Quality Control Based Tool Condition Monitoring

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ABSTRACT

Quality control and tool condition monitoring are two most important aspects of machining process. This paper studies the correlation between tool wear and surface roughness to explore the possibility of modelling the interdependencies between these two aspects. An experimental study is presented in this paper to model the relationship between product quality parameter i.e. average surface roughness and tool wear. Current study reveals that there is a strong positive correlation between surface roughness and tool wear. To map this relationship an ensemble (random forest) fault estimation model is developed for identification and estimation of cutting tool health state. The results from fault estimation model are then used to provide guidelines for future process monitoring and developing dynamic quality control policy.

Keywords: Quality control, tool condition monitoring, surface roughness, tool wear, random forest.

1. INTRODUCTION

Advancement in intelligent manufacturing process has led to better product quality, increased flexibility and higher productivity (Wiendahl, Elmaraghy, Nyhuis, Zäh, Wiendahl, Duffie, and Brieke, 2007, Wang, Wang, and Gao, 2013). Mainly these benefits are highly dependent on smooth operations of the various machine elements. Cutting tool is one such important element of the machining system (Zhou, Chen, Fuh, and Nee, 2000). In high speed machining process cutting tool usually suffers from rapidly increasing tool wear rate and the consequent degradation of workpiece surface finish as well as the drop in machined part dimensional accuracy. Also, in machining industry, 20% of the downtime of a machine tool is attributed to cutting tool failures (Kurada & Bradley, 1997). Therefore, Tool Condition Monitoring (TCM) plays a significant role in improving machine productivity, maintaining the quality and integrity of the machined part, minimizing material waste, and reducing manufacturing cost. Being the major cause of tool failure, identification and estimation of cutting tool health state is very important in the machining process (Zhong, Zhou, & Win, 2013). Many research works have been devoted to the methods that rely on the relationships between tool conditions and measurable signals of cutting forces, acoustic emission, vibration, current, etc. for tool wear detection. For example, Dimla and Lister (2000) analysed a relationship between measured signals (cutting force and vibration signals) and tool wear. Haber, Jiménez, Peres, and Alique, (2004) conducted an examination of tool wear monitoring in a machining process based on investigation of multiple signals. The analysis results discovered the relevance of cutting force and vibration signals signatures for tool wear development in high speed machining processes. Dimla (2000) carried out a comprehensive review of several methodologies for tool wear monitoring in machining using different sensor measurements.

In milling, "the cutting dynamics is governed by the interaction between tool structural vibrations and cutting forces" (Ruxu, Elbestawi, & Ullagaddi, 1992). Thus, the cutting force signal is reported to be the best indicator of tool conditions (Li, Lim, Zhou, Huang, Phua, Shaw, & Er, 2009). Although using cutting force signal is a promising method to monitor the tool condition, but it has some disadvantages. The major drawback of using force signals is the cost of the measurement device of a dynamometer and the big size of the dynamometer, which is not practical to mount with the workpiece (Zhong et al. 2013). Iulian and Dragos (2008) pointed out that "the dynamometer is costly, and the installation is rather inconvenient and can weaken the machine structure". Similar types of disadvantages are with other measurable signals like acoustic emission, vibration etc. Also, use of any type of monitoring technique adds extra cost on the overall manufacturing cost, which is considerably high. An online methodology for tool condition monitoring without the application of measurable signals will cut down the complexity with its assembly, as well as the added expense of measurable signal monitoring system. Such type of methodology is not reported in the literature.

The other important aspect of machining process is quality control, as maintaining the quality of the machined surface is of prime importance. For this quality control tools (viz. control charts) are designed and used regularly to monitor the process. For example, Yang and Jeang (1994) developed a surface roughness monitoring and quality control method, combining statistical analysis and physics of the tool wear. Tangjitsitcharoen and Damrongthaveesak (2013) developed a methodology for online surface roughness and quality control of the estimated surface roughness in turning operation. Colosimo, Moroni, and Grasso (2010) proposed a methodology for modelling of a machining process and ongoing monitoring of its stability that is based on online collected data. However, implementation of quality control is time consuming, which decreases the profitability and expands the expense.

Quality control and tool condition monitoring are important part of machining process. Thus, developing a joint methodology, that not only maintains the quality but also performs tool condition monitoring, will be a highly profitable option. Identifying and mapping the correlation between tool wear and surface roughness will help in getting rid of measurable signal monitoring system and its associated expenses, the only expense associated will be the cost of quality control. The results from such relationship can be used to provide guidelines for efficient process monitoring and dynamic quality control. Thus, in a single expense, both the purpose of quality control and tool condition monitoring will be accomplished. Such type of methodology is not reported in the existing literature of current research. Therefore, the main contribution of this paper is in an attempt to explore the correlation between tool wear and surface roughness, and developing a methodology for joint consideration of quality control and tool condition monitoring. Such, quality control based tool condition monitoring methodology will lead to greater cost savings in overall manufacturing cost. Since, milling is one of the most complex and widely used machining operations; the same is selected in this study.

