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SIMULATION OF MAINTENANCE ACTIVITIES FOR MICRO-MANUFACTURING SYSTEMS BY USE OF PREDICTIVE QUALITY CONTROL CHARTS

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ABSTRACT

In micro manufacturing, the determination and scheduling of maintenance activities can strongly impact the production efficiency of the corresponding production system. Thereby, the supervision of quality relevant parts, tools and components can be very complex, due to the limited spaces within the manufacturing devices. This article proposes an extension of quality control charts by adding predictive component. This component predicts at which point in time maintenance activities are required based on quality characteristics of the produced work pieces. The article further presents two simulation studies. These demonstrate that the extended approach can compete with well configured time-based maintenance strategies in terms of production efficiency and rejection rates. In addition the predictive nature of this extension can issue forewarnings for tool wear induced quality defects very early during production, allowing for a suitable integration of maintenance activities into the production schedule.

1 INTRODUCTION

During the last decades the demand for metallic micro components has increased continuously. While the components themselves become smaller, their complexity constantly increases with respect to their functionality and geometry (Wulfsberg et al. 2010; Hansen et al. 2006; Mounier and Bonnabel 2013). Besides of Micro-Electro-Mechanical-Systems (MEMS), which are generally manufactured using semi-conductor based processes, the demand for metallic micromechanical components increases similarly. These components are used for electrical or mechanical connections of and between MEMS as connectors, casings, contacts etc. In general, these micromechanical components cannot be manufactured using semi-conductor based processes, so that processes from the areas of micro forming, micro injection, micro milling etc. are applied (Hansen et al. 2006; Fu and Chan 2012). In particular, cold forming processes show great potential for the realization of an economic, industrial scale production of metallic micromechanical components. These processes can provide high throughput at comparably low energy and waste costs (DeGarmo et al. 2003). Using a combination of different cold forming processes in micro manufacturing, a highly flexible and efficient production system can be achieved (Scholz-Reiter and Rippel 2013). Nevertheless, combining different processes requires a careful planning and configuration of process chains (Scholz-Reiter et al. 2009). At this, high throughput rates of up to several hundred pieces per minute (Flosky and Vollertsen 2014), the inherently small tolerances of only a few micrometers as well as the occurrence of so-called size-effects (Vollertsen 2008) constitute major factors for an effective and precise planning and configuration of the involved process chains.

Compared to macro manufacturing, the occurrence of size-effects induces strong and frequent variations, with respect to material properties as well as to the overall behavior of the involved manufacturing processes (Rippel et al. 2017). In order to achieve an adherence to the planned production qualities and volumes, suitable methods for quality assurance have to be deployed. Thereby, the quality assurance includes the quality control (measurement and analysis) of workpieces as well as the definition of maintenance strategies for workstations and machines. In this context, the strong variances as well as comparably high repair and maintenance times render classical reactive maintenance strategies inefficient. In contrast, predictive strategies require reliable and constant measurements of the workpieces, which can be hard to acquire in micro manufacturing. This is due to the increasing measurement uncertainties concerning the calibration, systematic imprecisions and the repeatability, caused by increasingly smaller work pieces and features (Fleischer et al. 2008).

To cope with the challenge of developing and deploying suitable maintenance strategies, this article proposes an adaptive, simulation/prediction based method to determine optimal timeframes for maintenance activities. The following sections provide an introduction to the area of micro manufacturing and further describes the influence of size-effects as well as the constraints on maintenance strategies imposed by increasing measurement uncertainties. Section four describes the proposed method as an extension of classical quality control charts and summarizes two simulation studies conducted to evaluate the method in terms of production efficiency and its forewarning behavior. Finally the article concludes with a discussion and a description of future work.

2 MICRO MANUFACTURING AND SIZE-EFFECTS

While cold forming processes are well established in macro manufacturing, they cannot be scaled down for micro manufacturing without adaptations. A simple downscaling of those processes and the involved work pieces, tools and devices, is only possible up to a certain degree. With a decreasing scale, so called size-effects begin to emerge, requiring adaptations to the processes.

