

AN APPROACH TO DETERMINE THE SAMPLE SIZE FOR ACCURATE FLATNESS ERROR MEASUREMENT ON COORDINATE MEASURING MACHINES

Raghunandan R. and Rao P.V.

Department of Mechanical Engineering
Indian Institute of Technology Delhi, New Delhi - 110 016
E-mail: pvr Rao@mech.iitd.ac.in

Abstract: *The present day manufacturing environment requires accurate inspection of both dimension and form while minimizing the cost and time of inspection. Flatness error is an important form tolerance that is used for the control of machined surfaces. The evaluation of flatness error depends on a variety of factors such as selection of sampling plan - sample size and sample point locations, the method of evaluating the form error and the nature of the manufactured surfaces amongst which the sample size is very critical. In most cases the sample size is decided based on the experience of the inspector or is randomly selected which may not be the ideal methods if a high degree of accuracy is required for the evaluation of the flatness error. Investigations carried out reveal that the surface roughness influences the accuracy of inspection and can be used as a parameter for determining an initial sample size for the determination of flatness error. The experimentation involved the inspection on surfaces with different roughness and calculation of the flatness error was based on the Minimum Zone Method. The percentage discrepancy of measurement computed from experimental data is then used to determine the number of sample points (sample size).*

Key words: *Coordinate Measuring Machine (CMM), flatness error, sample size, surface roughness, Minimum Zone Method*

1. INTRODUCTION

The Coordinate Measuring Machine (CMM) is today an important device that enables rapid inspection to be performed accurately yielding considerable reduction in cycle times. To realize proper benefits from the use of CMM's it is necessary to have an efficient inspection planning process. In most cases, inspection planning relies on the experience of inspection planners and practices of the industry. Such processes can lead to inconsistencies in the inspection plan and consequently affect the productive use of CMM's. Hence it is important to have a systematic inspection plan that can help in the gathering of meaningful data in order to analyse the process and equipment conditions (Hwang et. al., 2002). In order to achieve consistent and robust plans some processes of inspection planning need to be automated to derive the advantage of accurate, fast and efficient computing.

2. SAMPLING STRATEGY

The sampling strategy essentially comprises of two components – the sample size and the distribution of the sampling points for inspection. Whilst the distribution of sampling points has been studied well, sufficient work has not been done for the sample size estimation. In most cases, the sample size is an educated guess of an experienced planner or is arbitrarily chosen leading to inconsistencies in accurate evaluation. The selection of the sample size is critical since sample size is proportional to the time and cost and savings in time can be achieved through a reduction in sample size (Kim & Raman, 2000). The determination of the sample size is a

complicated process since it is affected by many factors such as the manufacturing process used, tolerance specifications, error evaluation method and confidence level of measured results (Zhang et.al., 1996).

The nature of a surface is a direct result of the manufacturing process and hence the selection of the sample size would depend on the manufacturing process. Modeling of manufacturing processes can be very complex and time consuming and the availability of proven models is also very limited. Additionally manufacturing processes exhibit variations, and these variation can be such that one surface can differ considerably from another even though those surfaces may share the same features (Lee et. al., 1997). Despite these limitations, it still is an important factor needing consideration while estimating sample sizes.

The CMM is used for the measurement of both dimensional as well as form errors. The inspection of form error poses more challenges than the dimensional errors. The focus of this work is on the measurement of flatness error which is a commonly used form error specification by the designers to control a surface. Accurate flatness error inspection depends to a large extent on the sampling strategy that is adopted. The level of accuracy of inspection i.e. with respect to the actual flatness error will play an important role. Estimation of flatness error requires data that can properly represent the surface being measured and a poor sampling strategy can lead to either inferences being made from inadequate data or enhance the cycle times resulting from increased measurement.

3. SAMPLING SIZE

An important observation is that the CMM inspection by virtue of being a discrete measurement approach is essentially an approximation process and (Woo & Liang, 1993) indicate that if the sample size is infinite, the error in approximation approaches zero and whenever the sample size is finite the error must be non-zero. One of first efforts in this direction used a statistical approach based on process capability to determine the sample size (Yau & Menq, 1992). The British Standard BS 7172 which recommends that the sample size can vary from 5 to 15 points is another approach that was adopted by (Zhang et.al. 2000); (Beg & Shunmugam 2002). (Lin & Chen 1997) & (Fan & Leu 1998) based the estimation of sample size on the geometric features and elements, which suffer from the limitation that they do not consider the actual surface parameters. Another successful attempt includes a neural network approach for sample size estimation using the type of manufacturing process and tolerance band (Zhang et.al. 1996). A hybrid neuro-fuzzy approach considering the tolerance and geometry features was carried out yielding good results (Hwang et.al. 2002). The above literature points strongly to the fact that for good results the manufacturing process has to be accounted for while determining the sample sizes.

