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REAL-TIME MACHINING QUALITY INSPECTION FOR DESIGN FOR MANUFACTURING (DFM)

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A dynamic, globalized and customer-driven market brings opportunities and threats to companies, depending on the response speed and production strategies. One strategy is Concurrent Engineering (CE) that focuses on improving the product development process, by considering various factors associated with the life cycle of the product from the early stages of the product design. Design for Manufacturing (DFM) has proven to be an effective approach to implement CE concept. Recently, an important DFM concept in machining (i.e. a real-time inspection) has drawn much attention from both academia and industry. This is because intense domestic and international competition has put more emphasis on the part quality to achieve a shorter inspection time, improved part accuracies, and reduced scrap. The current methodology, using a machine mounted touch probe, suffers from the fact that the measurement accuracy is affected by the individual machine tool's positional accuracy and positioning system. To address this concern, the cutting experiments were conducted to collect touch probe measurement data. The data were analyzed to verify whether using a touch probe is suitable for real-time inspection. The analysis results show the touch probe has the higher capability index numbers and consistencies than the coordinate measuring machine (CMM), suggesting that the touch probe can be integrated into DFM as a means of real-time quality inspection.

Keywords: Touch probe; CMM; quality inspection; tolerance; CE; DFM.

1. Introduction

Product development process consists of two distinctive stages: product design and process design, where product design addresses the functionality of product while the process design focuses on the manufacturing and process planning.[1] Concurrent Engineering (CE) is concerned with improving the product development process by

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considering, during the early stages of the product design, of the disparate factors associated with the life cycle of the product. These factors include manufacturability, assemblability, process planning, testing, quality inspection, to just name a few. It has been proven that CE is an effective strategy for industry to maintain competitiveness in responding to the dynamically changing, globalized, customer-driven market. Some Japanese companies take half the time that US companies do to deliver major products (e.g. aircraft and automobiles).[17] This success comes from the fact that CE contributes significantly to the reduction of product development cycle.[38]

Extensive research has been done to explore CE techniques and tools. Prasad[36,37] classified the agents that influence CE into seven categories including talents, tasks, teams, techniques, technology, time and tools. He also categorized CE techniques into six levels with increasing degree of creativity and cooperation. These include network-based techniques, documentation-based techniques, variable-driven techniques, predictive techniques, knowledge-based techniques, and agent-based techniques. O'Grady and Young[33] reviewed methodologies on the implementation of CE and categorized them according to the tools used for the implementation. It is noted that one effective approach to implement CE is Design for Manufacturing (DFM). DFM takes any manufacturing related issues into account, e.g. selection of materials and machine tools, manufacturing methods, process planning, assembly methods, testing and quality control, etc. towards the product development to make sure that design features can be manufactured as easily as possible.[32] Because up to 70% of product's manufacturing costs are determined at the design stage,[30] DFM can potentially reduce the estimated 15%–70% of cost that is attributable to manufacturing and assembly[39] and increases 100% to 200% in productivity.[8] Besides the reduction in cost, DFM promises additional benefits in increased reliability, shorter time to market, especially, increased quality. Indeed, issues of great interest both from engineering and business perspective is improving quality while reducing the cost and the complexity of manufacturing processes in many manufacturing situations.