Vollertsen defines size-effects as “deviations from intensive or proportional extrapolated extensive values of a process, which occur when scaling the geometrical dimensions” (Vollertsen 2008). In this context, he defines intensive values as parameters, which are not expected to change due to a change of an object’s mass (e.g. its temperature or its density). In contrast, extensive values are expected to vary with a different mass (e.g. the object’s inertia force or its heat content). Basically, size-effects occur due to the inability to scale all relevant process parameters equally (Vollertsen 2008). For example, the downscaling of a metal sheet’s thickness can result in a varying density due to local defects, although it is considered an intensive variable. In macro manufacturing these variations can usually be neglected, while they can have strong influences in micro manufacturing. Moreover, technical limitations can further facilitate the occurrence of size-effects. For example, the downscaling of mechanical grippers is limited by technical factors. For very small work pieces, Van-der-Waals forces between the gripper and the work piece will eventually overcome the gravitational force. As a result, the gripper will not be able to release the work piece without aid. In summary, Vollertsen (2008) defines three distinct categories of size-effects (Figure 1):

- *Density size-effects* occur, when the density of a material is held constant while scaling down its geometrical dimensions. For instance, local deviations become more serious with a continuing miniaturization. Thereby, the distribution of local deviations within a material can lead to more delimited sets of good and bad parts.
- *Shape size-effects* occur due to the increasing ratio of an object’s total surface area, compared to its volume. An example of this category is provided by the described imbalance of the adhesive force in relation to the gravitational force.
- *Micro structure* size-effects occur because micro structural features (e.g. the grain size or the surface roughness) cannot be scaled down the same way as the geometrical size of an object. A consistent surface roughness can for example lead to a decreasing number of surface pockets, which reduces the effectivity of applied lubricants.

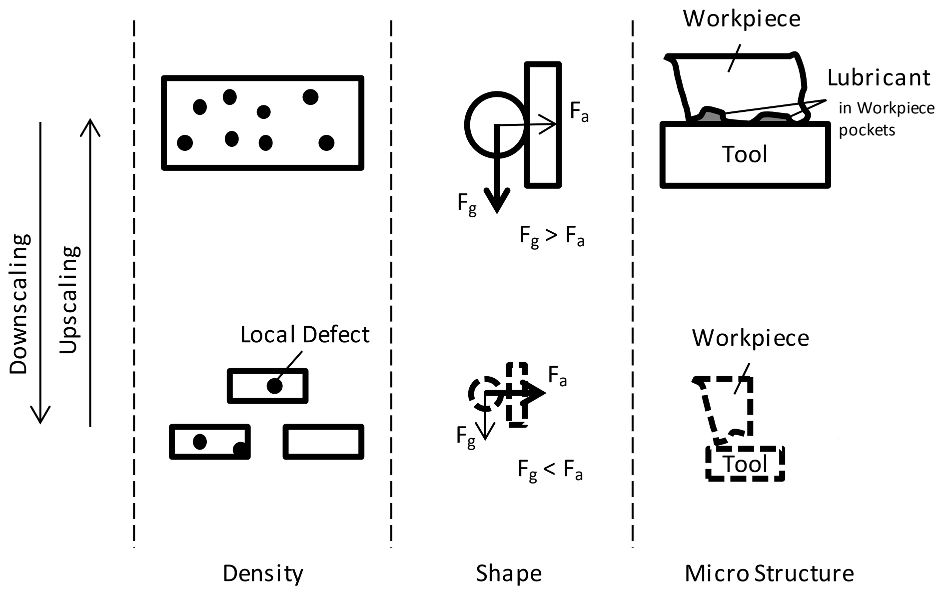


Figure 1: Categories of size-effects (Vollertsen 2008).

The occurrence of size-effects particularly affect the quality assurance. On the one hand, the processes themselves become harder to control, which requires more specialized methods for the quality control. On the other hand, maintenance requires specific strategies that can react quickly and assure a constant quality despite comparably high variations. Moreover, micro-structure size-effects can heavily influence the lifetime of tools used in micro cold forming. As indicated in Figure 1, these effects may for example induce inconsistencies when using lubricants, which leads to highly dynamic stresses on the tools and as a result, can render the prediction of a tools remaining lifetime complicated.

