PREDICTIVE ESTIMATION OF DYNAMIC DIMENSIONAL SPECIFICATIONS IN THE ASSEMBLING OF COMPONENTS COMING FROM LOW PRECISION MANUFACTURING PROCESSES

Carlos Hernández[1], Rainer Tutsch[1]

[1]Institut für Produktionsmesstechnik, Technische Universität Braunschweig, Schleinitzstrasse 20, D-38106 Braunschweig, Germany, carlos.hernandez@tu-bs.de

Abstract

Low precision manufacturing processes usually give rise to items that present a high (dimensional) variation. Therefore, when assembling these items special techniques have to be employed to minimize either the resulting stacked variation or the scrap level. However, full inspection (100%) is commonly required. The Statistical Feed-Forward Control Model (SFFCM) divides the system in two to apply iteratively the Statistical Dynamic Specifications Method (SDSM) on small groups of component items that are produced consecutively in a short-time interval. In a parallel manufacturing configuration, where the components are produced simultaneously in different lines, the adjustment offset generates an undesired bias. To approach the problem three different predictive models to estimate the adjustments were developed. Their properness was tried by means of designing a set of specific experiments and by simulating the production of lots of 1,000 assemblies made of two components having high dimensional variation. The effectiveness of the models was measured in terms of the reduction achieved in the mean shift and the standard deviation of the resulting assemblies' length and in the improvement achieved in the capability indices of the processes. Simulation results showed that whereas the predictive models helped reduce the average mean shift between 71% and 83%, the average standard deviation varied increased between 4% and 28%. In conclusion, the proposed approach helped reduce significantly the mean shift but not the standard variation. The resulting process capability indices, c_p and c_{pk}, revealed that none of the predictive models performed well enough to get rid of the offset problem.

Keywords: Assembling Technique, High Variation Manufacturing Processes, Statistical Dynamic Specifications Method, Statistical Feed-Forward Control Model, Predictive Specification Estimation.

1. INTRODUCTION

The Statistical Feed-Forward Control Model (SFFCM) was developed to solve the problem of assembling component items coming from low precision manufacturing processes in which the stacked (dimensional) variation reaches the order of magnitude of the nominal tolerance of the whole assembly. The key of the assembling technique based on SFFCM is the management of the specifications and tolerances of the inner components carried out by means of applying iteratively the Statistical Dynamic Specifications Method (SDSM).

2. STATISTICAL DYNAMIC SPECIFICATIONS METHOD (SDSM)

SDSM consists of a sequence of steps that help managing dimensional specifications and tolerances [1]. Let L_{assy} and t_{assy} be the target and tolerance of an assembly made of two components, 1 and 2, whose specifications have been set to L_j and t_j respectively (where j=1, 2).

$$L_{assy} = L_1 + L_2 \tag{1}$$

$$t_{assy} = \sqrt{t_1^2 + t_2^2} \tag{2}$$

Let the variation of the length of the items of Component 1 be the result of the superposition of a random component and a long-term drift (Fig. 1).

If a small subset *i* of items produced consecutively during a short-time interval were taken from the lot of Component 1, it would be found that 99.73% of the items fall within the band $\mu_{1,sub(i)} \pm 3\sigma_{1,sub(i)}$ (Fig. 1). Since the influence of the log-term drift is only partial there, the standard variation of the subset *i* is expected to be smaller than the one of the whole lot [2].

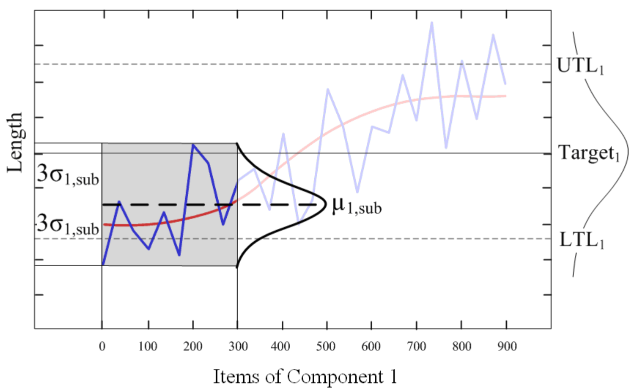

Fig. 1: Subset mean and standard deviation.

