Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 00 (2021) 000–000

www.elsevier.com/locate/procedia

54th CIRP Conference on Manufacturing Systems

# Predictive analytics in quality assurance for assembly processes: lessons learned from a case study at an industry 4.0 demonstration cell

Peter Burggräf[a], Johannes Wagner[a], Benjamin Koke[a], Fabian Steinberg[a], Alejandro R. Pérez M.[a], Lennart Schmallenbach[a], Jochen Garcke[b,c], Daniela Steffes-Lai[b], Moritz Wolter[b,d]

[a] *Chair of International Production Engineering and Management (IPEM), Universität Siegen, Paul-Bonatz-Straße 9-11, Siegen - 57076, Germany*
[b] *Fraunhofer Institute for Algorithms and Scientific Computing (SCAI), Schloss Birlinghoven 1, Sankt Augustin- 53757, Germany*
[c] *Institut for Numerical Simulation, Universität Bonn, Endenicher Allee 19b, 53115 Bonn*
[d] *Institut for Computer Science, Universität Bonn, Endenicher Allee 19a, 53115 Bonn*

* Corresponding author. Tel.: +49-271-740-4509; fax: +49-271-740-2630. *E-mail address:* alejandro.perez@uni-siegen.de

**Abstract**

Quality assurance (QA) is an important task in manufacturing to assess whether products meet their specifications. However, QA might be expensive, time-consuming, incomplete, or delayed. This paper presents a solution for predictive analytics in QA based on machine sensor values during production while employing machine-learning models based on logistic regression in a controlled environment. Furthermore, we present lessons learned while implementing this model, which helps to reduce complexity in further industrial applications. The paper's outcome proves that the developed model was able to predict product quality, as well as to identify the correlation between machine-status and faulty product occurrence.



*Keywords:* Machine-Learning; Predictive Quality; Production; Quality Assurance; Logistic Regression

## 1. Introduction

**(AP:**

- **Products' quality must always be guaranteed.**
- **In certain cases (especially in series assembly production) there is a delay between quality inspection and end of the production process high potential for producing scrap**
- **By doing quality inspection based on samples, there is still a risk of sending NOK parts to customers**
- **The cost of quality checks might be expensive**
- **Quality assurance is normally done at the end of production (for assembly processes)**
- **Early prediction of the production's quality would help to decrease the amount of scrap and the risk of sending NOK parts to customers**
- **Variable predictions by using machine learning models is currently widely used in diverse fields due to its accurate predictions with the data collected from the machines, prediction models can be implemented for specific predicted values**

**)**

## 2. Related Works

### 2.1. Quality check in production

**(AP:**

- **How quality check is done in production**
- **Concepts and sampling plan**
- **Attributive vs Variable measurements [VM has higher measurement accuracy, reason why it's better to use regression model]**

**)**

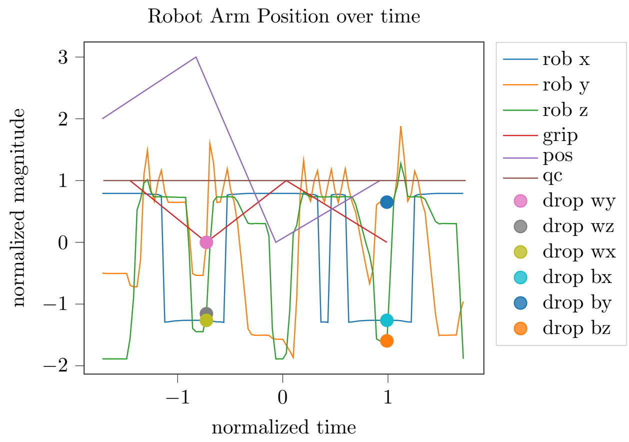


Fig. 1. Robot arm movement patterns.

### 2.2. *Predictive analytics in production*

**(AP: Predictive analytics as concepts. Implementation in production**

- **Predictive Maintenance**
- **Scheduling**
- **Other**

**If happens to be something with P.A. Quality Check**

- **Predictive analytics in production focusing in QA**
- **Existing approaches and methods**

**Note: Ideal is to find a gap in the literature, that proves why do we do it and why it is important )**

## 3. The case industry 4.0 demonstration cell

**(AP: What is the demozelle and why it is relevant as study case Description of the assemble process in the Demozelle Incl pictures )**

## 4. Methods

Data is collected from the demonstration cell and analyzed

### 4.1. *Measurement*

### 4.2. *Machine Learning*

## 5. Experiments

### 5.1. *Recording the data*

### 5.2. *Classifier optimization and testing*

We work with a total of 132 measurements. Each containing arm and belt data logs of individual cell runs. 20 samples are set aside at random for testing purposes, leaving 112 training samples. The random number generator seed is set to one in order to ensure the train and test set splits are identical for all experiments.

| | |
|---|---|
| Support Vector Machine | 95.% |
| Multilinear Perceptron | 95.% |
| Random Forest | 100.% |

Table 1. Method comparison for our annomaly detection task using the industry demo data test set.

We compare a total of three different classifier architectures on the data. A Support Vector Machine (SVM), a multilinear perceptron and a Random Forest structure. All three methods are trained using standard hyperparameters. [1] Results are shown in table 1. For 55 of the total 132 samples quality measurements indicate a problem. This sets the baseline over the entire data set, that would be obtained by simply labeling all samples as good. Over the entire data set, we require to classify more than 58.3% of the data correctly. The test set contains eight incorrect samples. We would therefore expect any naive classifier to produce a 60% accuracy, which we have to beat. In Table 1, we observe that this is indeed the case for all three approaches evaluated here. The random forest performed best in this case.

## 6. Conclusion

### 6.1. *Lesson Learned*

**(AP: explain experiences by doing the research)**

## 7. Conclusion

[1] In order to allow exact reproduction of these results source code is available at `https://github.com/manubrain/Demo-Cell-Classification`