PROCESS CHAIN BASED WORKPIECE VARIATION SIMULATION FOR PERFORMANCE UTILISATION ANALYSIS

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Abstract: Propagation of shape variations in multi-step manufacturing processes, constrained by tolerance chains, is the consequence of sequenced operations defined in process planning. A key task in process planning is to define in-process workpiece (IPW) tolerances for efficient production ensuring conformance to the product design specification and good utilisation of the manufacturing resources. A dimension dependency chart has been developed for analysis of linked IPW tolerance chains and simulation of shape variation propagation caused by systematic and random errors. The results show how the traditional process capability index, used as an acceptance criterion for IPW tolerancing, limits the process performance utilisation.

Keywords: Process planning, machining, tolerance chain, process capability index, dimension dependency chart

1. INTRODUCTION

Propagation of shape variations in multi-step manufacturing processes, constrained by tolerance chains, is the consequence of sequenced operations defined in process planning. A final part dimension is often a result of many process steps (PS) performed in different set-ups where each contributes to shape variations (Fig. 1) from diverse conditions; for example machining, re-clamping and measuring (Zhang, *et al*., 2007; Abellán and Liu, 2013). A challenging and important task in process planning is design of the in-process workpiece (IPW), including its tolerances, for efficient manufacturing and assurance that the final part dimensions will be within specification and that manufacturing process demands will be met.

The Dimension Dependency Chart (DDC) was first introduced by Bagge, *et al*., (2013) as a methodology for process planners to design and analyse IPW tolerance chains. The second edition of the Dimension Dependency Chart (DDC2) is developed as a part of the research presented in this paper. The DDC2 is the result of elaborating the DDC methodology to facilitate the use of process characteristics input data in addition to the data used in the first edition of the DDC. An overview of the DDC2 is illustrated in Fig. 2.

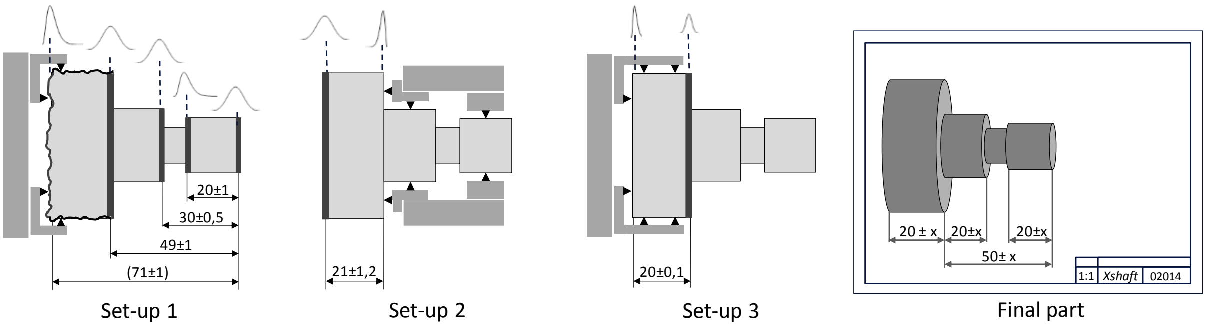


Fig. 1. Variations in multi-step manufacturing.

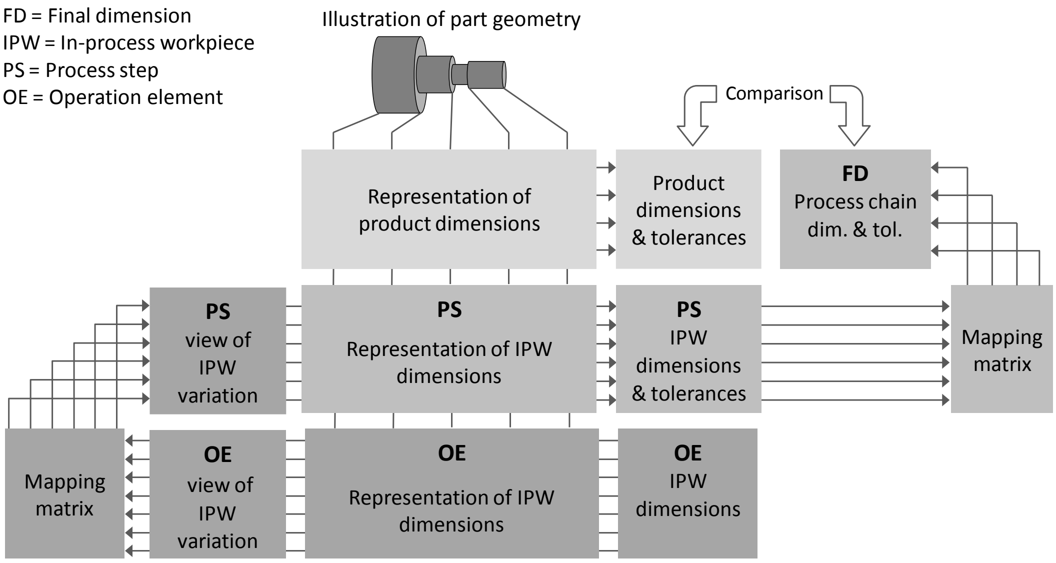


Fig. 2. An overview of the Dimension Dependency Chart 2 (DDC2).