In machining, a dimensional tolerance is one of the most significant quality characteristics.[1] To generate correct dimensions, the manufacturing process and the measuring instrument need to be equally capable.[26] For complex assemblies in which many discrete parts interact with other components, it is especially important to set the part dimensions and tolerances using information from a process capability study.[31] Since the tolerances affect greatly in the proper functioning of machined parts in addition to the production cost, any inspection routine for the tolerance needs to be planned and considered at the design stages to capitalize on the concepts of DFM. The inspection of dimensional tolerance needs to be planned during the product/process design stages to improve the overall efficiency of the production activities. Barreiro *et al.*[5] stated the importance of inspection planning: (1) it is important to devise a plan for inspection processes along the conceptual part design, (2) high speed coordinate measuring machines (CMM) are becoming widely used in the production lines, and (3) it is important to form a feedback loop between part inspection and manufacturing processes. The feedback loop is to correct a potential quality problem before the completion of the machining or prior to the production of subsequent parts.[26] Though important, the integration of dimensional inspection into product design has been largely neglected over the years.[5] Barreiro *et al.*[5,6] attempted to integrate inspection information into design and manufacturing processes. Other studies show the development effort of inspection models, mainly for the prediction of part quality characteristics in dimensional accuracy or surface roughness.[2,7,21,28] However, these models suffer from the shortcomings, such that the models are developed based on the data generated by a post-process technique (i.e. CMM) and the models have a very narrow scope and are very costly to develop. The models are therefore not suitable for the modern, dynamically changing production environment. In order to integrate the inspection into the framework of DFM, there is a need for a real-time quality inspection. To achieve this, a gauge capability analysis should be conducted first to establish a confidence in the measurement data. The main focus of this study is, therefore, to conduct the gauge study to vindicate the inspection process capability and the adequacy of the real-time measuring instrument. The findings in the study will help guide the way to implement the notion of concurrent inspection approach into product design cycle. The contributions of this research are three folds. First, a real-time inspection technique designed to feed the inspection information into manufacturing system is studies in tune with the DFM. Second, experiments are carried out to analyze the in-process gauge capability. Third, comparison study is conducted between the in-process gauging with a spindle touch probe and post-process inspection using a CMM. This paper is organized as follows. DFM and quality inspection are reviewed in Sec. 2. In Sec. 3, the experiment is discussed in detail followed by the result analysis in Sec. 4. Section 5 summarizes the research findings and the suggested future research.

2. DFM and Product Quality Inspection

Today's industry faces increased challenges caused by global competition, new technologies and electronic commerce. Companies must quickly manufacture high-quality, and low-cost customized product. DFM, an effective methodology, has attracted great attention. The realization of DFM concept requires product development team to understand current manufacturing technologies and methodologies including material requirement, computer aided process planning, quality control, test and inspection, etc. The current emphasis on quality and reliability and the current competitive state of the international market have resulted in greater visibility and increased responsibility for test and inspection[38] which are illustrated in Fig. 1 in the context of CE and DFM. In manufacturing, inspection is fundamental to ascertain the conformance.[26] The confidence in inspection gauges and measurement data play an important role in deciding whether the parts are being manufactured

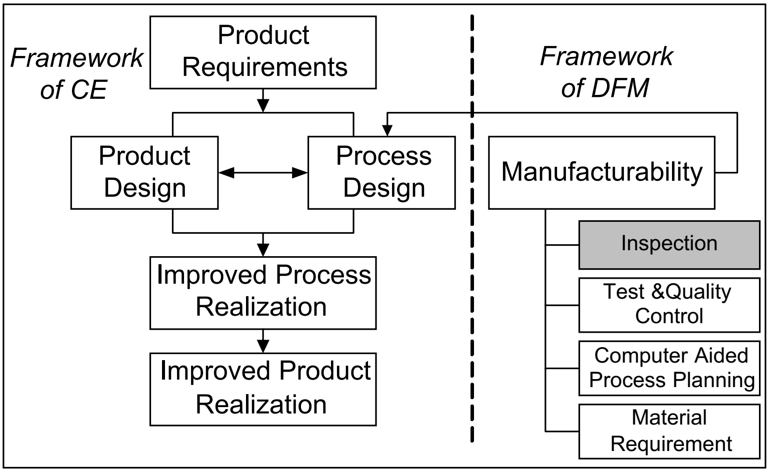


Fig. 1. Integration of inspection in the framework of DFM.

according to the design specifications and whether the manufacturing processes are in control. A traditional approach to tolerance inspection of machined parts is a post-process inspection, meaning that dimensions are checked after the part has been produced. This approach poses a serious problem since many defectives can be manufactured between inspections.[14,24] The recent progress in developing new, automated measuring instrument has led to the in-process, on-line, or real-time inspection, where critical dimensions are measured and verified while parts are being produced on the machine. The industry trend is to measure the dimensions while parts are still on the machine and correct any machining errors.[16,18,19,26,27,29,35,42] The immediate benefits of this approach include improved machining accuracy and reduced scrap. In case of rework, the savings in production time can be substantial because the part remains on the machine without disrupting the setup configurations. To realize the real-time inspection, the computer numerically controlled (CNC) machine tools are being equipped with a touch probe. Part dimensions checked by a touch probe are automatically fed into a CNC controller to compensate for any variations in machined features.[12,24] This is particularly important for a modern, computer controlled production environment, where very little human intervention is expected during the machining cycle.

