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Estimating Processing Times within Context-aware Manufacturing Systems

Martin Ringsquandl * **Steffen Lamparter** ** **Raffaello Lepratti** ***

* *Ludwig-Maximilians-Universität, Munich, Germany (e-mail: martin.ringsquandl.ext@siemens.com).*
** *Siemens AG, Corporate Technology, Munich, Germany (e-mail: steffen.lamparter@siemens.com).*
*** *Siemens AG, Digital Factory, Nuremberg, Germany, (e-mail: raffaello.lepratti@siemens.com)*

Abstract: Due to high volatility and dynamics in today's markets, manufacturers are required to react more quickly (e.g. frequent changeovers of products) to changing environments, but still ensure efficient production plans and accurate throughput estimates. Since, generally, processing times of machines are not fixed and depend on several variables, such as product type or material quality, accurate estimations of these times need to be available as basis for implementing production plans. Therefore, calculating high-accuracy estimates of processing times of all activities involved in manufacturing is an important task. The employment of statistical learning models (e.g. regression) for processing time estimations is not straightforward, since there are many situational dependencies to take into account. We refer to such dependencies as manufacturing *context* and propose a framework that integrates context information into a flexible production planning and scheduling scenario. We show that for frequent product changeovers, it is crucial to continuously adapt processing time estimators to the corresponding situation. Our approach shows increasing stability and accuracy of processing time estimates compared to state-of-the-art adaptive learning models. These estimates ensure more reliable production plans, and furthermore, context also reveals variables that influence estimation accuracy.

Keywords: Knowledge representation, machine learning, production planning

1. INTRODUCTION

The ever increasing volatility and dynamics in today's interconnected, global markets bring new challenges for manufacturing businesses. With trends shifting towards shorter product life cycles, greater product individualization and resulting build-to-order production strategies, manufacturers have to be able to react quickly to changing conditions or disruptive events along their supply chains, cf. Jovane et al. (2009). In order to still be able to fulfill orders and stay competitive, they require accurate, up-to-date estimates of future throughput and processing times of all production processes. Since these times are the basis for production planning and scheduling in manufacturing execution systems (MES), processing time estimation becomes an increasingly important task, see Mucientes and Vidal (2008).

In contrast to analytical approaches or simulation models, which use fixed or stationary distributed processing times of machines, the on-line estimation, for example via statistical learning models, of such times is challenging, because situational dependencies (e.g. changeovers, maintenance events, supplied material quality) can significantly influence machine's processing times. Therefore, the usage of such estimation models should be aware of these dependencies (*context*) that span across the entire manufacturing process, otherwise production plans and schedules become inefficient.

With the upcoming "availability of relevant data in real time through the interconnectedness of all instances related to the value creation process" (Bauernhansl, 2014, p. 630), there is a need for manufacturing systems to integrate across manufacturing, business, and product lifecycle processes. Similarly, Manufacturing Operations Management (MOM) systems also emphasize end-to-end integrated manufacturing, i.e. an extension to common Manufacturing Execution Systems (MES) that seamlessly connect to Product Life-cycle Management (PLM), shop floor data, and ERP, where models like ISA-95 facilitate data integration of business applications into manufacturing systems. Additionally, with new information models like OPC UA and AutomationML, MOM systems already are able to provide context information that can be exploited for analytic purposes such as processing time estimation.

In this paper, we propose an approach to integrate MOM context information to continuously update processing time estimation models and their dependencies to other variables of the manufacturing process. Additionally, we evaluate the approach in a simulation setting to show how context information can help to improve accuracy for up-to-date estimates of processing times in frequently changing environments.

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2. RELATED WORK

There are well-known machine learning approaches that deal with the problems of dynamic environments, i.e. adaptive learning, where the underlying data generation processes are prone to so-called *concept drifts*. See Dries and Rückert (2009) for a general overview of the field. Closely related to our problem definition, Kiseleva (2013) discuss the need for context-awareness in predictive models for user actions on websites. However, there have been no proposals made so far, which focus on the integration of context information in manufacturing systems.
Related to the use case in this paper, the problem of stochastic processing times for shop-floor scheduling and control (cf. Beck and Wilson (2007)), has been tackled by incorporating time estimation models for manufacturing systems using simulation models or queuing theory, as discussed in Herrmann and Chincholkar (2001). Mucientes and Vidal (2008) show the importance of incorporating domain expert knowledge into regression models for processing time estimation. Common downsides of most of these approaches are that they are meant for offline analysis and require pre-defined simulation models or they neglect the presence of concept drifts in the underlying data generation process (e.g. non-stationary distributions of machine's processing times) that depend on the current situation.

