Flank Wear Prediction in High-Speed Face Milling using Monte Carlo simulation method

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Abstract

In high-speed machining, Flank wear length is tough to predict due to significant dynamical change in the cutting zone. Therefore, using the traditional methods in predicting the flank wear may be varied from the accurate values. One of the practical alternatives is by using the Monte Carlo simulation method. This research compares three different scenarios in predicting the flank wear in high-speed face milling under dry conditions. The experiments were conducted using Box Behnken Design (BBD) in dry machining in high-speed face milling of AISI 1050. Six scenarios have been implemented: 50, 100, 250, 500, 1000, and 2000 simulated runs. The results were analyzed and indicated that even with the complexity of the process, the Monte Carlo method gave results high accuracy as compared with the actual experimental results with an error of 0.24%, 0.16%, 0.11%, 0.09%, 0.046% and 0.047%. Determining the optimum number of runs that give the minimum number of runs is time effectiveness. Finally, the optimum number of simulation runs was determined. knowing the best number of simulations runs that sane time and increase the accuracy is essential to increase the advantages of using MC method.

Keywords: High speed face milling, Monte Carlo, Flank wear

1. Introduction

One of the basic milling processes is the face milling that applied widely in some critical components of excellent plane machining of different industries, such as gear case, engine block, etc. With the current prominence on achieving higher productivity levels and higher precision, the face milling process has received considerable interest from many researchers. One of the approaches that increase the material removal rate in a minimum amount of time is by increasing the machining speed that will lead to an increase in material removal rate and then to shorter time to market. However, this will have some consequences, such as increasing the cutting forces and, later, the temperature. These consequences will lead to accelerating the tool wear, especially the flank wear, and as a result, it will shorten the tool life. However, in high speed machining, the cutting zone is under high pressure and highly dynamics. Therefore, predicting the output responses is a complex and important issue to the manufacturers. Many researchers tried to develop different models such as RSM (Rudrapati et al., 2020; Parida & Maity, 2019; Azam et al., 2015; Mia & Dhar 2018; Rao, & Murthy, 2018; Mir et al., 2012; Hazza. 2016; Mohamad, 2016). However, the high uncertainties that exist in machining process that may come from different sources such as: workpiece material, measurements process, cutting tool, machine, or the operator, the stochastic approaches may be more effective. Some researchers used a non-conventional approach such as fuzzy logic (Rajasekaran et al., 2011; Srinivasan et al., 2020; Kumar et al., 2018). Others used neural network (Özel & Nadgir , 2002; Uros et al., 2009; Hazza, 2013; Hazza, 2020; Ong et al., 2019).

One of the unconventional methods that can be used is the Monte Carlo (MC) method. MC method is a powerful and unbiased numerical tool that based on statistical measures. MC method involves generating a sampling distribution of a compound statistic by using point estimates of its component statistics and the asymptotic covariance matrix of these estimates and assumptions about how the component statistics are distributed (Preacher, K. J., & Selig, J. P. (2012). Ferson, S. (1996) mentioned that Monte Carlo methods have four significant limitations: it is a data-intensive that need a piece of empirical information has been collected, or unless the analyst is willing to make several assumptions in the place of such practical information; cannot be used to propagate partial ignorance under any frequentist interpretation of probability; cannot be used to conclude that exceedance risks are no more significant than a particular level; and cannot be used to effect deconvolutions to solve back-calculation problems. In his book, Mordechai (2011) presented about forty of the science and technology areas that Monte Carlo simulation was implemented. However, many researchers used and applied the MC method in the machining area of knowledge (Niaki et al., 2015; Kahraman et al., 2019; Liu et al., 2016; Zaharia & Morariu, 2015; Kurdi et al., 2005; Liu et al., 2016; Al Hazza & Saadah, 2019; Zhang et al., 2020; Lin, 2012; Karandikar et al., 2011; Kahraman & Öztürk 2019; Kowalczyk, 2018). However, using MC in simulation and modeling. One of the strongest features of MC method is the randomness in creating the output response in the boundary of the design. MC is computational algorithms rely on repeated random sampling to obtain numerical results. This concept is to use randomness to solve problems that might be deterministic in principle.

