Intelligent Human Systems Integration (IHSI 2023), Vol. 69, 2023, 295–301
https://doi.org/10.54941/ahfe1002848

Quality Forecasts in Manufacturing Using Autoregressive Models

Jan Mayer and Roland Jochem

Technische Universität Berlin, Deaprtment of Quality Science, Berlin 10587, Germany

ABSTRACT

Forecasting in quality control of products and processes create higher proactive intervention to manufacturing machines than established quality control methods. Main evidence can be drawn from the broad application scenarios and well performing recommender system using autoregressive models. This approach leads to higher process performance and improvements in implicit process knowledge of quality engineers and process owners. Furthermore, practicing quality forecasts in the manufacturing environment effectively reduces waste of resources and prevents of aftersales service effort. Thus, quality predictions serve companies to satisfy demands in sustainability. The applications' conformity with established quality control methods creates an extension to current industrial approaches to monitor production processes. The results of two case studies provide real world examples which describe the benefit of the approach in different forecasting environments. All of the predicted quality features were correctly predicted into the specification limits. Process qualification measurements are directly derived and don't indicate different recommendations compared to the true values. Advances in digitization within the manufacturing environment facilitate broader usage and similar applications of quality forecasting.

Keywords: Quality control, Process qualification, Predictive quality, Predictive process control, Quality management

INTRODUCTION

Companies in the manufacturing industry are facing a variety of challenges such as increasing product complexity and variety and the accompanying complexity of production processes (Goshime et al., 2019). The developments for more sustainability and optimized use of resources are additional societal requirements (Herrmann et al., 2014). Consequently, the demands of efficient solutions in quality management are also increasing. Innovative processes are needed to meet industrial challenges. Therefore, enhanced availability of data in production offers an opportunity (Wuest et al., 2016). Hence, the combination of associated process and manufacturing knowledge and data availability creates the possibility to improve product- and process-related quality as well as the use of resources. Established monitoring procedures enclosed in operative quality management benefit from this development to create proactive process intervention. As a consequence, machine learning methods are used to utilize and evaluate the collected data volumes. Their application in quality control enables the operation of smart solutions like the detection of anomalies in both product and process quality (Hyun Park et al., 2017). Recent research effort has been concentrating on single quality measurements and their prediction using high dimensional feature vector (Möhring et al., 2016; Teinemaa et al., 2019; Viharos & Jakab, 2021). However, there is no standardized algorithm to implement in any desired production environment. Especially in companies which contain a lower maturity degree in digitization and analytical prospects. Conclusively, the application of specific algorithms is highly dependent on the desired project output, human factors and the underlying infrastructure.

This paper focuses on a broad industrial approach for the application of quality measurements and further create forecasts of process qualification. The outcome leads to a proactive expert system providing novel intervention procedures in manufacturing and ramp up of production machinery.

Procedures for Process and Product Control

Existing reporting and monitoring tools like statistical process control (SPC) enhance process owners to continuously track manufactured products and processes. Nonetheless, the execution of the SPC is naturally reactive, as the monitored products have been already produced. This continuity for evaluating manufacturing processes is a common procedure to describe the capabilities of machinery in manufacturing industries. Therefore, multiple descriptive indices like process potential (C_p) and process performance (C_{pk}) are calculated from samples to assess manufactured products in relation to a distinct quality feature (Kane, 1986). Maintaining this evaluation over time allows interpretations about process quality. To achieve this information, it is sufficient for the evaluation to assess a measurable quality feature concerning its numerical characteristics. Furthermore, upper and lower specification limits (USL, LSL) are introduced by the process owners to define hard limits once the process is not in the desired quality range (MacGregor & Kourti, 1995). This procedure is described in literature as process qualification and is part of the SPC (Tsung et al., 2008). In spite of the broad industrial application of the SPC, describing samples does not allow a real- time evaluation of desired process capabilities. In addition, non-normal distributions of the chosen samples or multi-stage manufacturing processes decrease the interpretation of the process and its performance (Nikzad et al., 2018).