2. THEORETICAL PRELIMINARIES

2.1. Tool Wear

Tool wear can be stated as "the change in the shape from its original shape during a cutting process by gradual loss of the tool material" (Zhong et al. 2013). Tool wear in milling occurs at higher rate as the tool becomes dull. Due to which cutting forces and temperature increases and immediate loss of sharp edges occurs. After a certain point, tool wear can cause sudden failure of the cutting tool. (Tansel & McLaughlin 1993, Ertunc & Oysu, 2004). It can be illustrated in figure 1 by separating the wear stages as slight wear (regular stage of wear), moderate wear (micro breakage stage of wear) and worn-out as a function of tool life (Al-jonid, Jiayang, & Nurudeen, 2013, Wang, Yang, & Li, 2014). Tool wear affects the surface roughness of the workpiece, which is the main concern of a machining process. The power consumption from motors may also increase due to tool wear (Altintas & Yellowley, 1989, Zhang, Han & Chen, 1995). Thus, it is important to monitor and prevent the tool failure during cutting to achieve high product quality and efficient production.

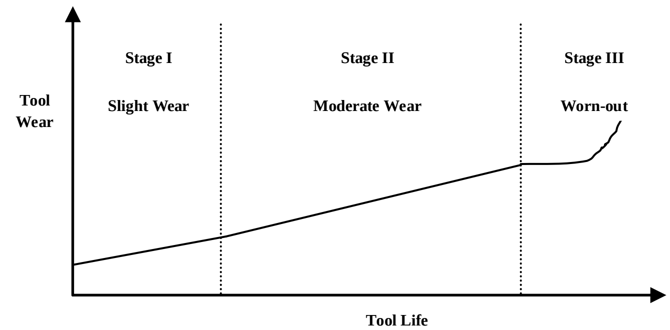

Figure 1. Tool wear stages.

2.2. Surface Roughness

Surface roughness is defined as "the result of irregularities arising from the plastic flow of chips during the machining" (Lou, Chen & Li, 1999). The most widely used parameters for surface roughness measurements are average surface roughness (Ra), ten point height of irregularities (Rz) and maximum profile peak height (Rp) (Zhong et al. 2013). In this work, average surface roughness is mainly used to measure the surface roughness of workpieces. Average surface roughness (Ra) can be calculated using equation 1 (Lou et al. 1999).

$$R_a = \frac{1}{L} \int_0^L |Y(x)|\, dx \tag{1}$$

where, L = sampling length, and Y(x) = coordinate of the roughness profile curve.

2.3. Quality Control

Quality control is an important methodology for asserting standards in manufactured products by testing some samples from output against the specification. Techniques provided in quality control are online quality control methodology to screen an on-going production process. Control charts are most essential techniques of statistical process control. Figure 2 illustrates a typical quality control chart. "The control chart is a graphical display of a quality characteristic that has been measured from the sample versus the sample number or time" (Montgomery, 2007). The chart has a center line that presents mean value of the quality characteristics corresponding to the in-control state. Two other horizontal lines, called the Upper Control Limit (UCL) and the Lower Control Limit (LCL). These limits are set so that if the process is in control, all of the sample points will fall between them. As long as the point plots within the control limits, the process is assumed to be in control, and no action is necessary. However, points that plot outside of the control limits is interpreted as evidence that the process is out of control, and investigation and corrective action are needed to detect and terminate the assignable cause for this behaviour.

In this study, the $\bar{x}$ and R control charts are used, which are widely used to monitor the mean and variability of variables. In $\bar{x}$ chart mean of samples are plotted in order to control the mean value of a variable. In R chart range of samples are plotted in order to control the variability of a variable.

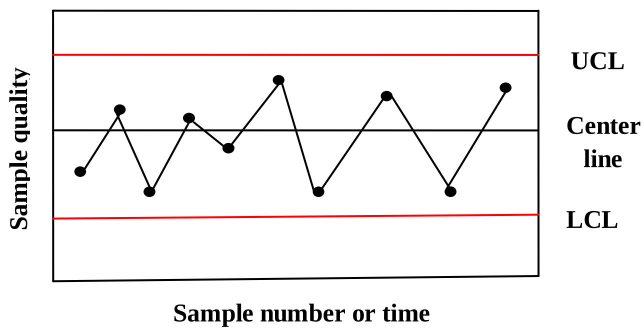

Figure 2. A typical control chart.

3. METHODOLOGY

Details of the proposed methodology are given in following sub-sections.

