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Fabian Steinberg

Machine Learning-based Prediction of Missing Parts for Assembly

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Findings from Production Management Research

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Fabian Steinberg

Machine Learning-based Prediction of Missing Parts for Assembly

Fabian Steinberg
Universität Siegen
Siegen, Germany

Dissertation zur Erlangung des Grades eines Doktors der Ingenieurwissenschaften
vorgelegt von Fabian Steinberg, M. Sc. eingereicht bei der Naturwissenschaftlich-
Technischen Fakultät der Universität Siegen, Siegen 2024
Betreuer und erster Gutachter: Univ.-Prof. Dr.-Ing. Peter Burggräf, Universität Siegen
Zweiter Gutachter: Univ.-Prof. Dr. rer. nat. Jochen Garcke, Universität Bonn
Tag der mündlichen Prüfung: 09. Februar 2024

ISSN 3005-1649 ISSN 3005-1657 (electronic)
Findings from Production Management Research
ISBN 978-3-658-45032-8 ISBN 978-3-658-45033-5 (eBook)
<https://doi.org/10.1007/978-3-658-45033-5>

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Acknowledgements

This thesis on the prediction of missing parts for assembly was written during my time as a research assistant at the Chair of International Production Engineering and Management (IPEM) at the University of Siegen, Germany. I would like to thank the people who contributed to the success of this work.

Special thanks go to Prof. Dr.-Ing. Peter Burggräf, holder of the IPEM chair, for the opportunity to do my doctorate and for his support, encouragement and trust in me as a person. The environment he created, the first-class education, the wealth of ideas and the collegial management style were ideal conditions for this work and for my personal development.

I would also like to thank Univ.-Prof. Dr. rer. nat. Jochen Garcke, Research Group Leader at the Institute for Numerical Simulation at the University of Bonn and Head of the Business Area Numerical Data-Driven Prediction at the Fraunhofer Institute for Algorithms and Scientific Computing SCAI, for his willingness to serve as the second expert witness. Dr.-Ing. Robert Brandt, holder of the Chair of Materials Systems for Lightweight Vehicle Construction at the University of Siegen, for assuming the chair of the doctoral committee, and Univ.-Prof. Dr.-Ing. Axel van Heel, holder of the Chair of Materials Science and Materials Testing, for being a member of the doctoral committee.

Many of my former and active colleagues at IPEM have had a decisive influence on the content of this work, and I am deeply grateful to them. The mutual helpfulness, the high motivation, the creativity and the friendship have always

given me new motivation. I would like to emphasize the cooperation with Dr.-Ing. Johannes Wagner, Benjamin Heinbach, Till Saßmannshausen, Rene Sauer, Alexander Becher, Philipp Nettesheim and Maximilian Schütz. Furthermore, I would like to thank my student assistants and the students who wrote their bachelor and master theses under my supervision, and continuously supported me in my work at IPEM. I would also like to thank Mrs. Mailin Klaas for the first-class administrative organization and for her sympathetic support throughout my time at the chair.

My deepest and most heartfelt thanks go to my wife Kristina Bieker-Steinberg for her loving support, her motivating encouragement and the space she has given me, as well as to my parents Birgit and Andreas Steinberg for their unconditional support on my life's journey and for encouraging me to change my career from industry back to academia. Without their loving support, this thesis would not have been possible.

Olpe
February 2024

Fabian Steinberg

Abstract

Manufacturing companies are faced with the challenge of managing increasing process complexity, while at the same time having to meet ever higher demands in terms of on-time delivery and product costs. Especially at points in the value chain such as assembly, where different material flows converge, it is often not possible to provide the components required for an order in a timely and synchronized manner. Early identification of missing parts at the beginning of assembly can help to take countermeasures to meet the required delivery dates. To achieve this, this thesis develops machine learning based prediction models that can predict potential missing parts at the start of assembly at an early stage in the value chain. The development of the models was carried out as case studies at manufacturing companies in the machine industry. As a basis for the development, an extensive systematic literature search was conducted on existing approaches for the prediction of lead times of production orders. The result was that no approach exists that takes into account the full complexity of manufacturing companies. In particular, with regard to the data used, it became clear that information about the product to be manufactured—so-called material data—has not been used up to now. Based on the systemic review, a model for predicting missing parts from in-house production was implemented. It was shown that classification approaches achieve the best possible model quality for components from in-house production. With the defined modeling approach—classification—it was then verified that material data has a significant influence on the model quality and is therefore relevant for the prediction of missing parts at the start of assembly. Finally, a model for predicting delivery delays in the purchasing process was implemented, which makes it possible to predict potential missing parts from suppliers at the

time of ordering. The case studies show that the use of machine learning for the prediction of missing parts in both in-house production and the purchasing process can identify delays in the start of assembly at an early stage. The developed models are therefore suitable as a support system for production planners and controllers as well as purchasing departments to improve material availability at the start of assembly.