The quality range is the deviation of the optimum measurement in positive and negative direction, i.e. USL and LSL. To what extent the quality range is taken is individually defined by the process owner (Bahria et al., 2019). The letter s corresponds to the estimated standard deviation of the process distribution.

$$C_p = \frac{UCL - LCL}{6s} \tag{1}$$

$$C_{pk} = Min\left(\frac{\mu - LCL}{3s}\ ;\ \frac{UCL - \mu}{3s}\right) \tag{2}$$

To finally specify if the process is qualified, a number of around 130 observations of the quality measurement is recommended. Thus, to find out what

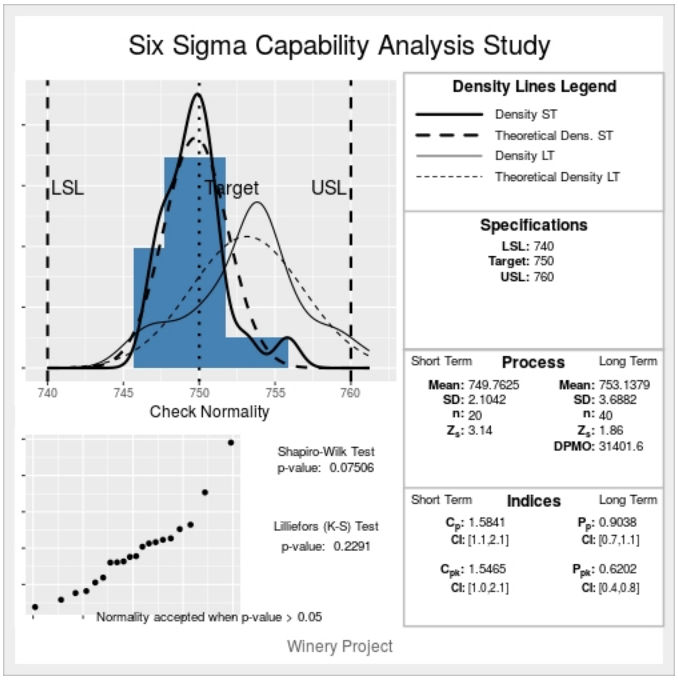

Figure 1: Six sigma process qualification dashboard (Cano et al., 2020).

kind of distribution is present, a statistical test and a histogram are used for the visualization of the result. This step is used to check if the process distribution is skewed or if the variance of the distribution is too wide for producing too many products outside the desired quality range, indicated by the C_p and C_{pk} value. The overarching concept can be found within methodologies of Six Sigma, which developed in the last years more

Proactive Process Intervention via Process and Product Quality Prediction

As main manufacturing branch, mass production combines the potential benefits of machine learning applications and their occurring challenges for product and process and monitoring. Thus, process owners require a proactive, user friendly and interactive forecast application regarding their product and process quality. Predictive quality control is one way of improving product- and process-related quality while taking advantage of greater data availability (Wuest et al., 2014). It represents an implementation of quality control in conjunction with data-driven quality forecasting. This application enables companies to conduct data-driven forecasts of product- and process-related quality. The aim is to use machine predictions as a basis for decision-making for action measures to be derived by the user (Möhring et al., 2016). On the basis of the large amounts of data and algorithmic evaluation, measures can be derived by process and utilization investigations. Among other things, future events with influence on the quality can be controlled in an improved way. In quality management, decision-making processes are based on extensive data collection and analysis. Due to the lack of data integration of quality management in general data collection in manufacturing, univariate forecasting using autoregressive models is used to overcome time consuming data processing steps. Nonetheless, Predictive quality control should be seen as a supplement to conventional methods, e.g. SPC.

Since the C_{pk}-value evaluates process quality over time, the forecast of process qualification handles single product measurements and time series. Similar applications of univariate forecasting are wide spread across multiple industry sections like healthcare, gas or tourism (Lim & Zohren, 2020). However, due to the individualized case adaption, frameworks like automated machine learning (AutoML) arose due to the last years (Hutter et al., 2019). Assessing the performance of self-learning applications like AutoML indicates no significant degradation (Paldino et al., 2021). Corresponding methodological applications create individualized ML pipelines and make use of autoregression. Autoregressive models investigate relationships based on values coming from historical parametrics of a single dependent variable (Kumar Soother et al., 2021). The evaluation criterion Mean Absolute Error (MAE) is calculated to decide which predictive algorithm setting contains least deviation to historical observations. Hence, the MAE forms the mean of all deviations with regard to the prognosis and the underlying basic truth according to the following formula:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| \widehat{Y}_i - Y_i \right| \tag{3}$$