3.1. Experimental Setup

In practice, tests and verifications of fault detection methods are easy to perform, because the faults can be easily simulated or introduced on the real industrial system. However, this is not the case for quality control methods where the change in quality characteristics is generally a consequence of a long and slow degradation of one or more components of the system. Thus, to test these methods, it is necessary to create the degradation through accelerated degradation tests of physical components and measure the quality characteristics throughout the life. For this purpose, an experimental setup is developed (see, figure 3). In the experiment, EMCO MILL E350 vertical milling machine is used as the test bed. A high speed steel 6mm flat end mill cutter with four cutting edges is selected for testing. Machining operation employed was face milling to create a flat plane surface on the workpiece, with constant operating conditions (feed = 300mm/min, speed =1000RPM, depth of cut = 0.25mm) in dry state. After every cutting process, surface roughness of the finished surface and tool wear is measured. A HANDYSURF E-25A/B tester was used to measure the surface roughness. Toolmakers' microscopy system was used to measure the tool wear of the milling cutter. During experiments utmost care has been taken while resetting the cutter, to minimize its effect on surface roughness. The setup is capable of providing real life data for quality control, as it covers in-depth quality aspects of machined products developed throughout the life of milling cutters.

3.2. Correlation between Surface Roughness and Tool Wear

Identification of correlation between surface roughness and tool wear will be of high significance. Thus, life tests are carried out to study the wear behaviour of milling cutters, i.e. all the cutters are run till it reaches a pre-defined level of wear. Two failure modes have been observed and recorded, viz. tool worn-out (if average wear value from four cutting edges reaches 0.746mm) and tool breakage. Figure 4 shows the tool wear measured in experiment with two different failure modes (worn-out and breakage) cutting tool. Average surface roughness (Ra) was also measured for each surface during the cutting processes. Figure 5 shows the average surface roughness of the workpiece and tool life of two cutters with different failure mode. The surface roughness value remains stable and small when the tool has very less wear. When the cutting tool reaches the failure state, the surface roughness value gradually increases, and then it significantly increases when the critical tool failure occurs.

From the experiments it is observed that identical cutting tools, even operated at same operating conditions, show different behaviour (because of inherent design variations), and may fail with different failure modes (worn-out and breakage). Such types of conditions significantly affect the performance of the process, for example see figure 5. It shows that average surface roughness values obtained from the two different cutters with different failure modes. The tool which failed from breakage is producing products with high average surface roughness from its initial age, while the worn-out tool is producing less rough products in its initial age and roughness increases as the tool reaches its end of life. If we see the wear pattern of both the tools in figure 4, it is clear that both the tools are having different wear behaviour. Thus, a correlation analysis is carried out; correlation measures the relationship between two variables (say, a and b). Correlation is used to determine whether the large values of first variables (say, a) are associated with the large values of second variables (say, b), and vice versa. Correlation coefficient is used to measure the strength of the relationship between two variables; this can be calculated using equation 2 (Zhong et al. 2013). The Pearson correlation coefficient (r) between the surface roughness and tool wear in case of tool breakage is found to be 0.859 and in case of worn-out tool is 0.807. This correlation study reveals that there is a strong positive relationship between the surface roughness and tool wear.

$$r = \frac{\sum(a_i-\bar{a})(b_i-\bar{b})}{\sqrt{\sum(a_i-\bar{a})^2(b_i-\bar{b})^2}} \qquad (2)$$

where, $\bar{a}$ is the mean value of variable a (Average surface roughness), $\bar{b}$ is the mean value of variable b (Tool wear).

3.3. Fault Estimation Model

As tool wear is the major cause of tool failure, identification and estimation of cutting tool health state is very important in the machining process, so that it can be replaced on timely manner. As shown from figure 4 and 5, tool wear and surface roughness exhibit a strong positive correlation. Thus, if we develop a relationship between surface roughness and tool wear, it will be of great interest. This relationship can be used for tool condition monitoring. A Fault Estimation Model (FEM) is developed to link one or more of the quality parameters like R_a, R_z and R_p with the health state of the tool. Input to this fault estimation model will be quality parameters and output will be the current health state (stage I, stage II or stage III) of the tool. The prediction of current health stage will help in tool replacement decisions.