3 MAINTENANCE STRATEGIES IN MICRO MANUFACTURING

In general maintenance strategies can be subdivided into five categories (Figure 2). While reactive maintenance strategies generally only react to imminent or already occurring failures, preemptive strategies focus on the prevention of failures. Thereby, time based strategies schedule maintenance activities in fixed intervals, which can be adapted to the respective processes requirements. Condition based strategies rely on sensory information in combination with (mathematical) models, which describe and estimate the condition of a tool, component or machine and trigger maintenance activities if the estimated condition undercuts a selected threshold. Predictive strategies generally use the same type of condition models as condition based strategies. In contrast, they try to predict the development of the tools, components or machines condition, in order to schedule maintenance activities in advance. In some cases, these predictive strategies can include quality related aspects as target criteria.

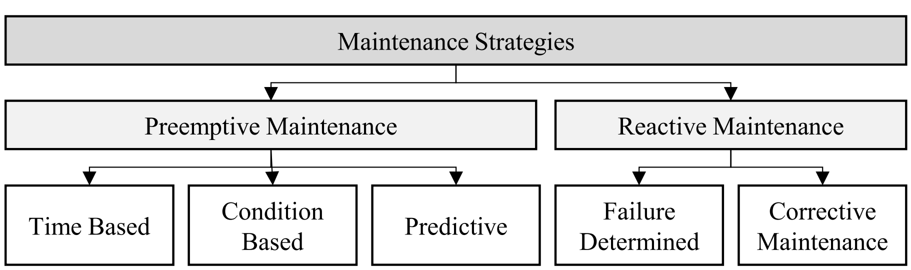


Figure 2: Classification of maintenance strategies (c.f. (Schenk 2010)).

In comparison to macro manufacturing, the application of classical maintenance strategies is complicated in micro manufacturing as they require precise knowledge about the processes involved (Jacobs et al. 2009). The comparably high measurement uncertainties combined with the high variances within the processes behavior can easily result in unsuitable intervals for time based strategies. Too short intervals lead to high costs for maintenance induced down times and spare parts, while too long intervals increase the risk of breakdowns or impact the product quality. Condition based or predictive strategies usually require a very detailed descriptive model of the involved processes, tools, components or machines, which in many cases cannot be acquired in micro manufacturing, often due to the occurrence of size effects. In contrast, the application of reactive strategies suffers the same problems as unsuitable time based maintenance strategies. Resulting from the high production rates in micro cold forming, machine breakdowns lead to comparably high down time costs. Additionally, the high costs for specialized tools or spare parts require suitable maintenance strategies to maintain an efficient production.

While most maintenance strategies focus on supervising and maintaining the condition of a tools, components or machines, others focus on determining the maintenance activities based on the quality criteria of the respective products. One particular strategy is the application of quality control charts (see e.g. (Gerboth 2002)) (Figure 3). Thereby, each process is assigned a number of quality control charts, each focusing on a particular, quality related statistical characteristic of the respective product. Examples for those characteristics can be a part's diameter or the average roughness of a metal sheet after manufacturing. Each chart is assigned a desired value as well as a set of tolerances between which the value may vary. Based on these values, intervention boundaries are calculated which are used to determine required maintenance activities. During production, the respective characteristics are measured and noted on the corresponding quality control chart. Quality control charts trigger maintenance activities if the intervention boundaries are exceeded. In addition they use an additional set of rules for triggering maintenance activities, which are based on statistical improbabilities. Examples for these are the occurrence of a so-called trend (6 consecutive measurements which either increase or decrease) a so-called run (9 consecutive measurements above or below the desired value) or a sequence of 14 points which are alternating above and below the desired value. In general, quality control charts are used as a part of the statistical quality control to trigger certain activities. Thereby, the design of appropriate charts in terms of distributions and boundaries is a challenging task (for more details on statistical process control and different types of quality control charts see e.g. (Oakland 2007).