It is reasonable to think that, at least for the subset *i*, the nominal tolerance t_1 had not been fully used and that part of it could have been spared to complement the nominal tolerance t_2 of a matching subset *i* of Component 2. In fact, it would have been possible to define another tolerance

$t_{2,adj,sub(i)}$ as follows (*hint: the subscript "adj" stands for "adjusted"*):

$$t_{1,sub(i)} = 3\sigma_{1,sub(i)} \quad (3)$$

$$t_{2,adj,sub(i)} = \sqrt{t_{assy}^2 - t_{1,sub(i)}^2} \quad (4)$$

On the other hand, if the subset mean $\mu_{1,sub(i)}$ had been known *a priori* then it would have been possible to define an adjusted target $L_{2,adj,sub(i)}$ for the matching subset i of Component 2 to help meeting the desired L_{assy}.

$$L_{2,adj,sub(i)} = L_{assy} - \mu_{1,sub(i)} \quad (5)$$

3. STATISTICAL FEED-FORWARD CONTROL MODEL (SFFCM)

SFFCM requires the separation of the system in two, a feeding and a controlled subsystem, so that an intermediate measurement step can be placed in between (Fig. 2). Thus, if a drift is detected in the output of the feeding Subsystem A, corrective adjustments could be made on the parameters, in this case target and tolerance, of the controlled Subsystem B.

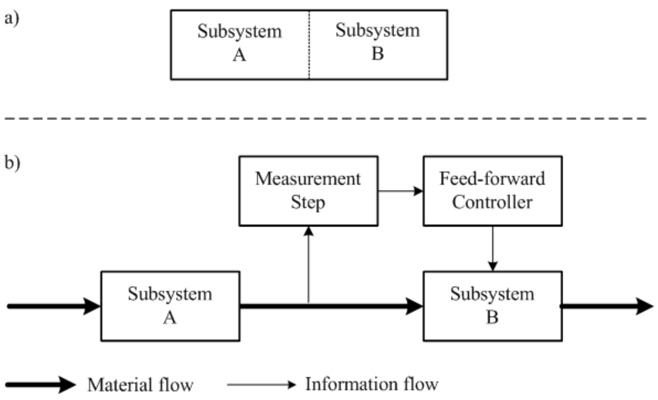

Fig. 2: Statistical Feed-Forward Control Model.

The size of the subsets is defined by the number of consecutive units coming out of the feeding Sub-system A that are considered at once to drawn the sample that will be used to determine the adjustments to the parameters of the controlled Sub-system B. In practice, the subset size determines the total number of adjustments.

In SFFCM, the sampling strategy comprises two aspects: the number of observations per subset and the selection method in which the sample will be drawn: either simple or systematic random sampling with individual or common selection pattern for all subsets [3].

4. PARALLEL MANUFACTURING

In a parallel configuration item components are fabricated simultaneously in different lines. Therefore, given that matching subsets are not produced one after another but at the same time, eventual variations detected in Subset k of Component 1 cannot be compensated immediately by adjusting the specification of the corresponding Subset k of Component 2 which is already fabricated (Fig. 3). Furthermore, the information retrieved from Subset k of Component 1 might not be even useful such as it is for a posterior adjustment of the specification of Subset $k+1$ of Component 2 because the variation of its matching Subset $k+1$ of Component 1 could be substantially different.