To develop an efficient fault estimation model, an ensemble classifier is needed. As a result, Random Forest (RF) is used to develop the fault estimation model. RF is utilized because of its high performance in modeling complex processes, unbiased estimate of the generalization error, high accuracy and fast build time (Liaw & Wiener, 2002). Originally proposed by Breiman (2001), the method adds an extra layer of randomness to the original bagging algorithm. It is more user friendly, intuitive, and is based on two parameters (the number of variables in the random subset at each node and the number of trees in the forest) only. Further, in contrast to most algorithms in literature (including discriminant analysis, support vector machines and artificial neural networks), it is dependent on the data values and is less sensitive to the values of the two parameters (Liaw & Wiener, 2002). Consequently, it is perfectly aligned to our needs, thus, we use this method to formulate the fault estimation model for cutting tools. In RF classifier each tree is constructed using the following methodology: Firstly, N number of training cases and M number of variables are taken in the classifier. m number of input variables are used to take decision at the node of the tree, here, m is kept lesser than M. A training set is selected for this tree by choosing n times with replacement from all N available training cases. Rests of the cases are used to estimate the error of the tree, by predicting their classes. For each node of the tree, randomly m variables are selected, on which to base the decision at that node. Then, the best split based on these m variables in the training set is calculated. Each tree is fully grown and not pruned. For prediction, a new sample is pushed down the tree. It is assigned the label of the training sample in the terminal node it ends up in. This procedure is iterated over all trees in the ensemble, and the average vote of all trees is reported as random forest prediction. For more details regarding RFs, the interested reader can refer to Breiman (2001).

For the current study, random forest of 100 trees, each constructed while considering 1 random feature is used. The life data used here is drawn from experiments conducted on five milling cutters. Health states of the milling cutters are classified in three stages and their wear scopes are shown in table 1. No specific method or technique is available to decide wear scope. In the present work health states are defined based on the literature (Wang et al. 2014, Al-jonid et al. 2013) and physical observation of change in the surface roughness of the produced surface with tool degradation during experiments. The complete life dataset from milling cutters comprises of 321 numbers of the samples. Model should not be validated on the same data used to create the classifier. Accordingly, the K-fold cross-validation method was chosen (Stone, 1974) in this study. The original sample is partitioned into K disjoint subsamples. Of the K subsamples, a single subsample is retained as the validation data for testing the model, and the remaining (K-1) subsamples are used as training data. The cross validation process is then repeated K times (the folds), with each of the K subsamples used exactly once as the validation data. Then, the K results from the folds are averaged to produce a single estimate of the classifier accuracy (Correa, Bielza, & Pamies-Teixeira, 2009). In our model we chose K=10. For performance assessment, accuracy of the testing results is calculated. Accuracy of a classification model is calculated as, the proportion of the total number of predictions that were correct (Wang et al. 2014). To check the applicability of developed model; computational time, that is the required time to learn and test the dataset is also computed. Moreover, to improve relevance and accuracy of prediction, an Advance Fault Estimation Model (AFEM) is also developed. In the advance model, with average surface roughness value two more parameters (R_z and R_p) are given as input. This advance fault estimation model can be used in the presence of extra information in terms of R_z and R_p in place of the fault estimation model to update the accuracy of the prediction. Table 2 shows the performance of both the developed models. Open source tool Weka (Version: 3.7.12) is used for training and testing the developed fault estimation models.

Table 1. Tool health states and its corresponding wear scope.

Tool Wear Classification	Stage I (slight wear)	Stage II (moderate wear)	Stage III (worn-out)
Wear value (mm)	< 0.27750	0.27750-0.56775	> 0.56775

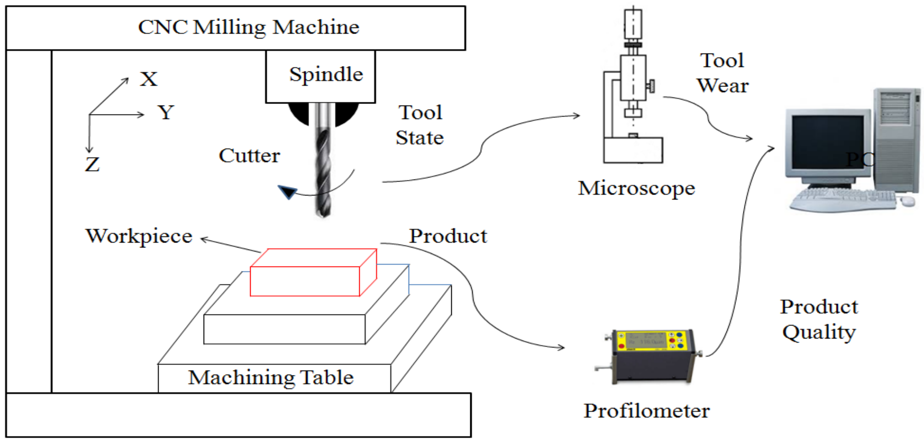

Figure 3. Experimental setup (line diagram).