2. Research Methodology

The statistical and artificial intelligence tools were used in this research. The experimental work was designed using response surface methodology (RSM). The experiments are carried out using CNC Gate Milling Machine type ECMI with ANILAM 5300 MK Control. This experiment was performed using coated carbide inserts (TNGA 160408), which is attached to a 65 mm diameter face milling cutter. Five inserts were attached to mill cutter for each run of the experiment. Flank wear for each insert was measured. Average flank wear for all five inserts is calculated. The work material used was a carbon steel S50 grade (AISI 1050) of dimension approximately 200x90x50 mm. The Machining operations were carried out under dry and near dry cutting conditions. Flank wear was measured every 100 mm of cutting length. The tests were carried out following ISO 3685 (1993) using tool life criteria of average flank wear: 0.3 mm. The box-behnken design (BBD) was used to design and conduct the experiments. 15 treatment were conducted. BBD are one of the response surface methodology (RSM) collections used to calibrate full quadratic models. BBD is rotatable. The ranges of cutting speed, feed rate and depth of cut were selected and shown in Table 1.

Table 1 Ranges of parameters for the experiment

Parameters	Minimum	Maximum
Cutting speed (m/min)	613	817
Feed rate (mm/min)	100	200
Depth of cut (mm)	0.1	0.2

Figure 1 shows the research flow chart methodology. The figure shows that the research iterative nature searching for the best number of MC runs. The simulation is stopped when no change in the accuracy based on the experimental results.

However, the advantages of BBD with small number of factors (four or less) with three levels of each factor, require few runs. By avoiding the corners of the design space, they allow experimenters to work around extreme factor combinations. BBD are used to calibrate full quadratic models for a small number of factors (four or less), require few runs. It is suitable for exploration of quadratic response surfaces and construction of a second order polynomial model, thus helping in optimizing a process using a small number of experimental runs. The BBD for three factors is constructed on a cube as shown in Figure 1.

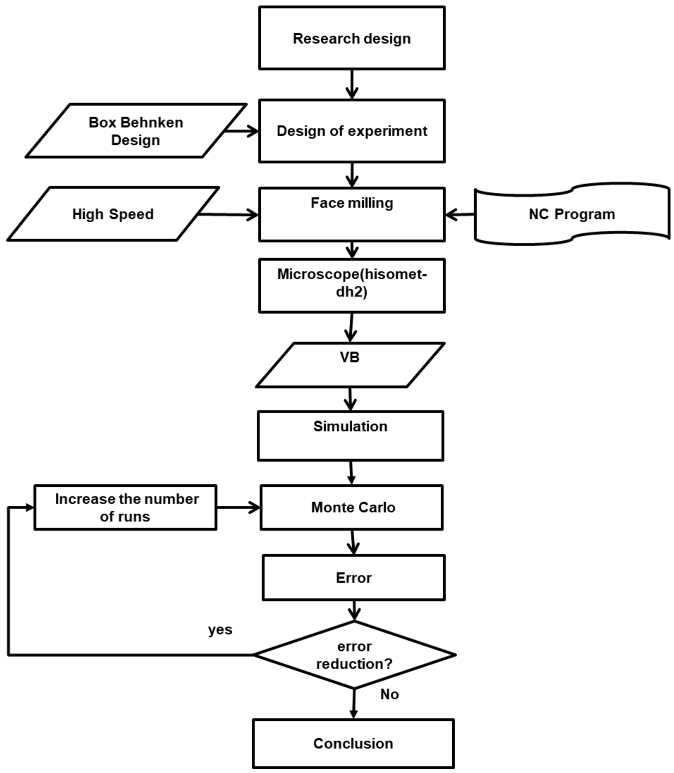


Figure 1: Research design

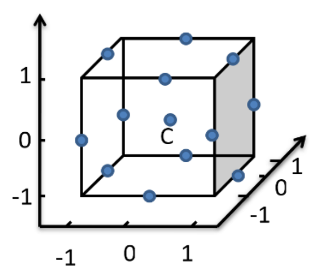


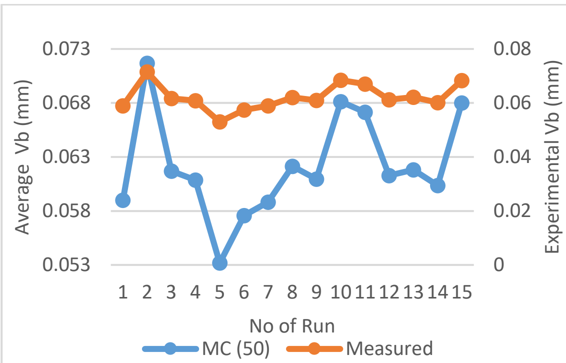
Figure 2: Box-Behnken Samples Distribution (three factors)