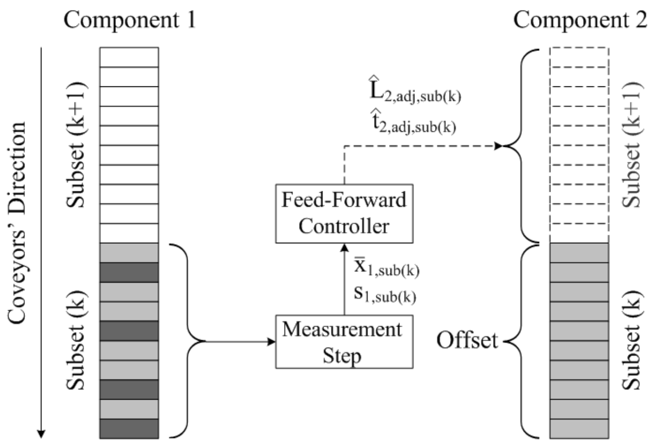

Fig. 3: Parallel manufacturing lines.

The idea to overcome the offset problem considers the utilization of a specific module to predict the statistics, sample mean and sample standard deviation, of Subset $k+1$ of Component 1 using the data retrieved from the inspection made on some of previous subsets of this component. The predicted statistics are then used as the input to the feed-forward controller so that the specification adjustment for Subset $k+1$ of Component 2 can be determined (Fig. 4).

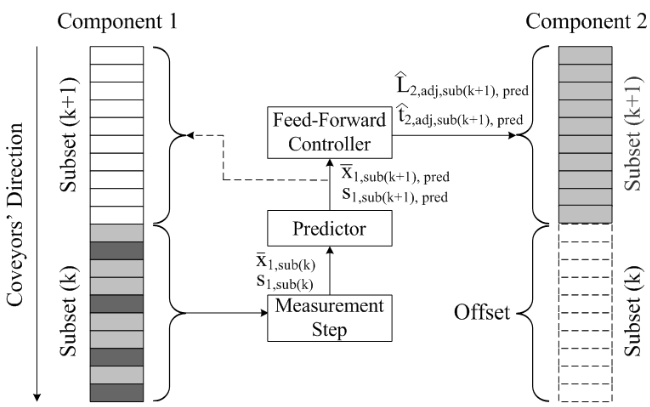

Fig. 4: Prediction module.

According to SFFCM, the prediction is repeated subset after subset until the all the component items of the lot are assembled. In particular, since the nominal specifications of Subset 1 of Component 2 will remain unaltered through out the process these units will have to be assembled such as they are.

5. PREDICTION MODES

The prediction module was equipped with three different algorithms to predict the sample mean. The first one uses the sample mean obtained from latest Subset *k* as prediction for Subset *k+1*. The second approach employs a robust regression algorithm that uses the data retrieved from some of the previous subsets. Among other benefits, this algorithm offers special robustness to outliers.

The third algorithm considers the construction of polynomials of second order whose coefficients are calculated using previously de-noised data coming from some of the previous subsets which are fitted in a least square sense. In both cases, the prediction of the sample mean is finally calculated averaging the points of the predicted curve. Although not necessarily true, for the purpose of this work the prediction of the sample standard deviation of the subsequent Subset *k+1* will remain identical to the one of the last inspected Subset *k*. In all cases, the predictor was fed with data coming from the last three inspected subsets.

6. EXPERIMENT DESIGN

Forty eight different experiments were defined to analyze the influence of three different factors: subset size, sampling strategy and prediction mode (Table 1). In all the cases, whereas the inspection rate was set to 30%; the subset size was set to 50, 100, 125 and 200.

Table 1. Experiments Design

Exp	Random Sampling		Subset Pattern		Prediction Mode		
	Simp.	Syst.	Com.	Indiv	Simp.	Rob.	Poly
1	√		√		√		
2	√		√			√	
3	√		√				√
4	√			√	√		
5	√			√		√	
6	√			√			√
7		√	√		√		
8		√	√			√	
9		√	√				√
10		√		√	√		
11		√		√		√	
12		√		√			√

7. SIMULATION

In work the production of a lot of 1,000 assemblies made of two components having high dimensional variation was simulated (Table 2). Each of the experiments mentioned above was replicated 500 times employing new populations generated by a Monte Carlo simulation.

According to the definition of SFFCM, Component 1 was meant to represent the feeding Sub-system A and Component 2 the controlled Sub-system B. Thus, the nominal specification and tolerance of the latter were the subjects of the adjustments.