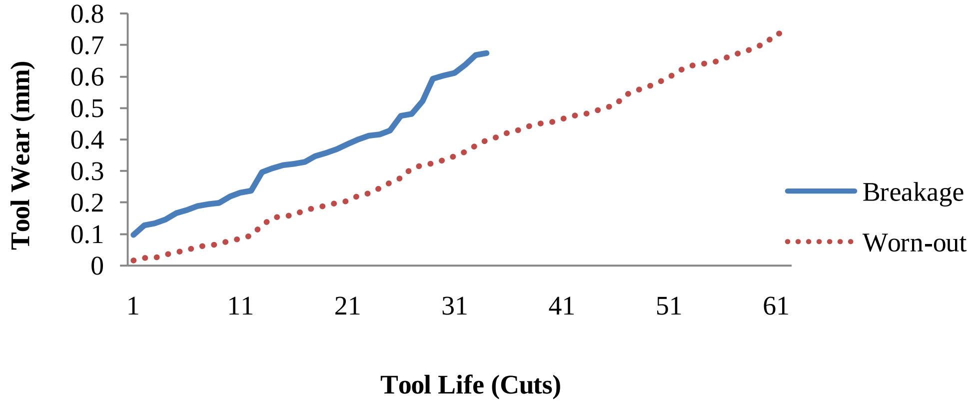

Figure 4. Tool wear versus tool life.

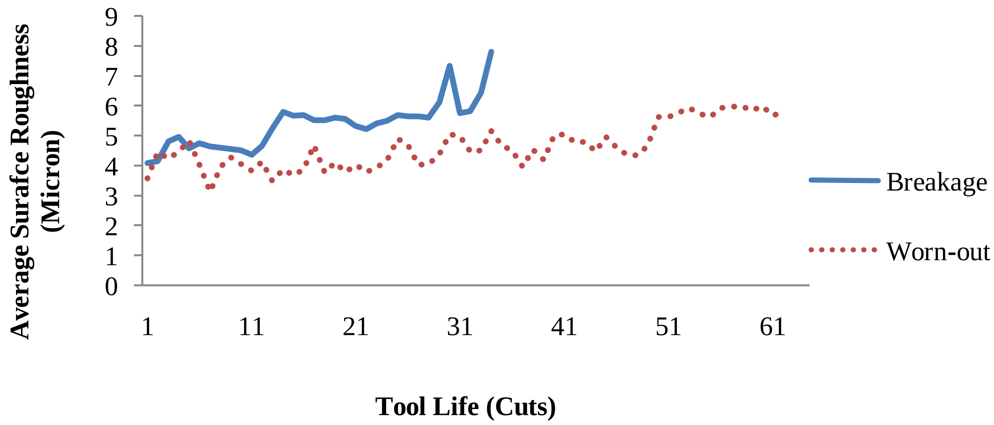

Figure 5. Average surface roughness versus tool life.

Table 2. Performance of fault estimation models.

Model	Accuracy (%)	Time (sec)
Fault Estimation Model	70	0.13
Advance Fault Estimation Model	82	0.17

The results from developed fault estimation models are promising and show potential to be practically applied under industrial constraints in reasonable computational time.

3.4. Process Monitoring and Quality Control Policy

A CNC milling process is used for Mild Steel (MS) plate manufacturing with fixed dimensions (165x100x20mm).

Average surface roughness (Ra) of the plate in horizontal direction is an important quality characteristic. The average surface roughness value is in micron. We wish to establish a statistical control of the average surface roughness of the plate in this process using $\bar{x}$ and R control charts. This will require setting of control charts limits. This is explained in the following sub-section.

3.4.1 Setting of $\bar{x}$ and R Charts

In order to get statistical control limits for $\bar{x}$ and R charts, common approach is to take some initial samples from the process considering the process was in control. In the current experiments, all the process related variables are kept constant, for example the operating conditions are kept constant throughout the process to achieve the desired dimensions. Similarly machine tool, workpiece material and the work environment etc. are same throughout the process. The only variable which changes periodically is the cutting tool, as it degrades with the time and eventually fails, thus it is to be replaced periodically. In order to get safe statistical control limit for $\bar{x}$ and R charts for future use, data from in control process are required. In the current manufacturing scenario cutting tool is the only variable in the whole process which changes periodically (because of failures). The current study revealed that different failure modes of the cutting tools have significant effect on the product produced from them (see, figure 4 and 5). This behaviour of different failure modes on the product quality is very important to be considered while setting the control charts. As in production process, the tool will vary timely, and will fail from different failure modes. Thus, initial samples taken for control chart setting are to be selected from different tools failed with multiple failure modes. With the help of developed experimental setup six milling cutters are run till failure, the life data generated from the experimental setup is important in the sense that they correspond to "normally" degraded milling cutters. This means that the defects were not initially initiated on the cutters and that each degraded cutter contains almost all the types of defects (worn-out and breakage). Three cutters from both the failure modes (worn-out and breakage) are observed.