In the absence of reliable manufacturing process models, this work investigates the suitability of using the surface roughness as a parameter that can be used for determining the sample size for flatness error measurement. Surface roughness can be considered as a local or micro error and it is relatively easy to measure. Flatness error on the other hand is a macro error and more difficult to measure. There maybe no direct relationship between surface roughness and flatness error, but both are direct results of a manufacturing process being applied with certain defined machining conditions and under the influence of other factors such as existing rigidity of the machine tool, chatter, tool wear etc. have used a as factors using a neural network approach information, was successfully developed This is only a guideline that indicates an assumption based approach which cannot guarantee an accurate estimation of the flatness error.

4. EXPERIMENTAL SETUP AND METHOD

In order to ascertain the use of surface finish as a parameter to determine the sample size, 4 rectangular block workpieces of size 65 mm X 65 mm X 20 mm were machined using different manufacturing processes which are listed in Table 1, which also gives the details of the Ra values of surface finish that were obtained. Ra was selected as the surface roughness parameter because amongst the commonly used parameters it can best represent a surface based on its definition. Since, Ra is calculated based on the areas above and below a central

line, in this case it becomes a suitable parameter than the other roughness parameters.

The first step was to study the behaviour of the flatness error with respect to changing sample sizes on the same surface and also between the different surfaces. 9 sample sizes - 10, 16, 20, 26, 32, 40, 48, 58 and 64 were selected randomly for carrying out the inspection. An additional sample of 314 points was also taken which is the aggregate of all the above 9 samples. The CMM used was Carl Zeiss with a single probe. To reduce errors while measurement an allowance of 2 mm was given on all sides of the surfaces to be measured making the effective area of inspection as 61 mm X 61 mm. The data from the CMM was captured and exported into a MS-Excel file for further processing.

Table1. Machining processes used and surface roughness obtained in the 4 work pieces.

Workpiece No.	Machining process	Surface Roughness (Ra)
1	Shaping	~ 9.0 μm
2	Rough face milling on conventional milling machine	~ 7.0 μm
3	Finish milling on milling machine	~ 3.5 μm
4	Surface grinding	~ 0.2 μm

The sample point locations were based on the Hammersley sequence which earlier literature establish as an efficient strategy (Kim & Raman 2000).

5. ESTIMATION OF FLATNESS ERROR

The basis for the flatness error estimation was the Minimum Zone method (MZM) since the other commonly used method i.e. Least Square method does not follow the standards intently and may not guarantee the minimum zone solution specified in the standards (Samuel & Shunmugam 1999). The flatness error computation by the MZM was carried out using computational geometry techniques. This approach was selected over other approaches since the literature shows that it shows greater promise to solve the minimum zone problem (Samuel & Shunmugam 1999); (Lee 1997). A programme was developed in MATLAB for this approach and the data was input from the Excel file.

The figures 1 to 4 show the variation of the flatness error with respect to the sample size. As can be seen from these figures the variations are significant for sample sizes less than 50 and that the variations decrease as the sample sizes increase. This behaviour is observed in the case of all four workpieces which has also been observed by (Badar et. al. 2003). It is also seen that in the case of a smoother surface the convergence of the error

will be at a smaller sample size than a rougher surface which gives a preliminary indication that the sample size for accurate inspection can be related to the surface finish. A curve fitting approach was then used as a tool in order to ascertain the flatness error at large sample sizes. This is necessary since the approximation error would approach minimum conditions only at larger sample sizes