However, one significant drawback is that inspection is performed on the same machine that produces the part, which leads to the limited measurement accuracy by the individual machine tool's positional accuracy and positioning system.[12,43] For example, thermal growth of machine tool structures is especially detrimental in controlling machining accuracy,[3] yet thermally-induced errors will be directly reflected on the performance of a touch probe. The dynamic behavior of the machine tool (e.g. the direction and speed of the machine slide as it moves toward the target position) also affects the measuring accuracy.[9] In order to use a touch probe as a means of in-process dimensional accuracy check, the measurement performance of the touch probe needs to be analyzed and possibly compared with the data obtained by other measuring instrument. The comparison will offer insights towards the extent of errors induced by the structural imperfection intrinsic to a machine tool that will be reflected on the touch probe, and will help decide whether the touch probe is capable of performing the real-time part quality assurance.

3. Laboratory Experiments

In this study, a state-of-the art, three-axis, vertical CNC milling machine (a brand-new Cincinnati Milacron Arrow 750 CNC VMC with 0.0001-in. repeatability), equipped with a touch probe (a Renishaw MP 700 surface sensing wireless probe with 0.00001-in. repeatability), was used to cut parts from blank workpieces of size $130\,\text{mm} \times 100\,\text{mm} \times 63.5\,\text{mm}$ in three different material types. The selected materials are those commonly used in industry: 6061-T6 Al, 7075-T6 Al, and ANSI-4140 steel. Figure 2 illustrates the touch probe mounted in the machine spindle and the finished blocks. For each material, a new cutting tool was assigned and the machining was carried out until tools wore out. A total of 20 parts were machined using 6061-T6 Al with a 1-inch diameter, 2-flute cobalt high speed steel (HSS) end mill. For 7075-T6 Al, 19 parts were produced with a HSS tool. For ANSI-4140 steel, 17 parts were finished with a 1-inch diameter, 2-flute, sintered, tungsten carbide end mill cutter.

The cutting parameters were analytically decided to minimize the chatter using a combination of CutPro software, a Kistler hammer kit and an accelerometer (a Kistler tri-axial accelerometer, $\pm 500\,\text{g}$, sensitivity $10\,\text{mV/g}$). Typically, the vibration is considered as one of the best indicators of mechanical equipment problem,[23] and the vibration during machining is especially harmful to the dimensional accuracy and surface finish of machined features. Consequently, the axial and radial depth of cut and cutting speed were tuned for a chatter-free machining. Each block has two stepped bores (65 and 50-mm diameters) and the bores were selected as the critical quality characteristics because circularity and cylindricity of machined parts constitute some of the most fundamental geometric features in engineering.[10] To ensure the proper functioning of round parts, permissible deviations from the true circle are allowed in the form of tolerance zones bounded by two concentric circles,[10] which dictate the desired dimensional and form accuracy.[41] The bores had a tolerance of $+/-0.1\,\text{mm}$ ($+/-0.00394$-in.), corresponding to the ISO tolerance grade of IT10. Tolerances were measured using the touch probe during the machining to simulate a real-time inspection. Once the machining is complete, the parts are removed from the machine, and the bore tolerances are measured with a Mitutoyo B403B coordinate measuring machine (0.0001-in. repeatability).

The most comparable measuring instrument in structure to the spindle probing system is a CMM. Both share common operating principles, such as an