The DDC2 defines linked IPW tolerance chains by integrating the involved PSs, assigned in the process plan. Each PS assigns geometric properties to the IPW, typically dimensions together with their variation. The IPW tolerances are set during process planning and define permissible IPW shape deviations. The effect of a process chain and the IPW tolerances can be calculated to estimate the final part shape variation and defines the allowed outcome of the manufacturing process.

How well the available manufacturing process outcome satisfies an IPW tolerance is a consequence of the behaviour of one or more separate machining operations, so called operation elements (OE). The behaviour of each OE can be defined in the DDC2 and assigned to the process steps in which they are involved. The combined behaviour of the OEs involved is calculated and then compared to the proposed PS IPW tolerance. The DDC2 also makes it feasible to compare the allowed outcome of the complete manufacturing process with the design requirements of the final part.

In process planning, there is a need to evaluate the planned manufacturing process regarding shape dimensions to be within tolerance. This must be done both for the complete process chain in relation to the final part specification and for each PS in relation to the corresponding IPW tolerances.

A well established method to evaluate the relation between manufacturing process behaviour and a desirable tolerance is to use some kind of process capability index (PCI). There are several variants of PCI but they are all based on a calculation where the required tolerance is put in relation to the variation of the process. One widely used PCI is “C_p” which can be calculated as: $C_p = (USL-LSL)/6\sigma$. C_p is the process capability index, USL and LSL are the upper and lower tolerance limits respectively and σ is the standard deviation of the process (Wu, *et al*., 2009).

Calculation of C_p requires a properly estimated standard deviation derived from normally distributed data and a process that operates in a state of statistical control (Wu, *et al.*, 2009). "Statistical control" implies that the process operates without a drifting mean value, typically recognised as a trend. The maximum acceptable number of out-of-tolerance dimensions is determined, followed by a probability based calculation of the corresponding lower limit of C_p.

PCIs are used both to evaluate final dimensions, where the tolerances are derived from the design specification, and separate manufacturing process steps, where the tolerances are defined in the process plan. A common application in which single process steps are examined is when the capability of a machine tool (C_m) is to be evaluated. C_m is a short-term capability index and the investigation does not allow considerations such as process control actions, different work materials or machine operators to influence the result. C_p is in turn a long-term capability index where all ordinary parameters in the manufacturing environment are supposed to have an impact on the result. C_m is often calculated by using information from either test-runs for new machine tools or from regular capability tests in the workshop and C_p by using information from production data bases or data from sources such as control charts or routine measurements.

PCI as an indicator of process abilities is based on the statistical assumption of normally distributed data, which implies that neither trends nor correlated data are allowed. In reality, most manufacturing processes show trends where the dimension mean value has a drift due to tool wear or temperature changes in the equipment (Abellán-Nebot, *et al.*, 2013). It is common that PSs are dependent on each other and often the underlying OEs interact or have coupled behaviours (Bagge, *et al.*, 2013), also described by Frey, *et al.* (2000). Typically, OE coupling occurs when the same cutting tool is used and the systematic behaviour will be the same. The DDC2 permits definition of coupled OEs and dependencies in the process chain. This opportunity is important and is in contrast to other research such as that of Frey, *et al.* (2000) and Abellán-Nebot, *et al.* (2011;2013) used in the analysis.

The first objective for this research is to evaluate PCI as an indicator in analysing IPW tolerance chains, a task in planning multi-step manufacturing processes. The second objective is to examine how the characterisation of causes of deviation, in the process chain and its behaviour, affects the performance utilisation of the defined process. The research approach is based on the DDC2 and an experimental setup where different scenarios have been assigned, simulated and compared.

2. SIMULATION OF DIFFERENT TOLERANCING STRATEGIES AND PROCESS BEHAVIOUR CHARACTERISATION

The DDC2 has for this research been developed as a workbench for process plan analysis; for evaluating how various tolerancing strategies and process behaviour characterisation result in different utilisations of manufacturing equipment performance. The subject for the process plan is the "Xshaft" shown to the left in Fig. 3.