The following assumptions were taken as valid:

- The lengths of the components' populations are normally distributed.
- There no correlation between the components' populations.
- The variation affecting the processes can be separated into a not controllable short term noise and a potentially controllable long time variation.
- The manufacturing processes under investigation are stable enough to respond predictably to the adjustments.

Table 2. Specifications [mm]

	Target	Tol.	Mean	St. Dev.	c_p
Assembly	30.00	1.00	29.55	0.29	1.15
Comp. 1	20.00	0.82	19.60	0.25	1.09
Comp. 2	10.00	0.58	9.95	0.15	1.29

8. SIMULATION RESULTS

Simulation results for the distribution of the resulting assemblies' length are plotted in Fig. 5, where each dot represents the average of 500,000 trials.

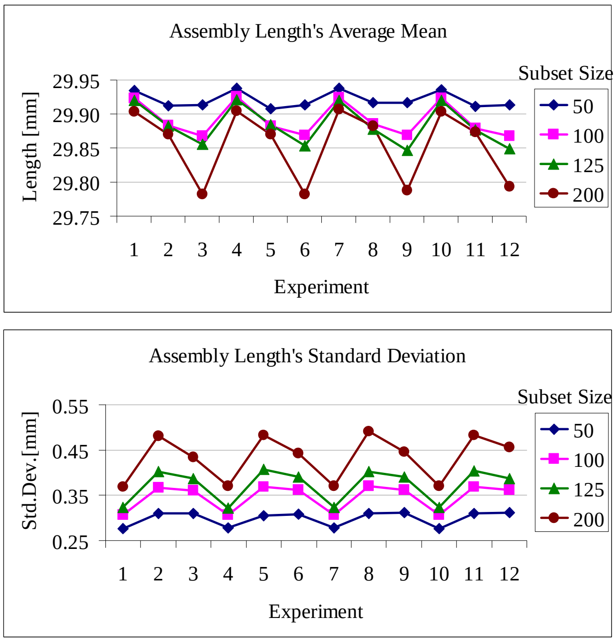

Fig. 5: Average mean (top) and average standard deviation (bottom) of the resulting assemblies' length.

It has been shown in previous works that the subset size has a deep influence on the system output [4]. However, newly experiments showed that the remaining factors are significant too. In particular, those experiments where the simple prediction mode was applied delivered systematically average assembly lengths closer to the nominal target L_{assy} and minimized the average assembly standard deviation $\sigma_{assy,adj}$. Whereas the highest reduction in the average mean shift was obtained from Experiment 4 with 86% (Fig.5 top), the highest reduction in the average standard deviation came from Experiment 1 with 4.3% (Fig.5 bottom). In both cases the subset size was set to 50 units.

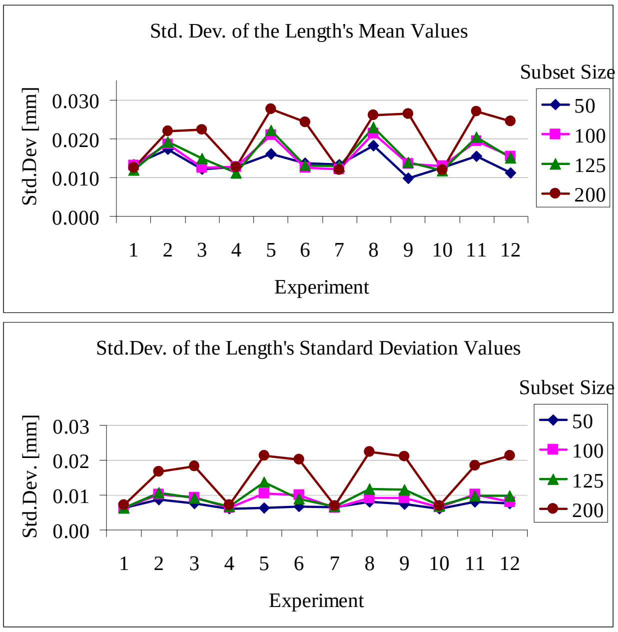

Fig. 6: Standard deviation of the mean values (top) and of the standard deviation values (bottom).