Industrial Case Studies Using Real World Data

Designing univariate forecasting procedures are dealing with less adjustment parameters than usual ML approaches. Nonetheless, predicting quality measurements is mainly influenced by the human factors interpreting the output (Joiner, 2007). In addition, the lead time of the manufacturing equipment is of great importance, as it defines the length of the forecast window. Therefore, short-, medium- and long-term forecast windows are assessed within the case studies and predictions outside the quality range are shown. Real and forecast C_{pk} values from the last 130 produced outputs indicate if a process intervention was truly recommended assuming the process is normally distributed.

The first application of the forecasting approach is examined with a high variance in the input data coming from a semiconductor manufacturer. The quality control takes place after 176 processing steps each representing a processing time of 1 second. The design of the autoregressive model is chosen to forecast the output of the next quality control ahead, once another product is manufactured. The true C_{pk} value refers to 0.106073. As can be seen in table 1, the forecasts which have been made are all within the specification limits of the quality range. Due to the low limit of the C_{pk} value, a process intervention would have been recommended in any case. However, the model is biased into the direction of predicting failures which can be seen from the decreasing C_{pk} value and the increasing MAE. This development is affected

Table 1. Results from the semiconductor case study.

Forecast Window	Forecast within Quality Range	Forecast C_{pk}	MAE
Short-term (1 Step)	100% True	0.105892	0.016
Medium-term (5 Step)	100% True	0.103495	0.048
Long-term (10 Step)	100% True	0.099043	0.078

Table 2. Results from the milling case study.

Forecast Window	Forecast within Quality Range	Forecast C_{pk}	MAE
Short-term (1 Step)	100% True	0.593069	10.247
Medium-term (5 Step)	100% True	0.575222	6.943
Long-term (10 Step)	100% True	0.602623	5.804

by the large amount of failures within the input data characterized in 971 observations.

As second case study, a data set from a mining operator is evaluated. On the contrary to the semiconductor process, this process is more stable and displays the percentage of silica which represents the quality measurement. As synthetic specification limits the quality range can be between 5% and 30%. One observation represents a sample drawn hourly from the production machine. The true Cpk value refers to a number of 0.595090. According to the quality prediction, similar results can be seen in Table 2. All predicted results were predicted within the specification limits. Analogous to the first case study, the Cpk value is decreasing. This is caused by the single time step prediction, which is not as accurate as the other scenarios. In spite of the outlier prediction, the model is improving with larger time frames as forecasting window.

CONCLUSION

Forecasting of quality measurements in manufacturing is providing domain experts valuable knowledge about future events of production machinery. The extension of established quality control procedures associated to Six Sigma can be accomplished by higher data volumes and faster data processing steps. The results of two real world case studies indicate the broad application potential of autoregressive models in quality control. Furthermore, other performance indicators can be derived by the prediction of single quality measurements, i.e. the Cpk value.

Nonetheless, there are limitations connected to the accuracy of the data collection and the necessity to predict as accurate as possible. There might be dependencies to the distinct applications decreasing the benefit of quality forecasts in manufacturing. In addition, the input into the autoregressive models do not include additional sensor data, which can make the analysis less biased, but also less flexible in its application.

ACKNOWLEDGMENT

The research leading to this work has received funding from the European Union's Horizon 2020 research and innovation program under Grant Agreement No: 958205.