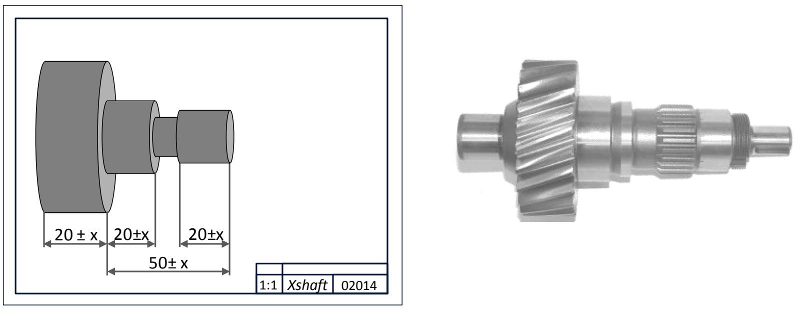


Fig. 3. Xshaft (left) and gear shaft (right).

The Xshaft is a fictitious part but it has distinctive features found in many gear transmission parts, such as the gear shaft in Fig. 3. The Xshaft is created to exemplify and explain the strategies for IPW tolerance chain design and analysis. This paper addresses the axial dimensions of the Xshaft with the intention that it be extendable to 3-dimensional geometrical dimensioning and tolerancing.

The manufacturing process for the Xshaft includes machining in three set-ups. The contribution from each OE to the PSs defined in the process plan, continuing to the final dimensions of the part, is illustrated in Fig. 4.

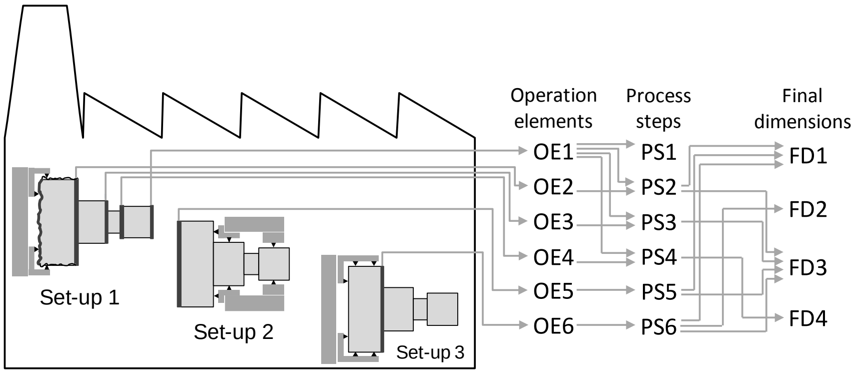


Fig. 4. Manufacturing process for the Xshaft.

The focus for the Xshaft case study has been to evaluate what can be achieved from the available manufacturing resources when used as defined in a process plan. The manufacturing resources have been assigned with process behaviour characteristics, like tool wear and random variations, to represent industrial conditions. Each operation is defined as an OE and the ability to create a shape feature on the Xshaft depends on the assigned behaviour of that OE.

The aim of the process planning task, as illustrated in this case study, is to find out the smallest variation on the final dimensions that a defined process chain can provide. The smaller the dimensional variation, the higher the performance of the process, and also the better for part design achieving potentially higher functional performance for the product. The evaluation criterion will be how well the potential process performance is utilised when different strategies for tolerancing and process behaviour definitions are applied to the process plan.

2.1 Simulation scenarios and evaluation criteria

Five scenarios have been subjects for simulation and are shown in Table 1. The motivation for the scenarios and the underlying tolerancing strategies both have two origins; common practice in industry and the new possibilities provided by the DDC2 itself. All five scenarios have been tested for two manufacturing facilities with different characteristics; these are called virtual workshop 1 and 2 (VW1 and VW2).

Table 1. Simulated scenarios.

Scenario	**Process behaviour characterisation**	**IPW tolerancing strategy**	**Expected outcome for FD 1-4**
PS:C_p	PS Standard deviation (σ)	C_p * 6σ	FD TE
PS:TE	PS TE	PS TE	FD TE
OE:TE	OE TE	Calculated PS TE	FD TE
OE:SE&RE	OE SE & RE	Calculated PS TE	FD TE
Reference	Pure process behaviour	N.A.	FD TE

Abbreviations: PS = Process Step; OE = Operation Element; FD = Final Dimension;
TE = Total Error; SE = Systematic Error; RE = Random Error.

The aim of each scenario is to evaluate how the applied tolerancing strategy and process behaviour characterisation influences the expected outcome of the final dimensions (FD 1-4) expressed as total error (TE). TE is a range of variation calculated as the difference between maximum and minimum of all values. TE is used for FD as well as for dimensions resulting from PS and OE. One scenario separates TE into the known and predictable systematic error (SE) and the “white noise” random error (RE). Like TE, both SE and RE represent the range of variation.