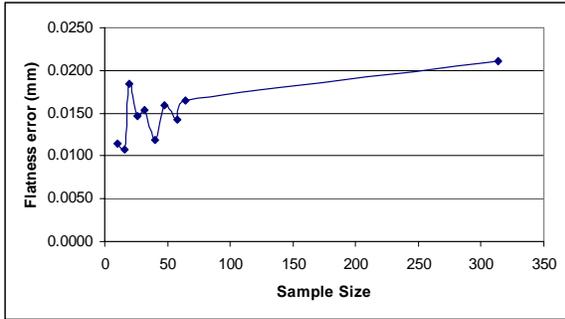


Fig. 1. Flatness errors for surface with Ra 0.2 μm

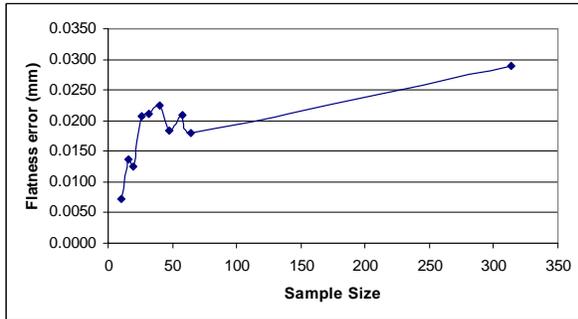


Fig. 2. Flatness errors for surface with Ra 3.5 μm

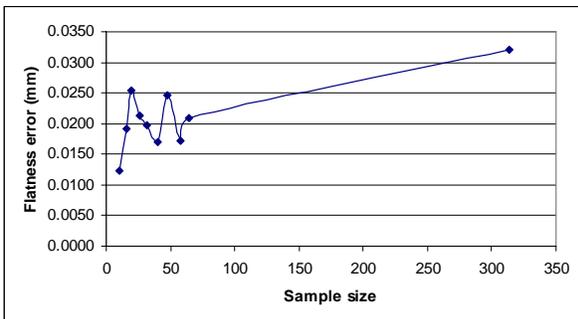


Fig. 3. Flatness errors for surface with Ra 7.0 μm

A logarithmic fit was identified amongst other fits since it provided the best results, when compared on the basis of R-square value of fits. This was carried out using the Curve Fit Toolbox in MATLAB. The general equation of the logarithmic fit used was:

$$f(x) = A * \log(x) + C \quad (1)$$

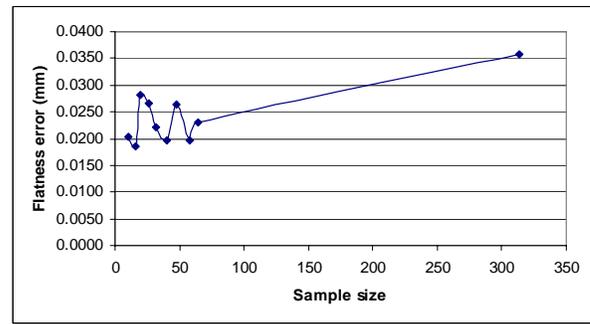


Fig. 4. Flatness errors for surface with Ra 9.0 μm

Table 2 gives the details of the results obtained from the curve fitting procedure.

Table 2. Results of the log. fitting procedure

Workpiece	Co-eff's (A & C) Y=A*log(x)+C		Goodness of fit (R-square)
	A	C	
Ra 0.2 μm	0.0029	0.06	0.85
Ra 3.5 μm	0.005	0.0006	0.88
Ra 7.0 μm	0.007	0.003	0.85
Ra 9.0 μm	0.004	0.01	0.83

Figure 5 shows the trend curves for the 4 samples. As mentioned earlier the above fits were analysed at a sample of 1000 points in order to determine the close to true value of flatness error. The literature sourced during this work does not indicate any method to ascertain this true value, except that in one experience 300 points were considered as an adequate assumption of a sample size for the true value (Kim & Raman 2000). It is assumed that this value of flatness error would be of high accuracy and more certainty and further increase in sample size would have negligible effect on the flatness error.

In order to be able to determine the sample sizes for a given level of accuracy it is necessary to compute the discrepancy of each measurement. The value of flatness error corresponding to 1000 points is used as the basis for computing the discrepancy. The discrepancy rate (r) was calculated using the formula used for calculation is “ $r = (a - b) / a * 100$, where ‘a’ is the flatness error at 1000 points and ‘b’ is the data value obtained from actual measurement.