Zusammenfassung

Produzierende Unternehmen stehen vor der Herausforderung, eine stetig wachsende Prozesskomplexität bei gleichzeitig steigenden Anforderungen an Termintreue und Produktkosten zu beherrschen. Insbesondere an Stellen der Wertschöpfungskette wie der Montage, an denen verschiedene Materialflüsse zusammenlaufen, gelingt es häufig nicht, die für einen Auftrag benötigten Komponenten rechtzeitig und synchron bereitzustellen. Das frühzeitige Erkennen von Verzögerungen bis zum Montagebeginn kann helfen, Gegenmaßnahmen einzuleiten, um die geforderten Liefertermine einzuhalten. Um dies zu erreichen, wurden im Rahmen dieser Arbeit maschinelle lernbasierte Prognosemodelle entwickelt, die potentielle Fehlteile zum Montagestart frühzeitig vorhersagen können. Die Entwicklung der Modelle wurde jeweils im Rahmen von Fallstudien bei produzierenden Unternehmen aus dem Maschinen- und Anlagenbau betrachtet. Als Grundlage für die Entwicklung wurde zunächst eine umfassende systematische Literaturrecherche zu bestehenden Ansätzen zur Vorhersage der Durchlaufzeit von Fertigungsaufträgen durchgeführt. Das Ergebnis war, dass bislang kein Ansatz existiert, der die gesamte Komplexität produzierender Unternehmen berücksichtigt. Insbesondere bei den verwendeten Daten zeigte sich, dass Informationen über das zu fertigende Produkt—so genannte Materialdaten—bisher nicht genutzt werden. Auf Basis dieser Untersuchungen wurde zunächst ein Modell zur Vorhersage von Fehlteilen aus der eigenen Produktion implementiert. Dabei zeigte sich, dass in diesem Bereich Klassifikationsansätze die bestmögliche Modellgüte erreichen. Mit der gewählten Modellierungsart—Klassifikation—wurde anschließend ermittelt, dass Materialdaten einen signifikanten Einfluss auf die Modellgüte haben und somit für die Vorhersage von Fehlteilen

am Montagestart relevant sind. Schließlich wurde ein Modell zur Vorhersage von Lieferterminverzögerungen im Einkaufsprozess implementiert, mit dessen Hilfe potentielle Fehlteile von Lieferanten bereits zum Zeitpunkt der Bestellung vorhergesagt werden können. Die betrachteten Fallbeispiele zeigen, dass durch den Einsatz von maschinellem Lernen zur Vorhersage von Fehlteilen in der eigenen Fertigung sowie im Einkaufsprozess Ursachen für Verzögerungen des Montagestarts frühzeitig identifiziert werden können. Die entwickelten Modelle eignen sich somit als Assistenzsystem für Produktionsplaner und -steuerer sowie Einkaufsabteilungen, um die Materialverfügbarkeit zum Montagestart zu verbessern.

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List of Abbreviations

€	Euro
AB	Adaptive Boosting
AdaBoost	Adaptive Boosting
ANN	Artificial Neural Networks
APS	Advanced Planning System
ASD	Assembly Start Delayer
BAG-DT	Bagged Trees
CAD	Computer Aided Drawing
CO	Combinatorial Optimization
CON	Constant
CRISP-DM	Cross Industry Standard Process for Data Mining
CSV	Comma Separated Value
CT	Control Theory
DecT	Decision Theory
DT	Decision Tree
ERP	Enterprise Resource Planning
GB	Gradient Boosting
H	Heuristics
JIQ	Jobs in Queue
KNN	K-Nearest-Neighbor
LINREG	Linear Regression
LOGREG	Logistic Regression
LP	Linear Programming
LR	Linear Regression

LSA	Latent Semantic Analysis
MES	Manufacturing Execution Systems
ML	Machine Learning
MLP	Multilayer Perceptron
NC	Numerical Control
NLP	Nonlinear Programming
NOP	Number of Operations
OP	Operation
OR	Operations Research
PC	Principal Component
PCA	Principal Component Analysis
PDM	Precedence Diagram Method
PLM	Product Lifecycle Management
PPC	Production Planning and Control
QC	Quality Criteria
QT	Queuing Theory
RAN	Random
ReLU	Rectified linear unit
RF	Random Forest
RQ	Research Question
SCM	Supply Chain Management
SVC	Support Vector Classifier
SVM	Support Vector Machine
tanh	Hyperbolic Tangent
TU	Time Units
TWK	Total Work
WIQ	Work in Queue

List of Symbols

ASD	Assembly Start Delayer
CD	Completion Date
DD_{finished}	Finished Date Deviation
DDL	Delivery Date Lateness
DD_{rel}	Relative Date Deviation
DD_{start}	Start Date Deviation
DOF_{actual}	Actual Finished Date of an Order or Operation
DOF_{target}	Target Finished Date of an Order or Operation
DOS_{actual}	Actual Start Date of an Order or Operation
DOS_{target}	Target Start Date of an Order or Operation
F	F-score
FN	False Positive
FP	False Negative
$G_{\text{left/right}}$	Impurity of the Left/Right Subset
I1	Initial Inventory
I2	Final Inventory
IC	Completed Inventory
ID	Disrupted Inventory
IP	Inventory in Process
IW	Waiting Inventory
$J(k,t)$	Cost Function
LT	Lead Time
LT_{actual}	Actual Lead Time of an Order or Operation
LT_{target}	Target Lead Time of an Order or Operation