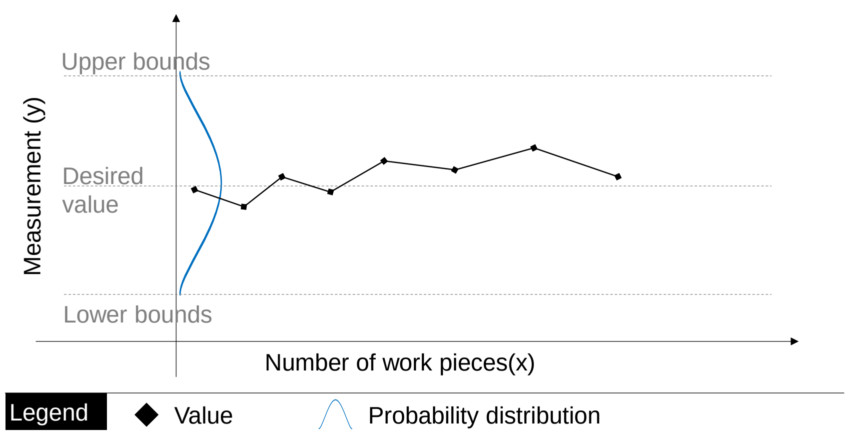


Figure 3: Quality control chart.

While quality control charts provide advantages for an application in micro manufacturing, they require detailed knowledge about the processes' behaviors to correctly configure the respective boundaries (Scholz-Reiter et al. 2010). Moreover, the rules used in quality control charts do not compensate for the high variances and measurement uncertainties. Finally, their reactive nature only leaves limited time to schedule suitable maintenance activities, without heavily impeding the production efficiency.

4 PREDICTION BASED DETERMINATION OF MAINTENANCE ACTIVITIES

In order to compensate for the described drawbacks of quality control charts, this section proposes an extension of the classical quality control charts. Therefore, a prediction component is added to the chart, substituting the statistically based rules (Rippel et al. 2015). As a result, possible defects can be detected in advance, while the charts high reactivity to failures is maintained. Furthermore, the extension only requires limited process knowledge to deliver good results.

4.1 Prediction Based Extension of Quality Control Charts

As with the original quality control charts, the prediction based extension uses a desired value for the assigned quality criterion, as well as defined tolerances. However, the intervention boundaries are replaced by a quality target, describing the probability of a work piece exceeding the tolerances. The aim is to predict at which point in time, the first work piece will exceed the tolerances with respect to the quality targets probability. In order to compensate for different measurement techniques, the prediction uses the notion of production batches. For example, the simulation study described in section 4.2 uses two different measurement techniques which require different measurement times. While the first technique can only measure one of every 120 pieces (batch size of 120) the other one can measure every single work piece (batch size 1).

As with the classical approach, each measurement is noted within the chart. As a result of the processes own variances as well the measurement uncertainties, each point is associated with a combined uncertainty with respect to its precision. In order to smooth these values, the prediction component uses regression methods to estimate the systematic shift within the mean or expected values over the measurements. Moreover, it characterizes the variance of the sample's measurements by calculating the residuals between the measurements and the regression curve. Using the regression curve as mean estimator and the calculated variance, the prediction component can derive an estimated distribution of possible values for each future measurement or work piece. At each time step, the prediction component uses these distributions to determine the first work piece that will exceed the tolerances with a probability equal or greater to the quality target (Figure 4). Particularly concerning batch wise productions, the component can decide if a batch can be manufactured, or if maintenance activities are required earlier.