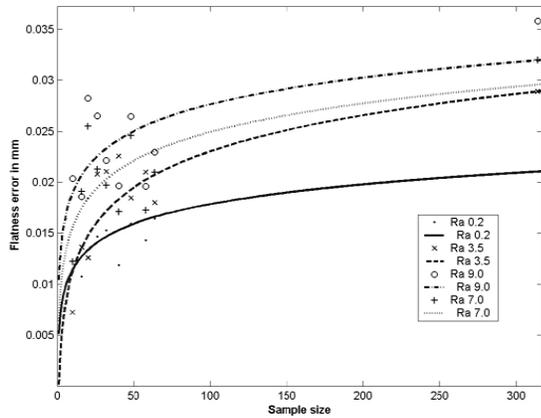


Fig. 5 Plots of log. fits for 4 workpieces

The discrepancy rates were calculated for each of the workpieces. Using this discrepancy data, a curve fit procedure was adopted to ascertain the trend of the discrepancy. The fitting was achieved through a rational fit given by $f(x) = p / (x + q)$ which gave reasonable results, which are shown in Fig. 6.

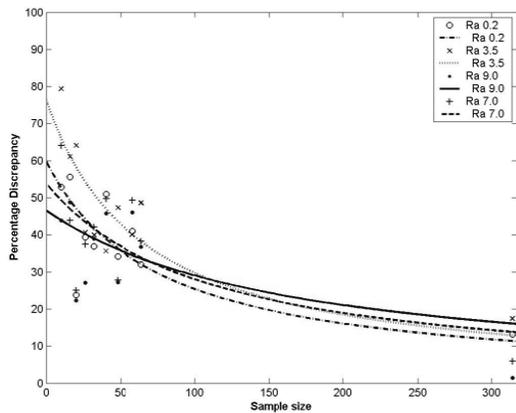


Fig. 6. Plots of discrepancy rates for each work piece

It can be seen from Fig. 6 for a given sample size that as the surface roughness increases the percentage discrepancy also increases, the increase being more pronounced at lower values of surface roughness. This is because of the reduced variability of a surface of good quality across its area and so a smaller sample can be a good representative of the population. Rougher surfaces will require more points since the variability of the surface is more. Also, inconsistency in measurement can arise from the fact that the probe has fixed diameter and the point of contact during measurement of rough surfaces may not be exactly at the bottom tip of the probe. This shows that surface finish does influence the accuracy of measurement. It can also be observed that for a given accuracy of measurement the sample size for a surface of good quality is lesser than that of a surface with poorer quality.

6. DETERMINATION OF SAMPLE SIZE

The sample size will depend on the level of accuracy of inspection that would be required. As can be seen from figure 6 with increase in level of accuracy the sample size will also increase and hence it is important to first decide the level of accuracy. It also be seen from the graph that for certain levels of accuracy (say less than 75%) the sample sizes that would be obtained would not be consistent. This is because of the large variations of flatness errors that were observed in each of the work pieces in the range of smaller sample sizes.

In order to determine the sample size for a desired accuracy of inspection and any given roughness value, an interpolation technique based on Newton's divided difference method is adopted. Based on the level of accuracy value that is input, the technique computes the polynomial equation in which the new surface roughness value is substituted to yield the sample size. The method also enables the determination of sample sizes outside the range of Ra values selected i.e. 0.2 to 9.0. Equations 2, 3 & 4 show the polynomial relation established for accuracy levels of 75%, 85% and 90% respectively.

$$0.39x^3 - 5.673x^2 + 24.374x + 98.05 \quad (2)$$

$$0.69x^3 - 8.353x^2 + 34.253x + 213.77 \quad (3)$$

$$1.06x^3 - 11.632x^2 + 46.219x + 358.473 \quad (4)$$

The sample sizes for these different accuracy levels and for input of different surface roughness are shown in Table 3.

Table 3. Sample sizes for a given level of accuracy

Accuracy level in percentage	Ra 2.0	Ra 5.0	Ra 11.0
75	~126	~127	~198
85	~254	~262	~498
90	~412	~431	~870

As can be seen the method can be effectively used to determine the sample sizes given a surface quality and level of accuracy of inspection.

7. CONCLUSIONS

This study establishes that surface finish can be effectively used as a parameter to determine the sample sizes for flatness error inspection. This in addition to other parameters such as part geometry, tolerance band and surface area can greatly help in determining the best sample size. The sample size increases with increase in the Ra value of the surface and hence poor quality surfaces will require more number of points to be sampled to obtain accurate value of flatness error. It is also seen that the sample size increases with the increase in level of accuracy

sampled to obtain accurate value of flatness error. It is also seen that the sample size increases with the increase in level of accuracy for the same surface roughness. The sample sizes obtained indicate that for accurate inspection of a certain degree a certain minimum number of points are required and that if this sample size is selected arbitrarily then inconsistencies can arise.

8. REFERENCES

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