3. PROBLEM DESCRIPTION

This section briefly introduces the general ideas of interconnected instances, data and processes and their value for data analytics, i.e. context-awareness of analytics in manufacturing operations management. Subsequently, an exemplary use case in a production planning scenario further motivates these ideas.

3.1 Manufacturing Context Knowledge

Our interpretation of context-aware analytics in manufacturing relates to the context definition of Dey (2001), i.e. *information that can be used to characterize the situation of an entity.* Here, the entities are components of manufacturing systems that affect data analysis. For example, the temperature monitoring of a welding machine could be affected by situational characteristics like current product type, the currently used welding rod, etc. If temperature monitoring behaves significantly different for two product types, it should be aware of its context.

Technically, we introduce such context as unified semantic data model, more precisely, as a (Description Logic-based) knowledge base comprising terminological and assertional knowledge, denoted as $\mathcal{O} = \langle \mathcal{T}, \mathcal{A} \rangle$. This data model serves as a semantic integration of all systems and data sources at MOM layer, e.g. common master data semantics in MES and PLM. Here, the TBox $\mathcal{T}$ defines a common terminology and holds for example knowledge about plant topologies: $\texttt{Robot} \sqsubseteq \texttt{Equipment}$, which means that every component of type `Robot` is also of type `Equipment`. This can be more conveniently expressed –relating to the W3C Resource Description Framework (RDF) [1] – in semantic triple form: $\langle \texttt{Robot}, \texttt{subclassOf}, \texttt{Equipment} \rangle$, where `Robot` is the subject, `subclassOf` is a property and `Equipment` is the object of the triple.

[1] http://www.w3.org/RDF/

The ABox $\mathcal{A}$ specifies assertions about concrete instances of the types defined in $\mathcal{T}$. For example, device type information: $\langle \texttt{Robo-1}, \texttt{type}, \texttt{Robot} \rangle$,
$\langle \texttt{Robo-1}, \texttt{observedProperty}, \texttt{Temperature} \rangle$. The last triple relates a concrete individual `Robo-1` with an observation named `Temperature` via the property `observedProperty`.

See Figure 1 for an exemplary manufacturing context model. Context types (classes) are annotated with a yellow circle, concrete individuals with purple diamonds. Moving from the model on the left hand side to the right indicates a context change, switching production from `P1` to `P2`. Such model changes can be obtained, for example, via an OPC UA client-sever architecture that distributes information model changes.

3.2 Context-aware Analytics

In formal language, given a set of analytic models $A = \{M_1, M_2, ..., M_k\}$ that can be employed for the same task, where each model is assigned a *local* context, denoted $\mathcal{O}_{M_1}, \mathcal{O}_{M_2}, ..., \mathcal{O}_{M_k}$, our goal is to find a mapping $\mathcal{F}$ from every possible context to analytic model.

$$\mathcal{F} : 2^{\mathcal{O}} \to A \tag{1}$$

As the data stream evolves, this function is necessary to find the best fitting analytic model for a given situation, for example, we want to pick the best temperature monitoring model M for a given context $\mathcal{O}$. Equations 2 show this situation.

$$\mathcal{F}(\mathcal{O}) = M^* \tag{2}$$

where M^* is the optimal analytic model with respect to some performance criterion, $\mathcal{O}$ is the current global context. One performance criterion

For a detailed description of the problem setting of context-aware analytic models in MOM see Ringsquandl et al. (2014).

3.3 Job Shop Scheduling Use Case

To make things more transparent, consider a manufacturing system like the one in Figure 1, where an MES controls several machines in a job shop production environment. Since the machine's processing times are not fixed, the MES uses simple estimates of the machine's average processing times for job shop scheduling and dispatching. However, due to frequent changeovers, maintenance events, and high variance of materials for different product types, these average estimates are imprecise, which ultimately leads to inefficient and non-optimal scheduling plans.

To overcome this shortcoming, the processing time estimator (*analytic model*) should become aware of changeovers, maintenance events, etc. (*context*).

Looking at the left data model in Figure 1, the ABox specifies: $\mathcal{A} = \langle \texttt{Robo-1}, \texttt{produces}, \texttt{P1} \rangle$,
$\langle \texttt{Robo-1}, \texttt{observedProperty}, \texttt{Temperature} \rangle$, ...
From this context, we know that `Robo-1` exhibits the properties `Temperature`, `Workload`, and `ProcessingTime`