REFERENCES

Bahria, N., Chelbi, A., Bouchriha, H., & Dridi, I. H. (2019). Integrated production, statistical process control, and maintenance policy for unreliable manufacturing systems. *International Journal of Production Research*, *57*(8), 2548–2570. https://doi.org/10.1080/00207543.2018.1530472

Cano, E. L., Moguerza, J. M., & Corcoba, M. P. (2020). *Quality Control with R*. https://www.qualitycontrolwithr.com/package.html

Goshime, Y., Kitaw, D., & Jilcha, K. (2019). Lean manufacturing as a vehicle for improving productivity and customer satisfaction. *International Journal of Lean Six Sigma*, *10*(2), 691–714. https://doi.org/10.1108/IJLSS-06-2017-0063

Herrmann, C., Schmidt, C., Kurle, D., Blume, S., & Thiede, S. (2014). Sustainability in manufacturing and factories of the future. *International Journal of Precision Engineering and Manufacturing-Green Technology*, *1*(4), 283–292. https://doi.org/10.1007/s40684-014-0034-z

Hutter, F., Kotthoff, L., & Vanschoren, J. (2019). *Automated Machine Learning*. Springer International Publishing. https://doi.org/10.1007/978-3-030-05318-5

Hyun Park, S., Seon Shin, W., Hyun Park, Y., & Lee, Y. (2017). Building a new culture for quality management in the era of the Fourth Industrial Revolution. *Total Quality Management & Business Excellence*, *28*(9-10), 934–945. https://doi.org/10.1080/14783363.2017.1310703

Joiner, T. A. (2007). Total quality management and performance. *International Journal of Quality & Reliability Management*, *24*(6), 617–627. https://doi.org/10.1108/02656710710757808

Kane, V. E. (1986). Process Capability Indices. *Journal of Quality Technology*, *18*(1), 41–52. https://doi.org/10.1080/00224065.1986.11978984

Kumar Soother, D., Hussain Kalwar, I., Hussain, T., Shankar Chowdhry, B., Mehran Ujjan, S., & Din Memon, T. (2021). A Novel Method Based on UNET for Bearing Fault Diagnosis. *Computers, Materials & Continua*, *69*(1), 393–408. https://doi.org/10.32604/cmc.2021.014941

Lim, B., & Zohren, S. (2020). Time Series Forecasting With Deep Learning: A Survey. Advance online publication. https://doi.org/10.48550/arXiv.2004.13408

MacGregor, J. F., & Kourti, T. (1995). Statistical process control of multivariate processes. *Control Engineering Practice*, *3*(3), 403–414. https://doi.org/10.1016/0967-0661(95)00014-L

Möhring, H.-C., Nguyen, Q. P., Kuhlmann, A., Lerez, C., Nguyen, L. T., & Misch, S. (2016). Intelligent Tools for Predictive Process Control. *Procedia CIRP*, *57*, 539–544. https://doi.org/10.1016/j.procir.2016.11.093

Nikzad, E., Amiri, A., & Amirkhani, F. (2018). Estimating total and specific process capability indices in three-stage processes with measurement errors. *Journal of Statistical Computation and Simulation*, *88*(15), 3033–3064. https://doi.org/10.1080/00949655.2018.1498096

Paldino, G. M., Stefani, J. de, Caro, F. de, & Bontempi, G. (2021). Does AutoML Outperform Naive Forecasting? In *The 7th International conference on Time Series and Forecasting* (p. 36). MDPI. https://doi.org/10.3390/engproc2021005036

Teinemaa, I., Dumas, M., La Rosa, M., & Maggi, F. M. (2019). Outcome-Oriented Predictive Process Monitoring. *ACM Transactions on Knowledge Discovery from Data*, *13*(2), 1–57. https://doi.org/10.1145/3301300

Tsung, F., Li, Y., & Jin, M. (2008). Statistical process control for multistage manufacturing and service operations: a review and some extensions. *International Journal of Services Operations and Informatics*, *3*(2), Article 19333, 191. https://doi.org/10.1504/IJSOI.2008.019333

Viharos, Z. J., & Jakab, R. (2021). Reinforcement Learning for Statistical Process Control in Manufacturing. *Measurement*, *182*, 109616. https://doi.org/10.1016/j.measurement.2021.109616

Wuest, T., Irgens, C., & Thoben, K.-D. (2014). An approach to monitoring quality in manufacturing using supervised machine learning on product state data. *Journal of Intelligent Manufacturing*, *25*(5), 1167–1180. https://doi.org/10.1007/s10845-013-0761-y

Wuest, T., Weimer, D., Irgens, C., & Thoben, K.-D. (2016). Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research*, *4*(1), 23–45. https://doi.org/10.1080/21693277.2016.1192517