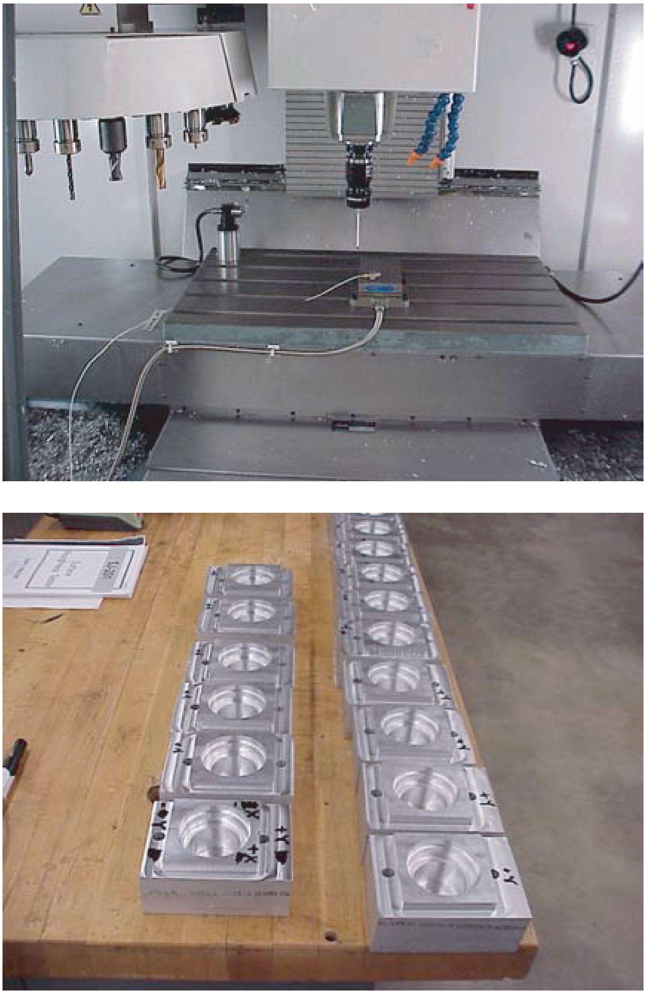


Fig. 2. A spindle mounted touch probe in the 750 CNC VMC and the finished aluminum blocks.

electro-mechanical touch probe. CMMs consist of a contact probe and a positioning system that locates the probe in a three-dimensional space relative to the part surface.[34] Like any other machinery, CMMs are not mechanically perfect, so problems such as direction-dependent error patterns in its touch probe and geometric, kinematical, stiffness, and thermal errors may arise during the use.[4,35] Different algorithms in CMM controllers can cause variations in measurement readings even when the same coordinate data are interpreted.[13] Despite that, CMMs are widely used in the manufacturing industry for precision inspection and quality control,[4,35] and recognized as reliable and flexible gauges suitable for assessing the acceptability of machined parts.[40] A fast probing NC program was developed using available probe commands in the Arrow 750 VMC to measure bore diameters. For each bore, the probe checked the diameters twice along the machine X and Y directions and reported the average values. Mid points along the height of the 65 and 50-mm bores were selected as the inspection point. After the parts were removed from the machine, the same points were measured using the Mitutoyo CMM. To reduce the temperature induced errors, all the machined parts and the CMM were kept in the same room, then the parts were measured as consistently as possible. Consequently, expansion or shrinkage of machined blocks due to ambient temperature variations was considered negligible. The collected data represent the comparison between two instruments, and the following section illustrates the experimental results and data analysis.

4. Analysis of Experimental Data

Tolerance represents the permissible variation in the dimensions of a part.[20] The tolerance in machining process will have a bound of permissible variations caused by many attributes. The tolerance can be denoted as a linear regression model in the form of:

$$\lambda_1 \leq \tau(\eta_i) = \left[\alpha + \beta_i \sum_{i=1}^{n} \eta_i\right] + \varepsilon_a \leq \lambda_2 \tag{1}$$

where λ_1 = a lower bound, η_i = a set of process attributes causing variations, τ = a tolerance function defined by η_i, α = a constant in the tolerance function, β_i = a set of coefficients for η_i, ε_a = a noise factor in machining, and λ_2 = an upper bound. The process attributes may include tool wear effect, machine vibration, tool deflection, hardness of machined parts, tool materials, machine set up, fixturing, elastic and plastic deformation of parts during machining, machine rigidity, machining parameters, machining inaccuracies induced by thermal distortion and static and dynamic positioning errors, machine and gauge operators, machine accuracy and repeatability and ambient temperature. Tolerance is measured by the gauges, which also have the variance. The total variation in the measurements is the summation of the gauge variation and the dimensional variation in the part. The gauge variation can be further divided into two components: the repeatability and the reproducibility of the gauge.[31] The study performed by Lee *et al.*[26] well addresses the two prominent sources of measurement uncertainties: (1) the imperfection of the instrument, and (2) the dimensional deviation of a measured feature. Therefore, the total variation in the part dimension can be represented in the form of:

$$\begin{aligned}\Delta(\tau,\eta) &= [[\tau(\eta_i) + \psi(\eta_j)] - \nu] + \varepsilon_b \\ &= \left[\left[\left[\alpha + \beta_i \sum_{i=1}^{n} \eta_i\right] + \left[\upsilon + \lambda_j \sum_{j=1}^{m} \eta_j\right]\right] - \nu\right] + \varepsilon_b \end{aligned} \tag{2}$$

where $\Delta(\tau, \eta)$ = a total variation in dimensions as a function of $\tau \& \eta$, ν = the nominal value, $\psi(\eta_j)$ = the gauge variation function defined by η_j, υ = a constant in the gauge variation function, λ_j = a set of coefficients for η_j, η_j = a set of attributes causing gauge measurement variations, and ε_b = a noise factor. The total variation (Δ) in bore diameter measurements is therefore represented as a difference between the nominal values (either 65 or 50 mm) and the measured values from the touch probe and the CMM, as shown in Figs. 3–5.