Twenty five initial samples, each of size five; have been taken from six milling cutters samples with different failure modes, when the cutter was operating in its healthy stage (considering the process was in control). The interval of time between samples is one hour. These samples are used for setting the $\bar{x}$ and R charts. When setting up the control charts, it is recommended to start with the R chart. Because the control limits on the $\bar{x}$ chart depend on the process variability, unless process variability is in control, these limits will not have much meaning (Montgomery, 2007). Using the initial samples from different cutting tools, we find the center line for the R chart as shown in equation 3.

$$\bar{R} = \frac{\sum_{i=1}^{n} R_i}{n} \tag{3}$$

$$\bar{R} = \frac{\sum_{i=1}^{25} R_i}{25} = \frac{20.034}{25} = 0.801$$

where, n = total number of samples, R_i = Range of the ith sample.

The control limits of the R chart are calculated as follows:

$$UCL = D_4\bar{R} \tag{4}$$

$$UCL = D_4\bar{R} = (0.3251)0.801 = 1.694$$

$$LCL = D_3\bar{R} \tag{5}$$

$$LCL = D_3\bar{R} = (0)0.801 = 0$$

where, the constants D_3 and D_4 are tabulated based on sample size (for sample size of 5, $D_3 = 0$ and $D_4 = 0.3251$) (Montgomery, 2007).

Since, the R chart indicates that the process variability is in control (see, figure 6); we may now construct the $\bar{x}$ chart. The center line is calculated as shown in equation 6.

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{n} \bar{x}_i}{n} \tag{6}$$

$$\bar{\bar{x}} = \frac{\sum_{i=1}^{25} \bar{x}_i}{25} = \frac{105.441}{25} = 4.218$$

where, $\bar{x}_i$ = Mean of the ith sample.

The control limits of the $\bar{x}$ chart can be found out as follows:

$$UCL = \bar{\bar{x}} + A_2\bar{R} \tag{7}$$

$$UCL = 4.218 + (0.577)(0.801) = 4.680$$

$$LCL = \bar{\bar{x}} - A_2\bar{R} \tag{8}$$

$$LCL = 4.218 - (0.577)(0.801) = 3.755$$

where, the constant A_2 is tabulated based on sample size (for sample size of 5, $A_2 = 0.577$) (Montgomery, 2007).

When the preliminary sample means are plotted on this chart as shown in figure 6, all the points are inside the control limits. Since, both the $\bar{x}$ and R charts depict control, it means that the process is in control under stated levels. This set of safe control limits are adopted for monitoring future production. This completes the setting of $\bar{x}$ and R charts limits for future use. The control charts shown here are made using Minitab (Version: 17.2.1). The conventional usage of the $\bar{x}$ and R control charts is explained in the next section.

3.4.2 Conventional Process Monitoring and Quality Control Policy

Once a set of safe control limit is established, the conventional way is to use the control charts for monitoring future production. Figure 7 illustrates the working of conventional process monitoring and quality control policy. Additional samples from the process, each of sample size five from the process (with a new cutting tool) were collected after the control charts were established and the sample values of $\bar{x}$ and R are plotted on the control charts with sampling frequency of one hour. The control chart detected out of control process at 6th sample. As the control chart shows an out of control process, it means that an assignable cause has occurred at that time. Conventionally, the operator is directed to check process variables viz. cutting tool, process settings, calibration etc. and then make the adjustments in an effort to bring the process back into state of control. This conventional usage of control chart will only detect occurrence of assignable causes, also fixed sampling frequency or sample size were used throughout the monitoring. It will be of great interest if we are able to detect the reason for assignable cause and simultaneously able to vary the sampling frequency or sample size while monitoring the process for early detection of out of control process.

3.4.3 Fault Estimation Model Based Process Monitoring and Dynamic Quality Control Policy

For early detection of out of control process, fault estimation model based process monitoring and dynamic quality control policy is proposed. In this process, the mean surface roughness is monitored with a $\bar{x}$ control chart, and the process variability is monitored by R chart. Notice that if the R chart displays an out of control point, operating personnel are coordinated to contact process engineering instantly. The current manufacturing process is having only one controllable variable, cutting tool. In this scenario, the high chance of assignable cause may be tool health. Thus, the developed fault estimation model is linked with the control chart in such a way; the sample quality data is fed as input to the fault estimation model to know the current health state of the tool without stopping the production. The fault estimation model can give three types of indication about the health of cutting tool:

1. Tool is in stage I (Safe Zone)
2. Tool is in stage II (Partial Safe Zone)
3. Tool is in stage III (Worn-out Zone).

Based on the output from fault estimation model some guidelines are proposed for each health stage of the cutting tool for process monitoring and dynamic quality control. When the health state of the cutting tool is identified as stage I (the stage I of the cutting tool indicates only slight wear have been occurred in the tool, and the tool is in safe zone), the process monitoring is continued with initial sampling frequency or sample size. As the fault estimation model indicate the shift in the health state of cutting tool from stage I to stage II, it means that moderate wear is now present in the tool and this can be the reason of assignable cause in near future. Being in partial safe zone, it’s not wise to discard the tool, here the decision on varying the sampling frequency or sample size is needed to be taken for early detection of out of control process in future. As the tool health state is identified as stage III (tool is now in worn-out zone), this indicate that tool wear will soon can cause out of control process, thus here further decision on varying the sampling frequency or sample size can be made for very early detection of out of control process. Also, as the tool is reached to its failure zone, tool replacement decision can be taken in a timely manner, and this will also eliminate the faulty product development and reduce losses because of tool failure viz. power consumption etc. Based on these guidelines smart decisions on quality improvement (cost of inspection can be managed efficiently), and timely tool replacement can be taken efficiently before tool failure.

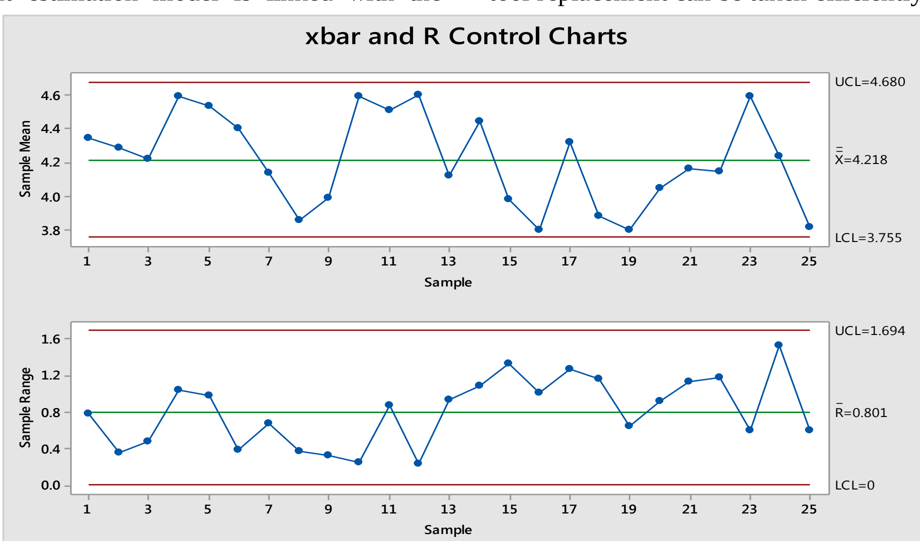

Figure 6. $\bar{x}$ and R charts.

Figure 7 illustrates the working of fault estimation model based process monitoring and quality control policy, applied on the same process data as used for conventional process monitoring and quality control policy. Additional samples from the process, each of sample size five from the process are fed as input to the fault estimation model to know the current health state of the cutting tool. From the results of fault estimation model it is identified that the current health state of the cutting tool is reached to stage II at third sample. According to the proposed guidelines, the decision on varying the sampling frequency is taken for future monitoring. Sampling frequency from the fourth sample is changed to half an hour from one hour for early detection of out of control process. With this change the control chart is now able to detect the out of control process early. The control chart detected out of control process at fourth sample. Table 3 shows the performance of fault estimation model based usage of control chart.

Table 3 Fault estimation model based usage of control chart.

Sampling frequency	1 hour	
Fault estimation model	Input	Output
	1^{st} sample	Stage I
	2^{nd} sample	Stage I
	3^{rd} sample	Stage II
Decision on change in sample frequency from 4^{th} sample onwards		
New Sampling frequency	1/2 hour	
Out of control process detection	4^{th} sample	

4. COMPARISON OF CONVENTIONAL AND FAULT ESTIMATION MODEL BASED PROCESS MONITORING AND QUALITY CONTROL POLICY

Table 4 and figure 7 shows the comparison of performance of conventional and fault estimation model based control chart policy in terms of product produced till detection of the out of control process. Till actual occurrence of out of control process twenty nine products were produced. Whereas, in conventional usage of control chart, total sixty products were produced from the process till the detection of out of control process. However, only thirty five products were produced from the process till the detection of out of control process through fault estimation model based usage of control chart. It is clear that the fault estimation model based process monitoring and dynamic quality control policy is capable of detecting out of control process very early than conventional policy. With the help of fault estimation model based control chart usage, we are able to reduce the number of faulty product development. As the difference between the products produced before the detection of out of control process is thirty one from conventional policy with actual occurrence, this is considerably high. Consequently, only six products were produced till the detection of out of control process from the fault estimation model based usage of control chart.