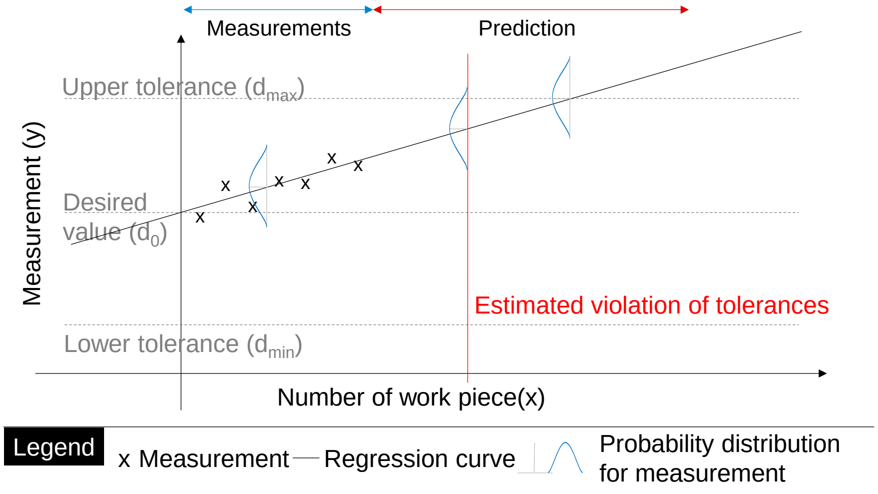


Figure 4: Prediction based quality control chart.

While the predictive quality control charts can use an arbitrary regression method, this article uses a simple polynomial least-square regression with different degrees of freedoms as mean estimator for the simulation studies described in sections 4.2 and 4.3. Thereby, a single degree of freedom tries to fit a linear function $f(x) = ax + b$ while a second degree polynomial regression tries to fit a parabolic shaped function $f(x) = ax^2 + bx + c$.

4.2 Simulation Study: Production Efficiency

In order to evaluate the proposed approach, a simulation study was conducted. As the quality of the prediction relies on the frequency of the measurements, the variance induced by the process as well as on the uncertainty associated with the used measurement technique, the simulation study uses a linear regression based on the following assumptions:

- The variance of the real values induced by the process follows a normal distribution and remains constant over time.
- The variance induced by measurement uncertainties follows a normal distribution and remains constant over time.
- The systematic shift of the real values induced by tool wear can be approximated by a linear function.

The simulation scenario consists of a single production process which is directly followed by the quality inspection process. The scenario assumes a constant production rate whereby the speed of the quality inspection varies. As a result, the differently sized batches are formed, depending on the selected measurement technique. For each batch, the respective measurement is considered as a surrogate for all work pieces contained. The scenario's order release strategy is selected to guarantee a consistent, full utilization of the production machine.

With respect to the quality control, two functions are implemented. First, after retrieving the measurements from the quality inspection process, the corresponding batch is either classified as good or bad. In case of a rejection, the batch is discarded and the appropriate amount of work pieces is queued for re-production. The second function is the triggering of maintenance activities. Therefore, two different scenarios are used. The first scenario uses the predictive quality control charts described earlier, in order to decide if another batch can be manufactured or if maintenance activities are required. The second scenario uses a time based maintenance strategy. The described production system was simulated using the discrete-event simulation *jasima* (https://bitbucket.org/jasimaSolutions/jasima).

Table 1: Scenario configuration

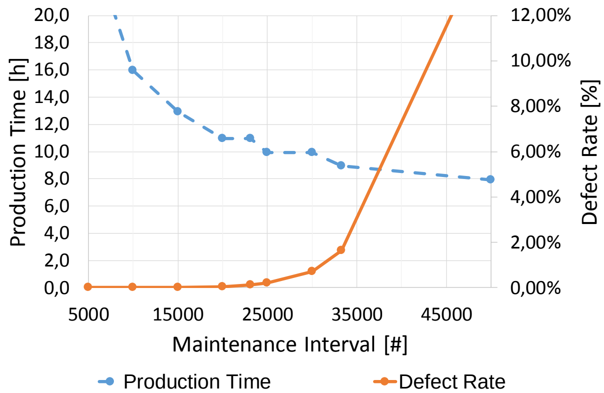
	Parameter	Value	
Scenario	Number of intact parts	100 000	
	Target Value / Tolerance	500µm ± 10µm	
	Repeated simulation runs	25	
Production	Diameter	*N*(µ=500µm, std.dev= 2µm)	
	Average shift of the expected value	10µm after 43 200 pieces (3 hours of production)	
	Process duration	0.25 sec (240 pieces/min)	
	Downtime for maintenance	1 hour	
Quality		Laser microscope	Plenoptic camera