3. Monte Carlo Modeling

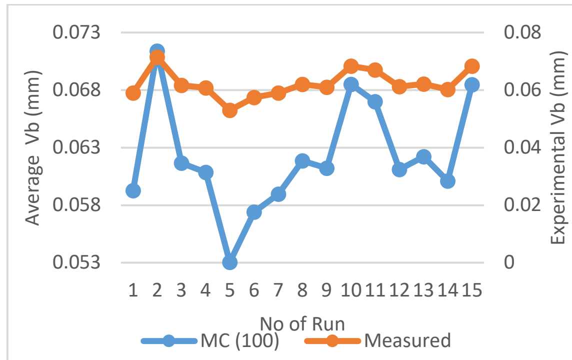
Monte Carlo method is working as a random number generator that produce an infinite stream of random variables that are independent and identically distributed according to uniform probability distribution (handbook). In this research, the results collected in the experiment were used to conduct different runs of simulation using the Monte Carlo (MC) Simulation method. The original data were analyzed statistically to be sure that the original data are valid to be used in the simulation. Fitting measures: R squared, adjusted R-squared, predicted R-squared, standard deviation, and signal /noise ratio are concluded in Table 2.
R^2, adjusted R^2, and predicted R^2. R^2 is a statistic that measures the amount of reduction in variability. Table 2 shows that the three measures are high enough and close to each other. The signal to noise is high enough to give confidence to the data collected. Finally, the standard deviation shows low value indicating that the data is uniform distributed and can be used as basis for uniform random number generator. The original data was used to run simulation using Monte Carlo method (MC) for six different scenarios: 50, 100, 250, 500, 1000 and 2000 runs. Figure 3 is comparing between each individual simulation with the experimental data. The left vertical axis is showing the average value of the simulation runs for each individual treatment that shown in the horizontal axis. Right vertical axis shows the experiment measured flank wear.

Table 2: Summary of fit

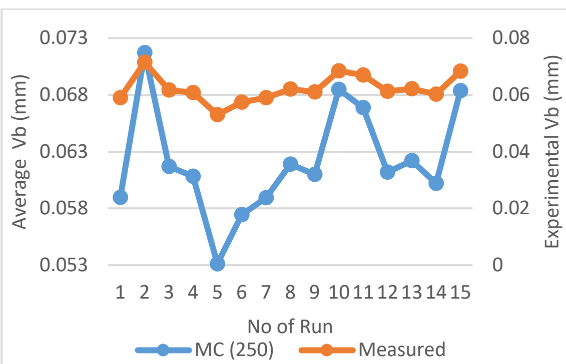
R-Squared	0.960245
Adj R-Squared	0.930428
Pred R-Squared	0.883631
Standard deviation	$1.265e^{-3}$
Signal /noise	20.91723