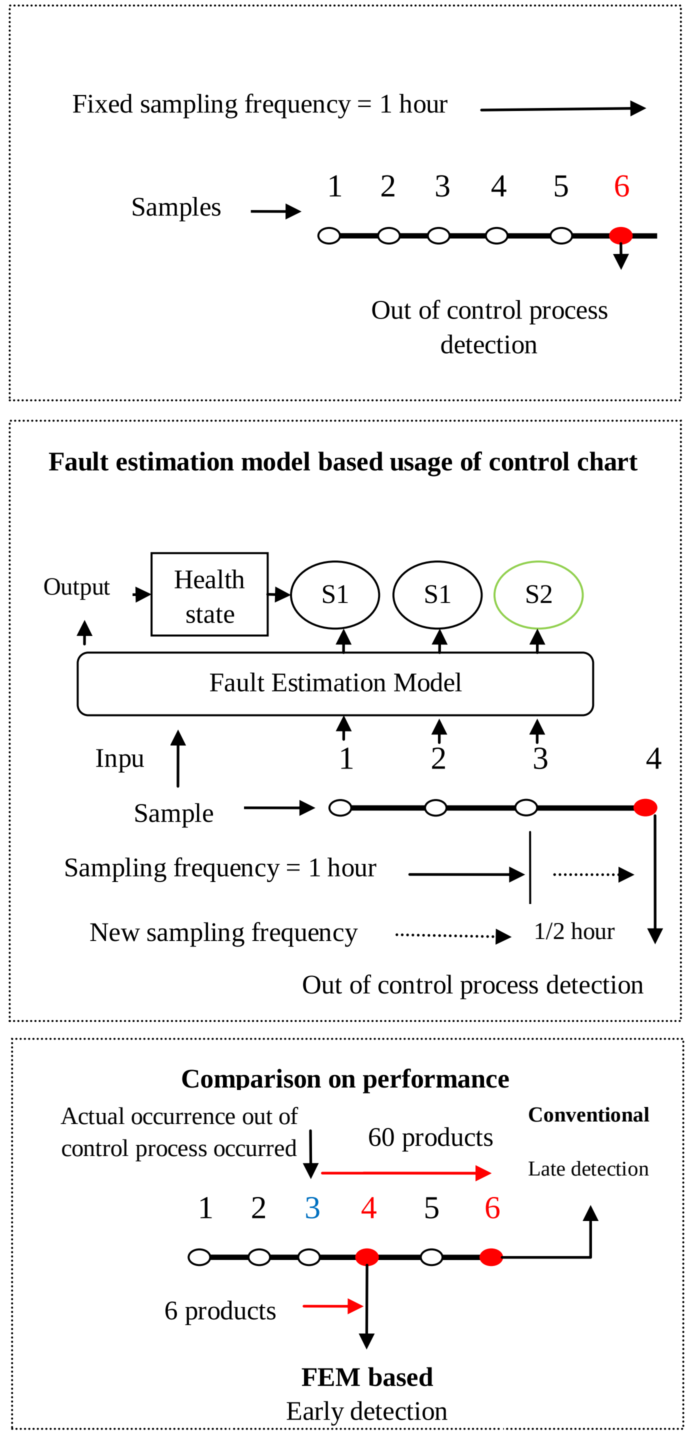

Figure 7. Illustration of conventional and fault estimation based process monitoring and quality control polices.

Table 4 Comparison of performance of conventional and fault estimation model based usage of control chart.

	Actual occurrence of out of control process	Conventional way of usage of control chart	Fault estimation model based usage of control chart
Products produced till out of control process detection	29	60	35

This joint methodology will lead to online monitoring of the production process as well as serve the purpose of tool condition monitoring. The developed quality control based tool condition monitoring methodology is of high importance for manufacturing industries in improving the performance of their machining process as well as reducing the overall manufacturing cost.

5. CONCLUSION

This paper explores the correlation between tool wear and surface roughness and utilizes the same for dynamic quality control and efficient tool replacement decisions. The major contributions of this paper are as follows:

1. An experimental study is carried out, which revealed that strong positive correlation exists between tool wear and surface roughness.

2. An ensemble (random forest) based fault estimation model is developed to map the relationship between surface roughness and tool wear.

3. Guidelines for process monitoring and quality control based on the results of fault estimation model are proposed. These guidelines will lead to efficient quality improvement as well as timely tool replacement decisions.

4. The fault estimation model based process monitoring and dynamic quality control policy is capable for early detection of out of control process than conventional usage of control charts.

The results of this study will promote and enable the establishment of a quality control based intelligent predictive monitoring system to estimate the useful life of the tools and detect the surface degradation prior to costly failure and damage to high valued workpieces.

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