Inspection	Process duration [s]	30 sec	0.1 sec
	Resulting batch size	120 pieces	1 piece
	Measurement uncertainty [µm]	±0,8 (±3std.dev)	±3 (±3std.dev)
	Quality target	max. 1% rejected parts	

The simulation's target values are production time for 100 000 good parts, as well as the rejection rate. The simulation assumes that the production machine produces work pieces with a normally distributed diameter of 500µm with a standard deviation of 2µm. Tool wear causes the mean value of this distribution to shift by 10µm after three hours of production at full capacity (43 200 produced work pieces), resulting in more than 50% of the produced work pieces to exceed the tolerances after this time. Performing maintenance at the production machine resets these values back to their origins. The only parameter to select for the predictive quality control charts is the quality target. This value describes the highest allowed probability for a work piece to be defect. For this simulation study the quality target was set to 1%. In terms of the quality inspection, two different measurement techniques have been selected exemplarily referring to (Weimer et al. 2014). Thereby, the laser microscope delivers highly precise measurements at a comparably slow measurement speed (one of each 120 work pieces), while the plenoptic camera is capable to measure every work piece at the cost of precision. The parametrization for the simulations is summarized in Table 1. Due to the different measurement speeds, batches of work pieces are constructed, whereby the last piece's measurement is considered representative for the overall batch. Thereby, the plenoptic camera is fast enough to measure every single work piece resulting in a batch size of one. In contrast, the laser microscope can only measure one of every 120 work pieces, resulting in a batch size of 120.

In order to evaluate the performance of the predictive quality control charts, a series of simulation runs of the described scenarios were conducted using a time based maintenance strategy with fixed intervals. Thereby, the production machine underwent maintenance after producing e.g. 5 000 or 10 000 work pieces. The results for these simulation runs can be seen in Figure 5a. For each of these simulation scenarios, the production time as well as the rejection rate were recorded. Using the settings in Table 1 (mean, standard deviation, shift, tolerances and quality target) an optimal maintenance interval of 23 101 work pieces was calculated and used as a benchmark. At this point the highest probability for a work piece to exceed the tolerances is at 1%. As can be seen in Figure 5, the overall rejection rate still remains far below the set quality target. This can be accounted to the fact, that the quality target limits the maximum probability of a work piece to exceed the tolerances. Previous work pieces retain lower probabilities due to the continuous shift assumed for these simulations.

Figure 5b summarizes the results of all simulation runs, including the predictive quality control charts using the laser microscope as well as the plenoptic camera as a reference. All provided numbers represent the average over all 25 repetitions for the corresponding simulation scenario. At this, the predictive strategy sometimes triggers 5 maintenance activities, resulting in the uneven results provided in the table. Compared to the optimal benchmark, the predictive approach achieves to sustain the quality target with only a slight increase in performed maintenance activities. Thereby, the overall production time increases by less than 2%. Comparing the measurement techniques, the faster technique results in a reduced rejection rate compared to the slower one. This can be accounted to the fact, that each single piece was measured and discarded compared to complete batches. Nevertheless, both measurement techniques only result in very small differences when it comes to the number of maintenances performed and the rejection rate.



(a)

Setup	Production Time[h]	Rejection Rate	No. of Maintenance
const(50000)	7,94	15,74%	1
const(33334)	8,94	1,64%	2
const(30000)	9,94	0,71%	3
const(25000)	9,94	0,22%	3
const(23101)	10,95	0,12%	4
const(20000)	10,95	0,05%	4
const(15000)	12,95	0,01%	6
const(10000)	15,95	0,00%	9
const(5000)	25,95	0,00%	19
Camera	11,15	0,05%	4,2
Microscope	11,15	0,13%	4,17

(b)

Figure 5:(a) Results for constant intervals. (b) Simulation results.

As a result, the simulation study shows that the predictive quality control charts can deliver comparable results to an optimized maintenance strategy. Nevertheless, for the charts, only a quality target has to be selected. In contrast, the deduction of optimal maintenance intervals requires a very detailed knowledge about the processes and measurement techniques, which can rarely be acquired in an industrial environment.