The graphs show that the difference between the touch probe and the CMM is very small. It is interesting to note that the measurements taken by the touch probe are consistently smaller than those of CMM data. This was opposite to the initial thought that the probe measurements would be bigger due to thermal expansion in the machine tool structure. The reduction in bore size as cutting continues can be explained by the tool wear effect. As tool wears, the width of cutting edge margin starts to decrease. If the cutting edge loses material, the tool diameter will get smaller gradually, which in turn causes the bore diameter to be smaller. The bore size measurements for steel are also smaller than those of aluminum. This is because the steel is much harder than aluminum, hence the resistance deflects the tool towards the center of bore during the cutting. For aluminums, the total variation is well within the tolerance bounds. For steel, however, the data are clustered around the lower bound. To test if the tool wear affects the bore tolerances, the cutting edges were measured by a machine vision system (a Sony CCD camera, a Matrox frame grabber, and a PC) and correlated with the bore size variations. The tool was removed from the machine after each block was finished and placed

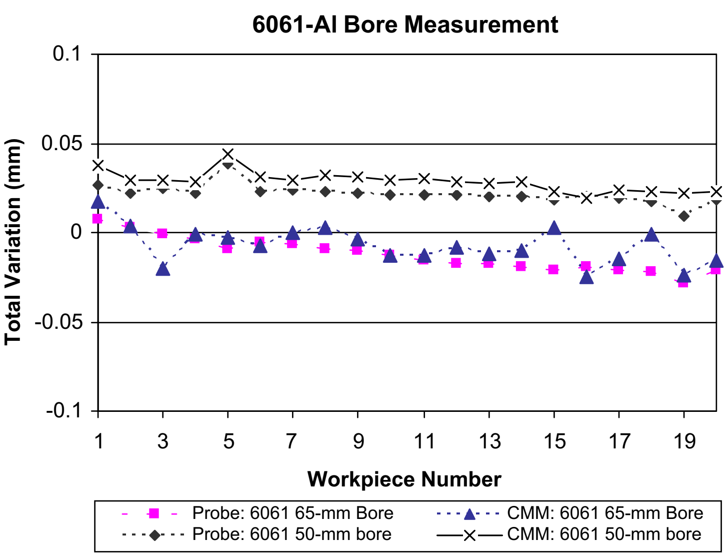


Fig. 3. The measurement of variation for 6061-Al.

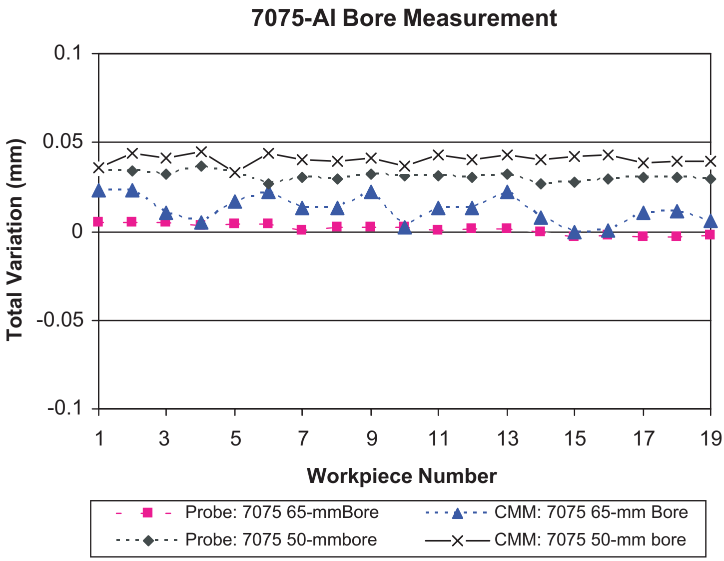


Fig. 4. The measurement of variation for 7075-Al.