All scenarios, except the reference, use these simplified representations (TE, SE or RE) of the process behaviour. These simplifications reduce the content of the process behaviour information, from being time (or part instance) dependent variables to being single values representing the variation magnitude.

The reference scenario represents, in contrast, a situation where time dependencies still remain and no simplifications or intermediate estimations in the process chain influence the expected outcome. In this scenario, the TE for each FD is a consequence of both the “pure process behaviour” assigned to each OE and its propagation through the process chain as defined in the process plan. The reference scenario is assumed to represent the unfiltered outcome of the available manufacturing resources and the highest possible performance, defined as 100%. This scenario allows the designer to define a part with the tightest possible tolerances and potentially the best functionality for the given manufacturing equipment.

The evaluation was made by comparing the reference scenario with the other scenarios by calculating a performance utilisation ratio (PUR) as: $PUR\ (\%) = 100*TE_{reference}/TE_{scenario}$.

Scenario using process step with capability criteria (PS:C_p). Process behaviour is here captured as the outcome of each process step. The only available information is σ and IPW tolerances are calculated to satisfy C_p=1,33. This capability level will theoretically result in 63 defects per one million opportunities (DPMO) and is commonly used as the threshold for what is deemed to be an acceptable process.

Scenario using process step with total error criteria (PS:TE). Process behaviour is captured from PS but represented as TE. To make this scenario comparable to the PS:C_p scenario, where 63 DPMO are acceptable, the TE is pruned from maximum and minimum values corresponding to 63 DPMO. Each PS tolerance will then be equal to the constrained TE.

Scenario using operation element with total error criteria (OE:TE). Process behaviour is measured for each OE and represented as TE. As the OE does not have any tolerances, the tolerancing will still be a matter for the PS. PS tolerances are calculated by adding the TE for the included OE.

Scenario using operation element with systematic and random error criteria (OE:SE&RE). Process behaviour is captured from OE but represented as distinct SE and RE. This gives the opportunity to eliminate systematic errors for a PS if the included OEs are known to be coupled. The PS tolerance is then defined to be the calculated TE as a result of conditional addition of SE and RE for the included OEs.

Scenario using dimensional variation on part instances (Reference). TEs for FD 1-4 are the results of time dependent addition of the pure process behaviours, from OEs to FDs via PSs in the process plan.

Virtual workshop (VW) 1 and 2. As the scope of this paper is to consider manufacturing processes showing not only random but systematic variations, the significance of these systematic variations is of interest. The pure process behaviour has been assigned to each OE and has both a systematic and a random term. The relation between the SE and the RE is what distinguishes VW1 from VW2. VW2 has OEs with a more pronounced SE than VW1. The SE/RE quotients for OEs in VW1 are approximately 1 while they all are 2 for VW2. Only the definitions of systematic behaviours have been changed between VW1 and VW2, the random definitions are exactly the same.

2.2 Simulations based on the DDC2 methodology

Simulations of the manufacturing process for the Xshaft were made using Vensim DSS software (by Ventana Systems, Inc.) in combination with the DDC2. Vensim is a generic platform developed for system dynamics simulations (Sterman, 2001) with a graphical programming interface and capabilities to include all the definitions needed for the purpose of making the tolerance chain analysis. A simulation model of the Xshaft manufacturing process was programmed in Vensim according to the DDC2 in Fig. 5.

