturing systems. Resource identifiers enable to associate the logged activities with the holding of each asset, thus enabling the construction of an availability model; for instance, to estimate the utilization as a performance measure. The addition of logs reporting resource status such as degradation states and condition monitoring data enable the estimation of the reliability of each resource, as illustrated in Figure 5. Moreover, production policies may be inferred from data by the joint analysis of state transition logs and condition monitoring data, using timestamps as event connectors. Table 1 also includes maintenance schedules and supplies timing data which are not specifically examined in the previous sections.

5. Conclusions and Outlook

In this paper, we introduced the problem of combining different process mining methods to extract digital models of complex manufacturing systems, and provided an overview of the data requirements for producing accurate digital representations. Different data types enable the extraction of models which represent specific aspects of a production system. This paper represents an initial effort in defining data requirements to extract such models. To achieve our overall research goal, which is to develop a framework that enables the combination of models extracted through different algorithms, further research is necessary. Below, we outline some of the main aspects which contribute to our research goal.

Further research will benefit from an assessment on the relation between available data in common manufacturing information systems (e.g., ERP, MES) and the type of models that can be developed with mining approaches. Moreover, the compatibility among modeled features and each modeling formalism has to be addressed. For instance, Petri nets are a good choice for representing blocking conditions, which are typical of machine failures or assembly points. Hence, the final modeling formalism is driven by the choice to model such features. The development of techniques for the exploitation of the automatically built models will enhance their exploitation in forward looking scenarios, and may imply the introduction of machine learning approaches. For instance, the discovery of a maintenance policy can be done with process mining approaches, while its optimization may benefit from the use of reinforcement learning algorithm applied to the digital instances. Last but not least, the integration of continuous data, such as condition monitoring data, into the overall modeling framework is yet another challenge. For instance, degradation states of machines may first need to be detected and diagnosed using, e.g., signal processing or machine learning approaches.

Further developments of this work include the formalization of data sources and formats in common manufacturing environments, mitigation strategies to deal with data quality and integration problems, the development of joint mining algorithms for the automated generation of digital models, and the development of techniques for validating the extracted representations.

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Table 1. Data requirements for building different models of manufacturing system features.

	Data	Expected Sources	Model Components
Minimum Requirements	Timestamps	MES	Material Flows and Policies
	Activities IDs (start and end)		
	Work-piece/Order IDs		
Additional data	Resource IDs	ERP, MES	Resource Availability
	Resource States Degradation States Condition Monitoring Data	PLC, SCADA	Resource Availability Resource Reliability Production Policies
	Maintenance Schedules	ERP	Resource Availability
	Whole System State	ERP	
	Supplies Timing Data	SCM	Resource Availability

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