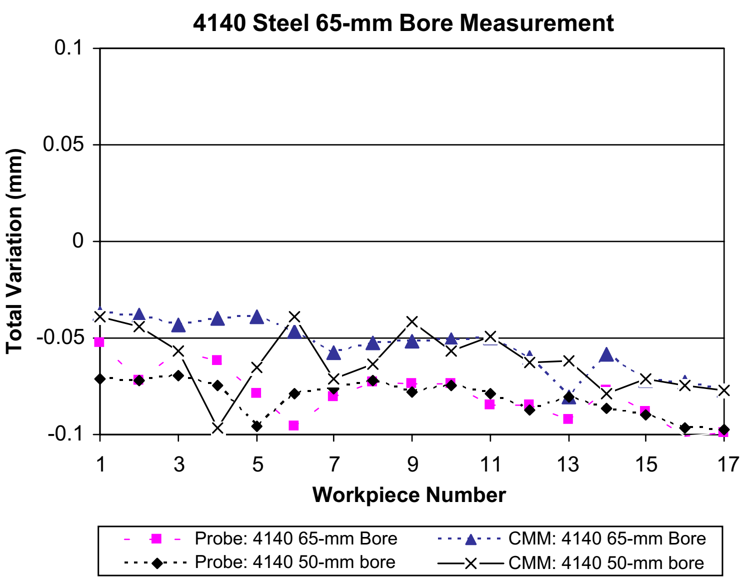
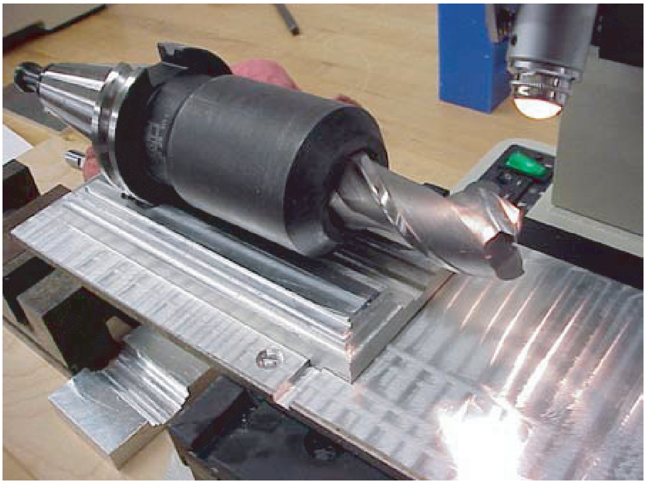
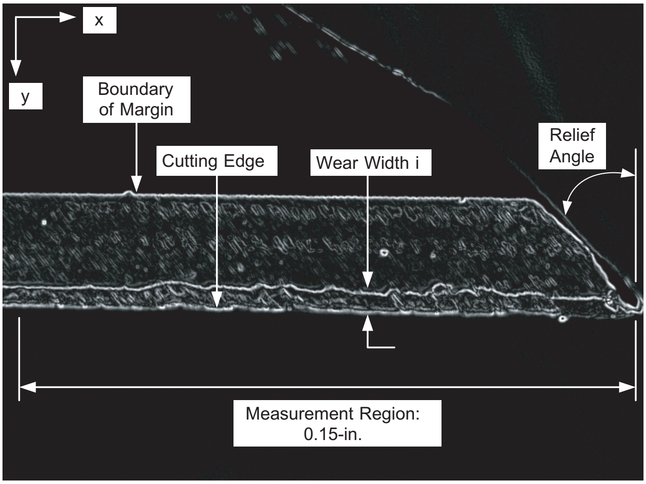


Fig. 5. The measurements of variation for 4140 Steel.

on a custom-build fixture to expose the cutting edge at a constant focal length (see Fig. 6). A high intensity directional light was used to illuminate the cutting edge. Once the pictures were taken, a series of image processing routines (i.e. noise removal, contrast enhancement and thresholding) was performed to improve the



(a)



(b)

Fig. 6. Cutting tool positioned in the fixture for image capturing (a) and the processed image showing the wear width and the boundaries (b).

picture quality. In addition, image analysis algorithms were developed to clearly delineate the edge boundaries.