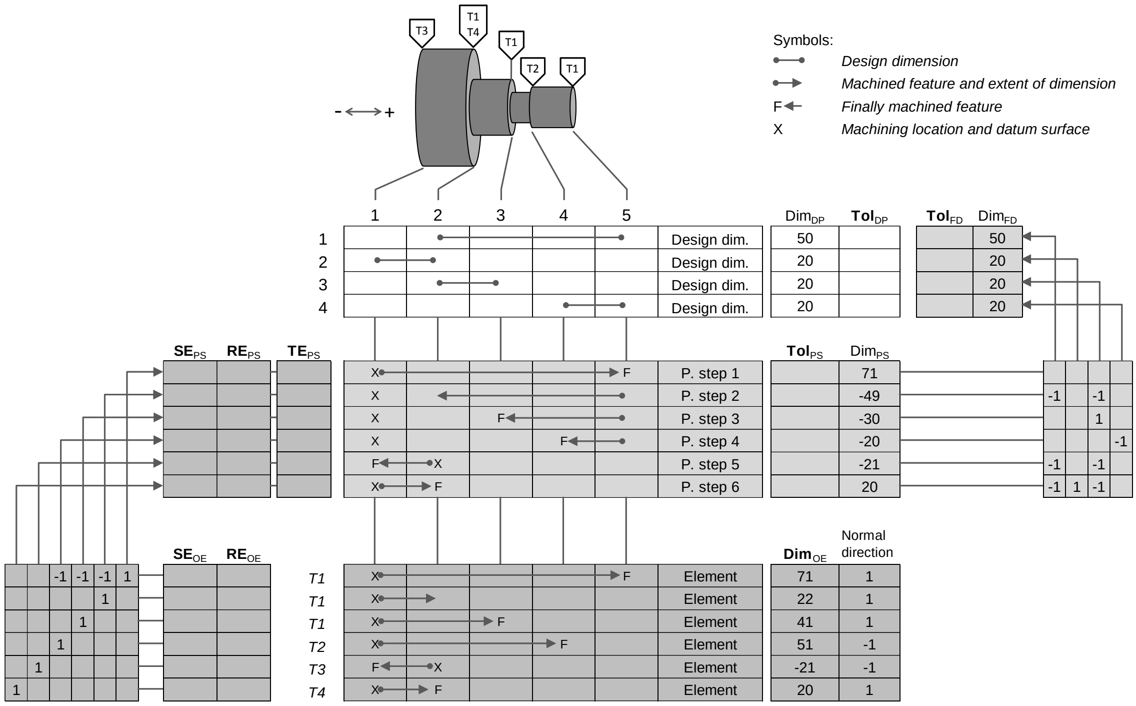


Fig. 5. DDC2 for the Xshaft manufacturing process.

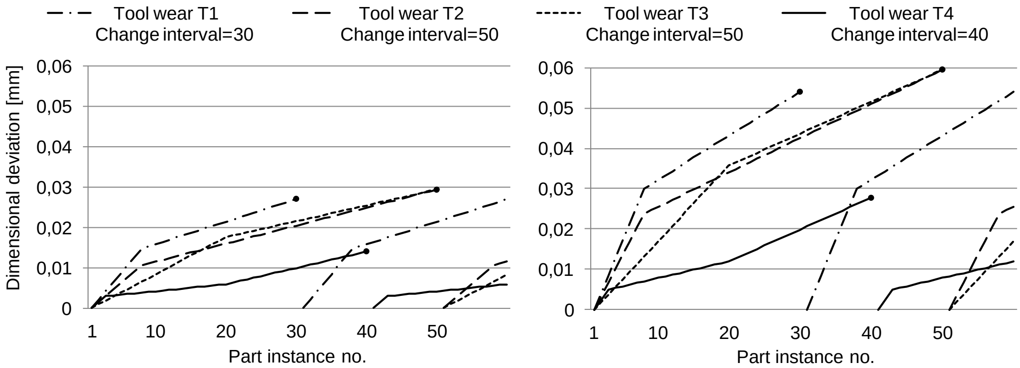


Fig. 6. Systematic error due to tool wear and tool change interval for VW1 (left) and VW2 (right).

To get information as relevant as possible from the DDC2-simulations, the process behaviours were defined on a realistic basis. Systematic process behaviours are based mainly on cutting tool wear effects recognised in industrial production. The definitions of systematic behaviour in the simulations are based on the curves for tool wear and change intervals in Fig. 6.

Each OE has both a systematic behaviour given by the used cutting tool and a random behaviour from normally distributed data generated by Vensim.

The virtual manufacturing process was simulated with these assigned process behaviours and the process chain definitions as described in the DDC2 of the Xshaft process plan. Each simulation run contained in total 100 000 virtually manufactured Xshafts. The simulations were performed as sensitivity simulations in sets of 1000, repeated 100 times with different noise seeds to generate independent random series. Examples of simulation input and output data in relation to the DDC2 are shown in Fig. 7.