4.3 Simulation Study: Forewarning Times and Prediction Behavior

The simulation study described in the last section focused on benchmarking the proposed predictive approach in terms of production efficiency. Nevertheless, it assumed a simplified linear trend to describe tool wear and as a result used a linear regression method. Moreover, the simulation study only used the predictive approach to decide if the next batch can be manufactured safely.

In order to assess the approaches behavior with respect to forewarning times and prediction accuracies for more realistic wear behaviors, a different simulation study is presented in this section. A high forewarning time is required to enable an appropriate planning and integration of maintenance activities into the production schedule. Thereby, the predictive quality control charts use the provided measurements to predict when (in how many measurement cycles) the quality target will be exceeded and thus, when maintenance is required. A higher forewarning time enables a more efficient scheduling of appropriate maintenance activities, while shorter forewarning times can result in more unsuitable schedules, leading to increasing machine down times. In contrast to the first study, this one only focuses on the measurements itself and the corresponding predictions of required maintenance activities. Therefore, the simulation generates normally distributed measurement values, following a predefined trend with a set standard deviation (including process variations and measurement uncertainties). To increase the prediction accuracy for commonly found "saw-tooth" shaped curves, a quadratic polynomial regression (two degrees of freedom) method is used for the predictive quality control charts and compared to a linear polynomial regression (only one degree of freedom). Each simulation was repeated 20 times to compensate for random effects. The overall simulation values were set to a target value of zero with a tolerance of ± 10 and a quality target 1%. With each additional simulated measurement, the quality control chart estimates at which measurement the tolerances will be exceeded. In general, sixteen different scenarios are simulated. Thereby, two linear and two non-linear (quadratic) trends are used to simulate tool wear, either as a simplified linear trend or as a "saw-tooth" shape, commonly found in practice as a result of tool wear (compare Figure 6 for an example on the curve shape). Each of these functions is simulated with two different values for the variance (standard deviation) of the corresponding normal distribution. Thereby, the standard deviation always corresponds to 5% and 10% of the tolerance to represent different levels of process stability and/or measurement precisions.

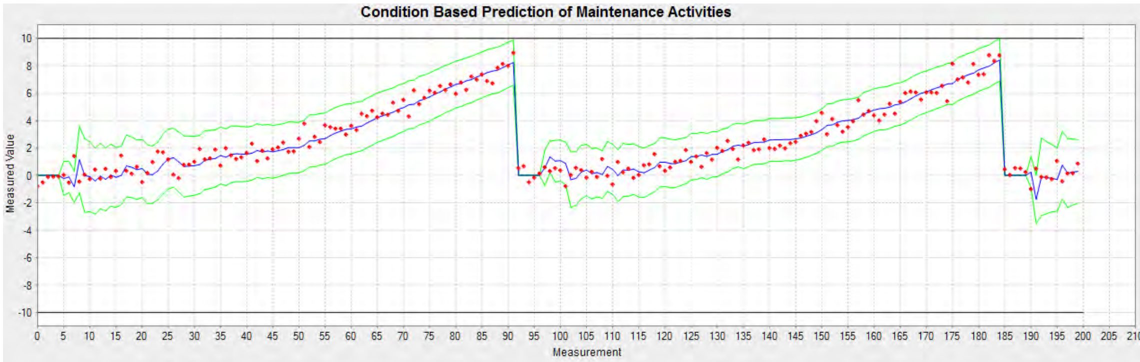


Figure 6: Exemplary simulation result for $N(0.001\ x^2; 0.5)$: Measurements (Dots), expected values (blue line), confidence interval (green lines).

Table 2 summarizes the simulation results for these configurations. Thereby, the simulation assumes a constant timeframe between each measurement so that the measurements index corresponds to a fixed point in time. The table depicts the measurement at which the tolerance intervals are exceeded the first time and the quality target is violated (Maintenance at). The second column (predicted at) contains the index of first measurement, after which the maintenance activity is predicted steadily. Thereby, the prediction is considered steady, if no more than two consecutive predictions vary strongly (±2 Measurements) from the required maintenance. The forewarning columns depict the number of measurements between the first prediction and the required maintenance, as well as the percentage of (life-)time that remains when the forewarning was issued. At this, a forewarning issued at measurement 6 of 10 would result in a percentage of 40%.