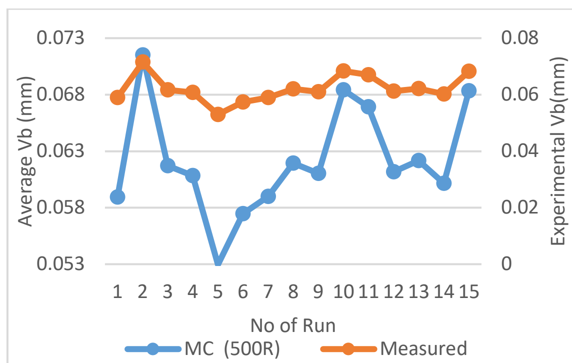
a. 50 Run



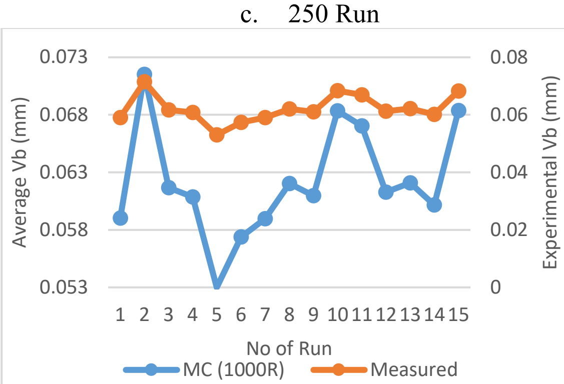
b. 100 Run



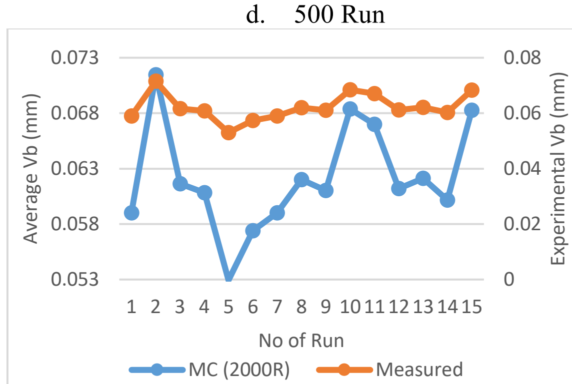
c. 250 Run



d. 500 Run



e. 1000 Run



f. 2000 Run

Figure 3: experimental values vs simulated values

The results show that the accuracy and the error percentage based on the experimental results improved with the increasing of simulation runs as shown in Figure 3.

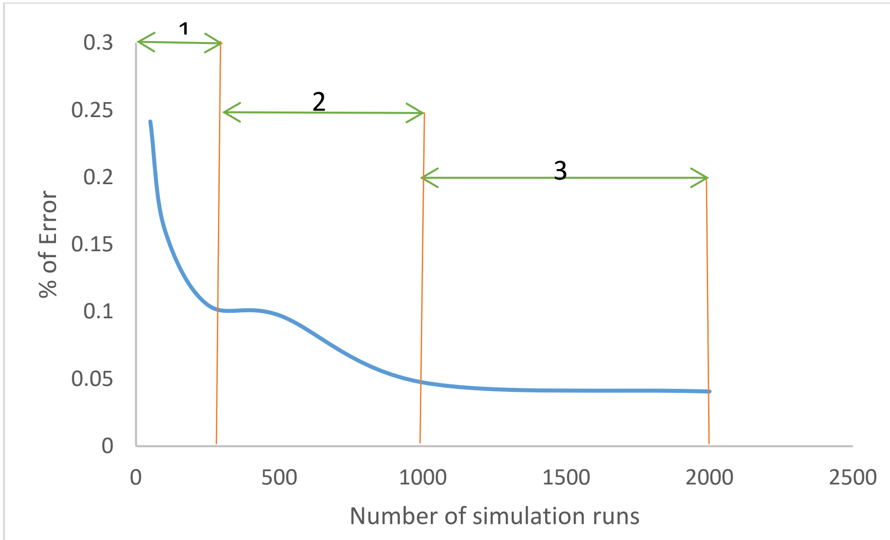


Figure 4: Error percentage compared to the experimented results

However, as shown from the Figure 4, this improvement is not a linear relationship. In a low number of simulations runs, the increase can be extremely fast concerning the reduction of error percentage as shown in stage 1. Up to a specific point, the line relation's attitude was changed to be mostly linear with small slop as clear in stage 2. However, after a particular number of runs, the change will not be worth to spend more time in the simulation because there are no significant change as shown in stage 3.

4. Conclusions

Monte Carlo simulation method based on experimental work in high speed face milling under dry conditions was conducted. The experimental work done using BBD that needs 12 different treatments with three center points. Therefore 15 different treatment were conducted. The following conclusions are drawn from the experimental investigation:

1. Monte Carlo method shows high efficiency in simulating and predicting the flank wear length with incredibly low values of error based on the measured real values.
2. The results show that the simulated runs have high correlation with high predictability with the values of the number of simulation runs can play an important role in prediction.

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Biography

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