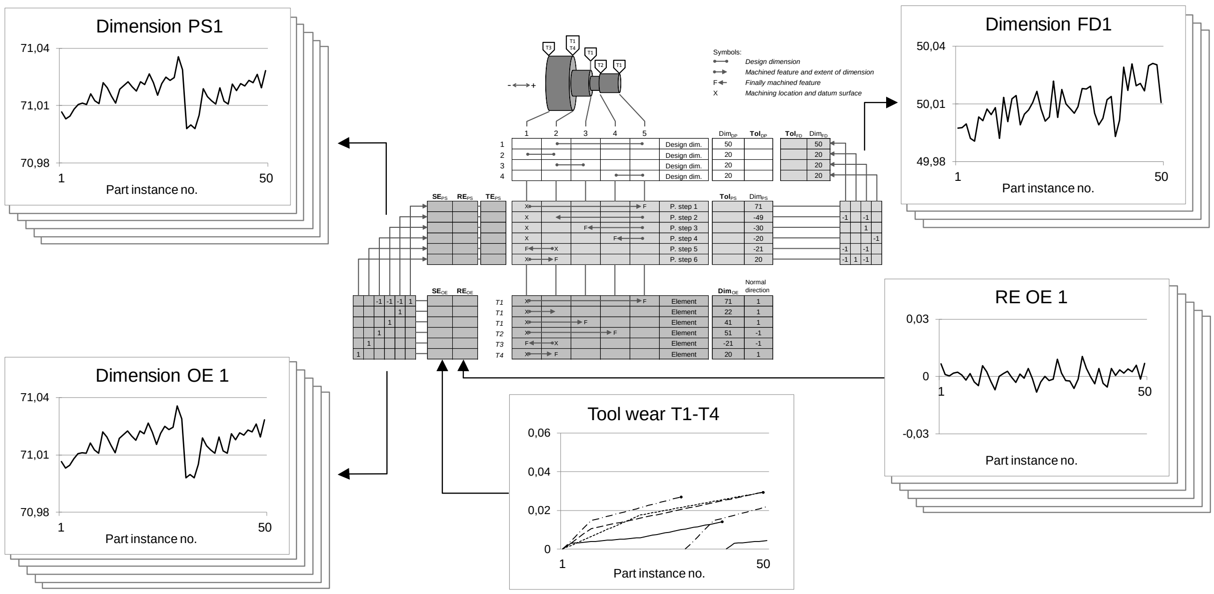


Fig. 7. Vensim simulations applied on the DDC2.

3. SIMULATION RESULTS

The simulation results for each scenario were collected and the PUR was calculated for every FD. Fig. 8 shows the results for FD1-4 to compare the tolerancing strategies.

In this investigation, VW1 and VW2 exemplify two different conditions when analysing the tolerancing strategies. It is of no interest to compare which is the best, because they are not competing with each other. The reason for having them in the same diagrams is to evaluate how the workshop characteristics affect the difference in performance utilisation and to draw conclusions about different tolerancing strategies.

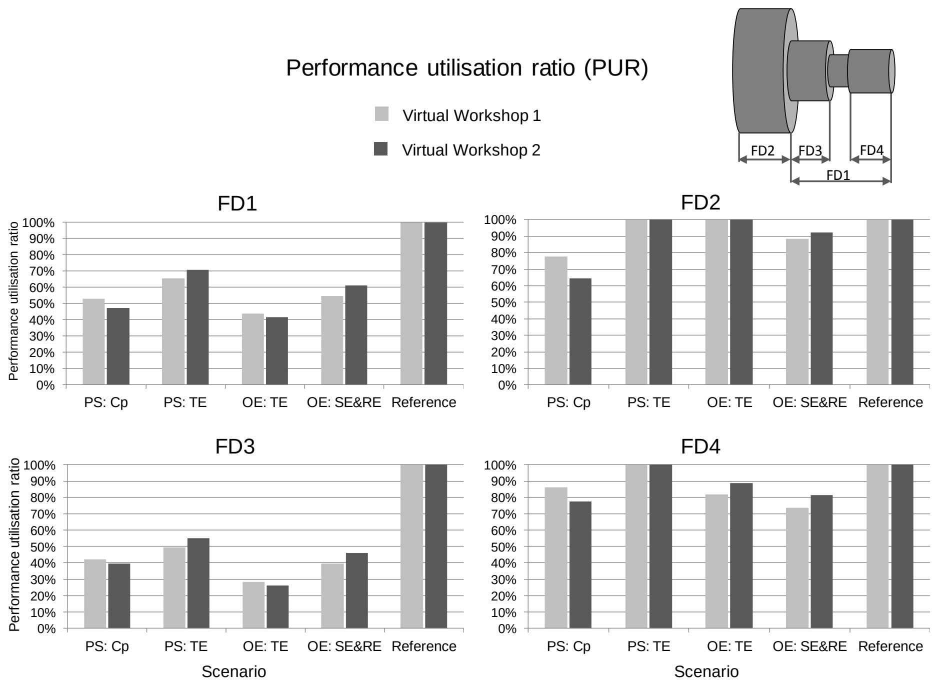


Fig. 8. Simulation results - Performance utilisation for FD1-4.

4. ANALYSIS AND CONCLUSIONS

Performance utilisation ratio (PUR) is affected by different tolerancing strategies and process behaviour characterisation, as well as the workshop conditions and process plan structure–coupled operation elements and process chain length.

The effect of process chain length. All tested tolerancing strategies include simplified representation of the process behaviours, which affects the tolerance calculations and the performance utilisation ratios (PUR). SE, RE and TE are all instances where the information about process behaviour is reduced to be a constant range of a max-to-min spread, assumed to include the worst case. No information about time dependencies or statistical distributions can be derived from these static values. When OEs or PSs are combined into a manufacturing process chain each individual worst case contribution will stack up into worst case FDs. This phenomenon is clearly recognised in the simulation results in Fig. 8 where FD3 shows very low PUR compared to reference. FD3 is the result of four OEs and four PSs and the worst case stack shows a significant effect. In contrast, FD2 has a much better PUR thanks to the fact that it contains only one OE used in one PS.