Table 2: Simulation Results

Function	**Sigma**	**Maintenance at**	**Predicted at (average)**	**Prediction Std.-Dev.**	**Forewarning [# Measure-ments]**	**Forewarning [% of time]**
Degrees of Freedom: 2 (Polynomial/Quadratic Regression)						
$0.001\ x^2$	0,5	92	51,2	8,51	40,8	44,35%
	1	82	54,7	11,93	27,3	33,39%
$0.005\ x^2$	0,5	41,5	19,7	3,79	21,8	52,59%
	1	37,5	22,85	3,76	14,65	39,05%
$0.1\ x$	0,5	84	56,55	8,82	27,45	32,69%
	1	69	59	6,93	10	14,44%
$0.05\ x$	0,5	167	123,75	18,22	43,25	25,90%
	1	135	115,3	13,28	19,7	14,64%
Degrees of Freedom: 1 (Linear Regression)						
$0.001\ x^2$	0,5	97,50	86,35	2,06	11,15	11,44%
	1	92,00	83,90	3,74	8,10	8,80%
$0.005\ x^2$	0,5	44,50	36,25	1,66	8,25	18,53%
	1	41,50	33,60	4,22	7,90	19,00%
$0.1\ x$	0,5	86,00	33,25	9,06	52,75	61,34%
	1	70,50	40,15	9,51	30,35	43,11%
$0.05\ x$	0,5	170,00	69,15	11,17	100,85	59,34%
	1	141,00	96,40	13,93	44,60	31,63%

As it can be seen in Table 2, the predictive approach results in relatively high forewarning times if the correct regression technique is used (quadratic for the non-linear functions, linear for the linear functions). Thereby, the wrong assumption reduces forewarning times to less than half or even further. Nevertheless, a forewarning was triggered for every simulation run. As a result, the wrong assumption will strongly decrease the advantage of long forewarnings required for efficient maintenance planning, but will still prevent violations of the quality target. In general, the forewarning time strongly depends on the selected standard deviation (sigma). Thus, a more stable process can be predicted more easily.

5 CONCLUSION AND FUTURE WORK

This article described and evaluated a prediction based adaptation of quality control charts for the deduction of required maintenance activities in micro manufacturing. The approach uses measurements of the manufactured products in order to predict at which measurement, work piece or batch of work pieces the selected tolerances will be exceeded with a predefined probability. Thereby, the approach only requires very limited knowledge about the underlying processes. In a first simulation study, the approach is evaluated in terms of production efficiency and benchmarked against an optimized, interval based maintenance strategy. The second simulation study aims at evaluating other characteristics of the approach, in particular the forewarning time. As shown by these studies, the approach performs quite well in terms of the rejection rate and the number of maintenance activities issued. In terms of the forewarning time, the performance strongly depends on the selection of a suitable regression method, as well as on the processes stability.

Although the scenarios presented in this article depict artificial scenarios and do not represent real world applications, they cover a broad range of possible scenarios applicable to real world applications. In particular the variation of batch sizes (e.g. due to different measurement systems), process variances (induced by more or less stable manufacturing processes and measurement systems), and trends (particularly the different extends of “saw-tooth” curves) provide a good insight on the charts behavior in real world applications. As can be concluded from the results in Table 2, the predictive approach performs best, if the underlying process is relatively stable with a suitable tolerance field. If either the tolerances decrease or the variance increases, the uncertainty within the prediction can lead to additional, unnecessary maintenance activities. In such “unstable” cases, it can be advantageous to introduce additional quality controls or quality control strategies and trigger these based on the prediction results instead of concrete maintenance activities. In addition, increasing batch sizes can result in increasingly high rejection rates or defect work pieces as complete batches are discarded or classified as good parts. In such cases, additional quality controls of single work pieces can prove advantageous if the probability for defects nears the tolerance. Therefore, the approach can easily extended to issue such activities when reaching predefined thresholds. Future work will focus on the evaluation of this approach under real conditions. Furthermore, additional techniques for the regression and the estimation of the confidence intervals will be evaluated.

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