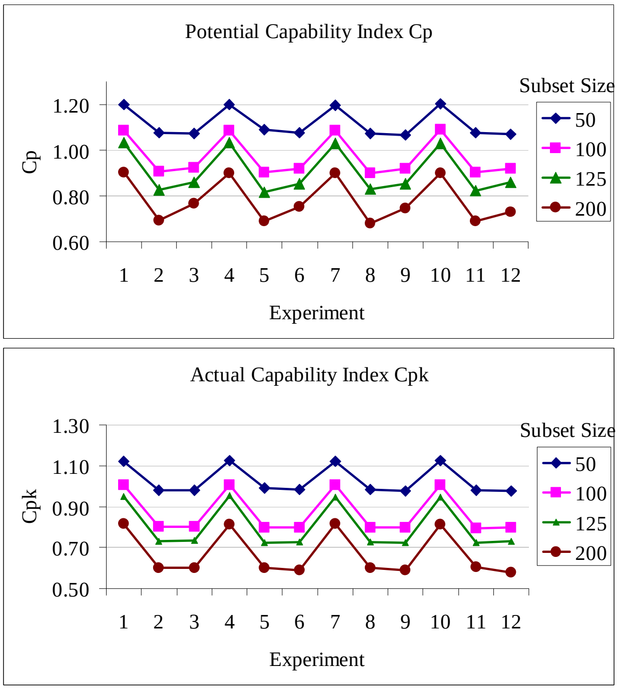

Fig. 7: Potential capability index c_p (top) and potential capability index c_{pk} (bottom)

Given that average values only provide information about the central tendency but not about the dispersion of the values, it is necessary to have a look at the standard deviations of the averaged mean (Fig. 6 top) and of the average standard deviation (Fig. 6 bottom) to realize the impact on the whole process. In this case, both a large subset size and the prediction model affect negatively the process precision.

A different way to visualize the results is through the process capability indexes, c_p and c_{pk} (Fig. 7). A process is considered as capable when it exhibits a c_p higher than 1.33. Although, commonly used, the potential capability index does not consider the shift of the mean. Therefore, it is not less important to have a look at the actual capability index c_{pk} as well (Fig. 7 bottom).

9. CONCLUSIONS

Although, not capability index higher than 1.33 was finally achieved, the simulated application of SFFCM on a parallel configuration made possible to obtain significant reductions in the average mean shift and in the average standard variation. As a consequence of the high reduction of the average mean shift, the actual capability index c_{pk} increased significantly from 0.63 up to 1.13.

Simulation results showed that none of the predictive algorithms proposed in this work performed well enough to get rid of the offset problem completely. However, when the subset size was small enough (50 items), the simple prediction mode delivered systematically good numbers. Albeit, at higher cost in terms of the number of adjustments.

Finally, in spite of not being specifically thought for dealing with offset problems, the application of SFFCM proved to bring important benefits under these conditions. However, it is still necessary to design more sophisticated prediction algorithms to produce better numbers.

ACKNOWLEDGEMENTS

Carlos Hernández gratefully appreciates the funding of his research stay at TU Braunschweig by CONICYT.

REFERENCES

[1] Hernández C., Tutsch R., 2012. *Statistical Dynamic Specification Method for Allocating Tolerances*. 12th CIRP Conference on Computer Aided Tolerancing. April 18-19, Huddersfield, UK.

[2] Burr I., 1979. Elemetary *Statistical Quality Control*. Marcel Dekker Inc. Ch.8 p.192.

[3] Ostle B., Mensing R., 1975. *Statistics in Research*. 3rd ed. The Iowa State University Press. Ch.3 p.52.

[4] Hernández C., Tutsch R., 2012. *Sampling Strategies and Long Term Variation Modeling for a Statistical Feed-Forward Controller*. XX IMEKO World Congress “Metrology for Green Growth”. September 9-14. Busan, Republic of Korea.