The effect of C_p, total error (TE) and the distribution of data. A common feature for all FDs is that the PS:C_p scenario shows a lower PUR than the PS:TE scenario. IPW tolerances for each PS in the PS:C_p scenario are calculated to fulfil C_p=1,33. As explained in the introduction, one prerequisite for making such probability based calculations is that the outcome of the PSs is normally distributed. This restriction on established PCIs to be used only for processes under statistical control and with normally distributed data is much emphasised by Wu *et al*. (2009). Only PS2 and PS3 show normally distributed output data as illustrated in Fig. 9. The normally distributed output of PS2 and PS3 resulted in IPW tolerances that were nearly the same for both scenarios PS:C_p and PS:TE.

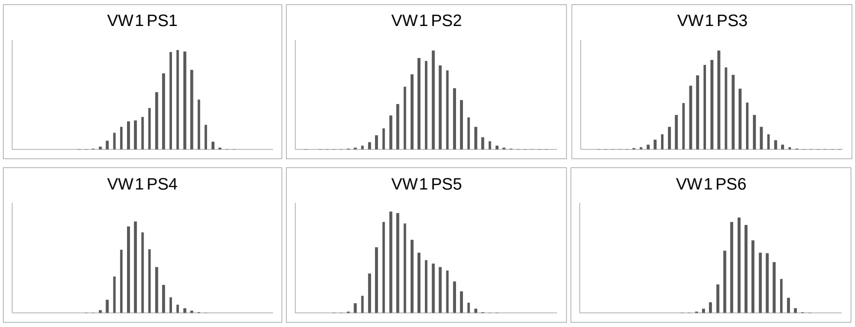


Fig. 9. Histograms illustrating simulated distributions for VW1 PS1-6 IPW dimensions.

The cause for this phenomenon is that the probability calculation estimates the outcome very well if data is normally distributed and the number of measured parts is high. IPW tolerances for PSs with non-normally distributed data were significantly higher in the PS:C_p scenario than PS:TE scenario. All FDs contain at least one PS with non-normally distributed data and the worst case calculations therefore result in lower PUR for scenario PS:C_p than PS:TE.

Why do both PS2 and PS3 show normally distributed data in Fig. 9, despite that they are results from OEs with non-normally distributed output caused by systematic errors (tool wear)?

What is seen here is the effect of smart process planning tricks to reduce variations by using coupled OEs. As the same cutting tool is used for all OEs contributing to PS2 and PS3 the systematic error is eliminated (Gerth, 1997) and the outcome will follow a normal distribution. This is illustrated in Fig. 10 where the systematic error for PS2 is eliminated thanks to the use of tool T1 both in OE1 and OE2.

The PS systematic error will also be reduced, but not eliminated, when the OEs have similar systematic behaviours and a time dependent relation. This makes them semi-coupled. The time-dependency requires, for instance, a distinct definition of tool change and process control strategy to keep the coupling.

The effect of coupled operation elements (OEs). Comparison of the results from scenarios OE:TE and OE:SE&RE shows different effects depending on observed FD. FD1 and FD3 show higher PURs for the OE:SE&RE scenario than for the OE:TE scenario. The situation for FD2 and FD4 is the opposite.

The reason is that the benefits of using the OE:SE&RE strategy can only be gained if there are coupled OEs. Coupled OEs permit elimination of SE, which is the case for both FD1 and FD3. The reason why FD2 and FD4 get lower PURs is that they cannot take any advantage of coupled operations by elimination of SE but suffer from the drawback of calculating TE based on separated SE and RE. The calculated TE (TE_{calc}) is the worst case sum of SE and RE and will in practice exceed the simulated TE due to reasons of probability as illustrated in Fig. 11. The probability for a coincidence of an extreme random error value and an extreme systematic error value is very low.

