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Hasan Tercan

**Machine Learning-based Predictive  
Quality in Manufacturing Processes**

**SHAKER  
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**BERGISCHE  
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# **Machine Learning-based Predictive Quality in Manufacturing Processes**

Qualitätsprognosen in Fertigungsprozessen mittels maschinellem  
Lernen

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Hasan Tercan

Erstgutachter: Prof. Dr.-Ing. Tobias Meisen

Zweitgutachter: Prof. Dr.-Ing. Daniel Schilberg

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**Hasan Tercan**

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Internet: [www.shaker.de](http://www.shaker.de) • e-mail: [info@shaker.de](mailto:info@shaker.de)

## Abstract

The digitization of manufacturing processes opens up the possibility of data-driven quality predictions based on machine learning (ML), also known as predictive quality. The predictions can be used by process experts to initiate quality improvement actions in the process. Although the core concepts of predictive quality are based on well-known data processing and ML methods, further research is needed to establish them in manufacturing. On the one hand, there is a lack of transferable approaches for the successful realization of predictive quality. On the other hand, there are significant challenges to overcome, especially since the collection of representative data in manufacturing processes is costly and the processes are characterized by constant change. This thesis addresses these research gaps. First, a generic process model for predictive quality, called MERLIN, is presented that describes the steps necessary to realize a predictive quality application. The process model consists of four iterative phases: formalization (definition of the process and data scope), data preparation (collection and processing of representative manufacturing data), model building (training and validation of an operational learning model), and model usage (monitoring and model updating in case of process changes). In addition, to reduce the amount of data required to train predictive quality models, two approaches are developed to incorporate data from manufacturing simulations into model training. One is a simulation-to-reality transfer learning approach, where an artificial neural network (ANN) is first pre-trained on simulation data before being finetuned on real manufacturing data. The second is a learning-based approach to reduce the simulation-to-reality gap of manufacturing simulations. Finally, a continual training method called MAS-Cloning is developed to efficiently train an ANN across changes in the manufacturing process. The goal of this method is to maintain prediction accuracy during model updates while improving training and data efficiency. This is achieved by combining the regularization method memory-aware synapses (MAS) with a transfer of pre-trained network weights. Overall, the thesis provides important research contributions for the realization of predictive quality in real manufacturing processes. It also provides a foundation for future research to establish predictive quality as a data-driven component of quality assurance processes.

## Kurzfassung

Die Digitalisierung von Fertigungsprozessen eröffnet die Möglichkeit datengetriebener Qualitätsvorhersagen auf Basis von Methoden des maschinellen Lernens (ML), auch Predictive Quality genannt. Die Vorhersagen dienen als Entscheidungsgrundlage für Prozessexperten, um frühzeitig qualitätsverbessernde Maßnahmen im Prozess einzuleiten. Obwohl Predictive Quality im Kern auf bekannten Methoden der Datenverarbeitung und des ML basiert, besteht für seine Etablierung weiterer Forschungsbedarf. Zum einen fehlen umsetzungsorientierte und übertragbare Ansätze zur erfolgreichen Umsetzung von Predictive Quality. Zum anderen sind zentrale Herausforderungen zu bewältigen, insbesondere da die Erhebung repräsentativer Daten in Fertigungsprozessen aufwändig ist und die Prozesse durch ständige Veränderungen gekennzeichnet sind. In dieser Arbeit werden diese Forschungslücken adressiert. Zunächst wird ein generisches Prozessmodell für Predictive Quality, genannt MERLIN, vorgestellt, welches die notwendigen Schritte zur Realisierung einer Predictive Quality Anwendung beschreibt. Das Prozessmodell besteht aus vier iterativen Phasen: Formalisierung (Definition des Prozesses und des Datenumfangs), Datenvorbereitung (Sammlung und Aufbereitung repräsentativer Produktionsdaten), Modellbildung (Training und Validierung eines lauffähigen Lernmodells) und Modellnutzung (Überwachung und Aktualisierung des Modells bei Prozessveränderungen). Um den Datenaufwand beim Training von Predictive Quality Modellen zu reduzieren, werden zusätzlich zwei Lernansätze entwickelt, die darin bestehen, kostengünstige Daten aus Fertigungssimulationen für das Modelltraining zu nutzen. Zum einen handelt es sich um einen Transfer-Learning-Ansatz, bei dem ein künstliches neuronales Netz (KNN) zunächst auf Simulationsdaten vortrainiert wird, bevor es auf wenigen realen Daten weiter trainiert wird. Zum anderen handelt es sich um einen lernbasierten Ansatz zur Fehlerreduktion einer Fertigungssimulation. Schließlich wird eine kontinuierliche Trainingsmethode namens MAS-Cloning entwickelt, um ein KNN über Änderungen im Fertigungsprozess hinweg zu trainieren. Ziel dieser Methode ist es, die Vorhersagegenauigkeit bei Modellaktualisierungen beizubehalten und gleichzeitig die Trainings- und Dateneffizienz zu verbessern. Dies wird durch die Kombination der Regularisierungsmethode Memory-Aware Synapses (MAS) mit einem Transfer von vortrainierten Netzgewichten erreicht. Insgesamt leistet die Arbeit wichtige Forschungsbeiträge zur Realisierung von Predictive Quality in Fertigungsprozessen. Darüber hinaus bildet sie die Grundlage für zukünftige Forschungsarbeiten, um Predictive Quality als integralen, datengetriebenen Bestandteil von Qualitätssicherungsprozessen zu etablieren.

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# Publications

During my time as a scientific researcher at the Institute of Information Management in Mechanical Engineering of the RWTH Aachen University and at the Chair of Technologies and Management of Digital Transformation of the University of Wuppertal, the following peer-reviewed publications have been published.

## Conference Publications related to Dissertation

Tercan, H. and Meisen, T. (in press). Online Quality Prediction in Windshield Manufacturing using Data-Efficient Machine Learning. *Proceedings of the 29th ACM SIGKDD Conference on Knowledge Discovery and Data Mining*. (2023)

Maack, R., Waubert de Puiseau, C., Sokolova, A., Atspha, H., Tercan, H. and Meisen, T. Reducing the sim2real-gap in extrusion blow molding using random forest regressors. *Manufacturing Letters*. 33, 843-849 (2022)

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Tercan, H., Deibert, P. and Meisen, T. Continual learning of neural networks for quality prediction in production using memory aware synapses and weight transfer. *Journal Of Intelligent Manufacturing.* 33, 283-292 (2022)

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Maschler, B., Vietz, H., Tercan, H., Bitter, C., Meisen, T. and Weyrich, M. Insights and example use cases on industrial transfer learning. *Procedia CIRP.* 107, 511-516 (2022)

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# Abbreviations

<b>ANN</b>	artificial neural network
<b>CAD</b>	computer aided design
<b>CFD</b>	computational fluid dynamics
<b>CNN</b>	convolutional neural network
<b>CRISP-DM</b>	cross-industry standard process for data mining
<b>DoE</b>	design of experiments
<b>EBM</b>	extrusion blow molding
<b>FEM</b>	finite element method
<b>GNN</b>	graph neural network
<b>KDD</b>	knowledge discovery in databases
<b>LSTM</b>	long short-term memory
<b>MAE</b>	mean absolute error
<b>MAS</b>	memory-aware synapses
<b>ML</b>	machine learning
<b>MLP</b>	multilayer perceptron
<b>MSE</b>	mean squared error
<b>QA</b>	quality assurance
<b>RMSE</b>	root mean squared error
<b>sim2real</b>	simulation-to-reality
<b>SVM</b>	support vector machine
<b>UC</b>	use case





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