Once the edges were separated, the measurement region was selected. The region is about 0.15 inch from the tool end, which is corresponding to the depth of cut. To measure the tool wear, the region was divided into 10 equally spaced intervals and each interval was measured to get the average values as a tool wear measurement. Since there are two cutting edges in the tool, this step was repeated. The system was calibrated using a high-grade Mitutoyo gage block and it was found that the pixel sizes at the specific focal length were 0.00024-in. in pixel width (x) and 0.00025-in. in pixel height (y). When compared with the wear measurements taken by the Mitutoyo tool maker's microscope, the difference was less than 5%. The tool wear is therefore the average of the product of pixel numbers along the y-direction and the pixel height:

$$\lambda = n^{-1} \sum_{i=1}^{n} 0.00025 \cdot \varphi_i \tag{3}$$

where $\lambda =$ the average wear width along the measurement region, $n = 20$ and $\varphi_i =$ the number of pixels at interval i. The wear measurements are plotted in Fig. 7, showing the increasing pattern in wear width as cutting continues. The correlation analysis was performed for the tool wear and the total variation in measurements to ascertain whether the bore size variation is mainly due to the tool wear effect. The equation used is in the form of:[22]

$$r = \sum (\Delta_i - \bar{\Delta})(\lambda_i - \bar{\lambda}) \cdot \left[\sqrt{(\Delta_i - \bar{\Delta})^2} \sqrt{(\lambda_i - \bar{\lambda})^2} \right]^{-1} \tag{4}$$

where $r =$ a correlation coefficient ($-1 \leq r \leq +1$), $\bar{\Delta} =$ the average of total variation, $\bar{\lambda} =$ the overall average of the average wear width. The correlation coefficient for aluminums is -0.932 and -0.794 for steel blocks, which clearly indicate the strong relationship between the two variables.

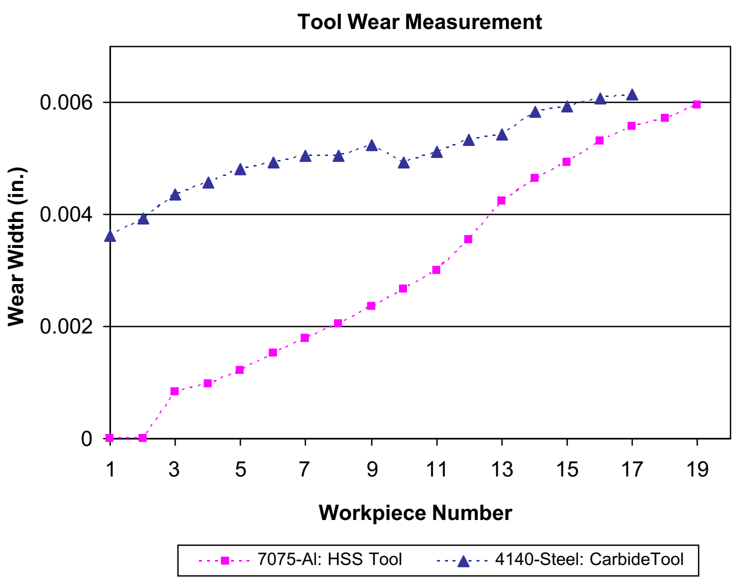


Fig. 7. The graph of tool wear measurements for 7076-Al and 4140 steel.

The total variation in the measurements (Δ) is affected by the process capability as well as the gauge capability. In the case of machining bore diameters, the performance characteristic of machine tool is the-nominal-the-best (NB) type.[25] The index of process capability describes the actual capability of a process to generate a specific quality characteristic consistently within specifications. Process capability ratio (PCR) or process capability index (PCI) compares the spread of the process with the width of the tolerance.[25,31] Among the five PCI's (C_p, C_{pk}, k, C_{pu}, C_{pl}), the NB type PCI assumes the following form:[25]

$$C_p = \frac{USL - LSL}{6\sigma} \tag{5}$$

where USL = the upper specification limit, LSL = the lower specification limit, μ = the process mean, and σ = the process standard deviation. $C_p = 1$ means that about 99.73% will fall within the tolerance specifications (about 2,700 defects per million), and $C_p = 1.5$ represents only 4 defectives out of one million produced.[31] The downside of C_p is that it only considers the variability of the process and does not consider the location of the process mean, which means that the performance of the process degenerates rapidly as the process mean deviates from the nominal value.[25] C_{pk}, on the other hand, is the one-sided C_p that considers the process centering, represented in the form of[25,31]:

$$C_{pk} = \mathrm{Min}[C_{pu}, C_{pl}] = \mathrm{Min}\left[C_{pu} = \frac{USL - \mu}{3\sigma}, C_{pl} = \frac{\mu - LSL}{3\sigma}\right] \tag{6}$$

$$C_{pk} = [1 - k]C_p, \quad \text{in which } k = \frac{|\mu - M|}{(USL - LSL)/2} \tag{7}$$

where μ = the process mean, M = the specification midpoint ($M = (LSL + USL)/2$), and k = the deviation of process mean from the M ($0 \leq k \leq 1$), hence the k is inversely proportional to the $C_p \cdot C_p = C_{pk}$ means that the process is at the center of the specifications, and the process is off-centered as $C_p > C_{pk}$. Therefore, C_p measures the potential capability of the process, while C_{pk} represents the actual process capability.[31] Process capability index numbers were calculated using the Minitab™ statistical software based on the total variation measurements that follow a normal distribution. Analysis results are illustrated in Table 1, illustrating higher process capability numbers and lower standard deviations of the measurements taken by the touch probe when compared to the CMM data. This can be explained by the consistency in the touch probe measurements due to automation, while the CMM data contain additional variations in measurements such as operator repeatability and slight inconsistencies in setup. Overall, the probe measurement data have 54.5% higher C_{pk} as compared to the CMM. The steel, however, displays considerably lower values than those of aluminums. The hardness of material affects the machining accuracy and this phenomenon has been directly reflected on the C_{pk} numbers.

Table 1. Process capability index for the touch probe and the CMM data.

	Variation Mean (mm)	St. Dev. (mm)	k	C_p	C_{pk}
6065 65-mm, Probe	−0.0125	0.00959	0.1252	3.5	3.0
6065 65-mm, CMM	−0.0072	0.01055	0.0721	3.2	2.9
6065 50-mm, Probe	0.0218	0.00531	0.2179	6.3	4.9
6065 50-mm, CMM	0.0287	0.00576	0.2865	5.8	4.1
7075 65-mm, Probe	0.0012	0.00295	0.0120	11.3	11.2
7075 65-mm, CMM	0.0123	0.00787	0.1230	4.2	3.7
7075 50-mm, Probe	0.0310	0.00250	0.3102	13.3	9.2
7075 50-mm, CMM	0.0404	0.00306	0.4042	10.9	6.5
4140 65-mm, Probe	−0.0792	0.01413	0.7922	2.4	0.5
4140 65-mm, CMM	−0.0546	0.01427	0.5457	2.3	1.1
4140 50-mm, Probe	−0.0811	0.00949	0.8111	3.5	0.7
4140 50-mm, CMM	−0.0616	0.01611	0.6161	2.1	0.8

5. Conclusions

The intense international and domestic market competition has driven the attention of manufacturers on automation of manufacturing systems as a means for increased productivity and product quality. For the discrete part industry, in-process gauging or real-time part inspection has become very important to reduce the number of scraps and to rectify the defective parts while they are still fixed on the machine. In such an environment, the capability of a touch probe has to be well understood in tune with the product tolerance requirements. Also, the extent of variations in such an environment (e.g. many combinations of different tool and work materials) makes it very difficult to formulate a quality prediction model, hence there is a need for developing and implementing real-time inspection techniques into machining processes. In order to form a feedback loop for real-time machining error compensation, the confidence in the measurement data need to be established first. At the same time, the performance characteristics of machine tool have to be established so that the probe measurement data can be effectively used to rectify the defective parts and to improve the efficiency of the machining quality inspection.

In this context, this study focused on the analysis of two types of gauges. The experimental data show that prior to incorporating the touch probe as a means of real-time inspection, some cautionary measures need to be taken in terms of analyzing the characteristics of machine tool. This is more important when harder materials (e.g. high strength steel versus soft aluminum) are machined. The realization of DFM that incorporates the inspection into the process design stages, therefore, has to be considered from a broad spectrum, which includes type of machine tool, machine tool characteristics, accuracy and repeatability of machine tool, extent of thermal and other machining errors, type of cutting tools and work materials, machining parameter settings, type of features to be machined, inspection methods, the confidence of gauge measurements, and accuracy and repeatability of gauge. Those factors need to be analyzed to predict whether the variations in machined features would be within the limits of tolerance specifications, which will be investigated as a future work for this study.

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