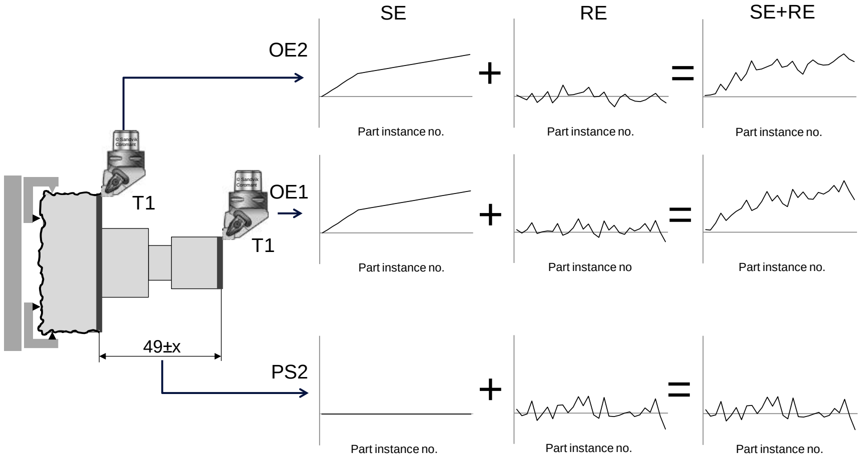
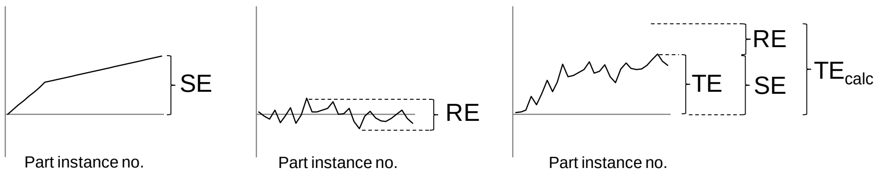


Fig. 10. Elimination of SE as a consequence of coupled OEs.



$$SE+RE = TE_{calc} \quad ; \quad TE_{calc} \geq TE$$

Fig. 11. The distinction between a probability based total error (TE) and a calculated total error (TE_{calc}) as the sum of systematic error (SE) and random error (RE).

Workshop characteristics. There are some differences in effects from the tolerancing strategies when studying results from VW1 and VW2 in Fig. 8. For strategy PS:C_p, VW1 shows less relative decrease in performance than VW2 but for OE:SE&RE its shows more decrease than VW2. The explanation for this behaviour relates to the predictability of the outcome from each workshop and the chosen representation of PUR.

VW1 has less systematic error than VW2 which makes outcome more normally distributed. This is an advantage for VW1 when using the PS:C_p strategy for tolerancing and calculation of PUR. This also shows the effect for the OE:TE strategy when applied on long process chains with many OEs (FD1 and FD3).

Though less systematic error should be an advantage for VW1, it does result in a lower degree of short term predictability than VW2. VW2 has more systematic error in relation to random error and is therefore relatively more predictable than VW1. FD4 shows a result for OE:TE where VW1 suffers from being less predictable relative to VW2.

5. CONCLUSIONS

Using C_p in the IPW tolerancing strategy decreases the PUR, especially for high C_p values and long process chains. In the presented case study the use of TE instead of C_p=1,33 gives a higher PUR.

Separating SE and RE is useful if there are coupled, or semi-coupled, OEs. SE for the PS will in these cases be eliminated or reduced.

Simplified definitions of process behaviour result in an underestimation of the process performance. The longer the process chains, the bigger the underestimation. Detailed definitions and knowledge about process behaviour are vital for high PUR. PUR is potential element of a key performance index for process planning.

6. FUTURE WORK

Developing the DDC2 towards neat analysis of both 2D and 3D tolerance chains is desirable. This will preferably be done to support use of the geometrical product specifications (GPS) standards to its full extent.

As the DDC2 provides a representation of the underlying mechanisms for a manufacturing process, it has the potential to be a good platform not only for tolerance and variation analyses, but for risk analyses. If the risk of different failures through the process chain can be defined in the DDC2 and the final effect can be evaluated, the purpose of the commonly applied process failure mode effect analysis (P-FMEA) is achieved.

One finding of this paper is that the use of C_p, as a requirement for IPW tolerancing, decreases the PUR. To gain higher PUR, as a result of well balanced process plans, further work has to be done to find other criteria in IPW tolerance evaluation than the traditional PCIs.

Other subjects to be considered are conditional and dynamic behaviours of the manufacturing system. For example forged blanks usually show rather large dimensional variations and impact cutting conditions such as depth of cut. A variation in depth of cut implies changed cutting force and in turn a displacement of the cutting tool, resulting in dimensional deviations. The OE behaviour therefore depends on the condition of, for example, each blank. Dynamic behaviours can be identified in multiple levels as the *process chain level* and the *machine tool level*.
Measuring and process control strategies will be represented as feedback loops facilitating dynamic simulations on the *process chain level*. A potential option is to integrate representations of the dynamic behaviour on the *machine tool level* that contribute to the definition the OE behaviour. Examples of models for dynamic behaviour of machining systems are given by Nicolescu (1991) and Archenti (2011).

There is also cause to test how different logistic strategies influence the manufacturing process. If the material flows are sequenced from one operation, and for example SE (trends) in dimensions can be recognised, it is supposed that it will be easier to control the process in the next operation than if the material flow is scrambled. Including material flow aspects and control strategies in the DDC2 structure is of interest.

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