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Design of an Adaptive Controller for Cylindrical Plunge Grinding Process

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Abstract

In modern competitive manufacturing industry, machining processes are expected to deliver products with high accuracy and good surface integrity. Cylindrical plunge grinding process, which is a final operation in precision machining, suffers from occurrence of chatter vibrations which limits the ability of the grinding process to achieve the desired surface finish. Further, such vibrations lead to rapid tool wear, noise and frequent machine tool breakages, which increase the production costs. There is therefore a need to increase the control of the machining processes to achieve shorter production cycle times, reduced operator intervention and increased flexibility. In this paper, an Adaptive Neural Fuzzy Inference System (ANFIS) based controller for optimization of the cylindrical grinding process is developed. The proposed controller was tested through experiments and it was seen to be effective in reducing the machining vibration amplitudes from a 10^{-1} μm to a 10^{-2} μm range.

Keywords: Grinding process, chatter, ANFIS, kinematics

1. Introduction

In cylindrical plunge grinding processes, the occurrence of chatter vibration is critical. This is because it compromises on the accuracy and surface finish of the ground part, (Hongqi and Shin 2007). Cylindrical plunge grinding processes are inherently susceptible to chatter, (Inasaki 1999, Franciszek 1999).

Over the years, many researchers have attempted to develop models for the grinding process. The result is a number of models, each attempting to look at, or emphasize on, a specific area of the grinding processes. Also, modeling generally involves a trade-off between the accuracy of the model and the difficulty (or possibility) of obtaining the necessary information or parameters. As a result, there have been attempts to use other unconventional methods for the control of the grinding process. Jason and Rogelio (2005) carried out a study on cylindrical grinding open architecture and feed rate control by power feedback. The controller that was developed applied PID control techniques. It used Kalman filter and state variable feedback to control the velocity and hence the feed rate.

Fernandes et al (2009) simulated an active vibration control system for the center-less grinding machine by use of finite element method. Based on the updated finite element model of the machine, the structural modifications were performed to incorporate active elements. The reduced structural model was integrated in the cutting process model to give a tool that was adapted for the purpose of simulating different control laws. Shaw et al (1997) used magnetic Barkhausen noise method to develop a control system for the grinding process. The controller was used to detect small changes in the level of surface residual stress and hardness which would allow the detection of grinding damage at its onset. The controller that was developed focused on detection and avoidance of destruction of the work piece. Janez et al (2003) developed methods for chatter detection by use of acoustic emissions. The methods employed entropy and coarse-grained information rate (CIR) as indicators of chatter. Entropy was calculated from a power spectrum, while CIR was calculated directly from fluctuations of a recorded signal. Lee and Kim (2001) investigated external plunge grinding using the current signals of the spindle motor through a hall sensor under different machining conditions. A relationship between current signals and the metal removal rate in terms of the feed rate was induced.

Jae and Song (2001) used acoustic emission signals generated during machining to determine the relationship between grinding related vibration and characteristics of changes in signals. Also, neural network was applied to the diagnosis system.

Hodge and Thomas (1999) developed an adaptive force controller for the grinding process which was achieved by use of a real time grinding model, where an adaptive pole-zero cancelation technique was developed and implemented to reduce the grinding process variation. Albizuri et al (2009) used a simplified model of the center-less grinding machine to simulate the behavior of several commercially available piezoelectric actuators. Based on these simulations, a selection of proper actuators and their optimal location was obtained and the control system implemented. Junkar and Filipic (2001) controlled the plunge grinding process by use of power spectrum of vibration signals. This was done by use of an inductive machine learning system. The controller was used to predict the grinding wheel performance in real time. Saravanan et al (2002) developed a genetic algorithm (GA) based optimization procedure. The algorithm was used to optimize grinding conditions, that is, wheel speed, work piece speed, depth of dressing and lead of dressing, using multi-objective function model with a weighted approach for surface grinding process. Ding et al (2007) used a neural network (NN) and fuzzy logic approach in prediction and control of work piece size in the grinding process.

As can be seen, all of the above studies have used varied approaches for controlling the grinding process. However, there is none that can be said to be fully efficient on its own. Also, there have been little attempts to control the vibrations during the grinding process. This could be due to the complex nature of the process, which makes it difficult to develop analytical models for the process. In this paper an adaptive controller that would optimize the grinding process by controlling the machining vibrations without the need for an accurate process model is presented. With a comprehensive dynamic model of the grinding process, chatter vibration can be predicted and its occurrence prevented, either by design of a chatter-free process, or process controller.

2. Dynamic model of the cylindrical plunge grinding process

In the dynamic model, chatter vibration is assumed to be a two dimensional problem as shown in Figure 1.

The following relationships were obtained for the forces in the tangential and normal directions.

$$F_n = F_n'\cos(\beta_g + \psi) - F'_t\sin(\beta_g + \psi) \quad (8)$$

$$F_t = F_n'\sin(\beta_g + \psi) + F'_t\cos(\beta_g + \psi) \quad (9)$$

The defections d_n and d_t in the normal and tangential directions, respectively, can be obtained as follows,

$$\delta_n = F_n / K_{eq} \quad (10)$$

$$\delta_t = F_t / K_{eq} \quad (11)$$

Where K_{eq} is the dynamic grinding coefficient and is a function of the work piece stiffness, K_w, grinding wheel stiffness, K_g and machine stiffness, K_m.

$$\mu = \frac{F_t}{F_n} \quad (12)$$

where μ is the coefficient of grinding, (Ioan 2007). The deflection d is given by,

$$\delta = \delta_n\sqrt{1 + \mu^2} \quad (13)$$

The deflections are computed as a function of time.

3. Design of the adaptive neural fuzzy logic controller

An Adaptive Neural Fuzzy Inference System (ANFIS) based fuzzy logic controller (FLC) has been developed. This system is preferred because of its ability to improve both the system performance and adaptability, (Jang et al 1997, Mohammed 2006). A set of training data is presented to the ANFIS and the membership functions and the rule base for the FLC are then obtained from the ANFIS. These parameters are used for tuning the FLC. The FLC works in a closed loop to control the vibrations resulting from the grinding process by selecting the appropriate grinding parameters based on the amplitudes of vibrations.

The proposed controller has the amplitudes of vibration in the normal and tangential directions (δ_n) and (δ_t) respectively as the inputs. Figure 2 shows the block diagram for the proposed controller. The output of the controller is a DC voltage that ranges between 0 and 10 V. The voltage is matched to motor speeds between 0 and 1430 rpm, that is, 0 V represents 0 rpm (the lowest speed) while 10 V represents 1430 rpm (the highest speed). For example, a speed of 700 rpm is represented by 4.895 V. The controller calibration curve is shown in Figure 3.

Figure 4 represents Gaussian type membership functions for the two inputs. The reason for the use of Gaussian type of membership functions is because of their ability to represent the nonlinear nature of the problem better than other membership functions, such as the triangular and the trapezoidal functions.

The nomenclature for the membership functions is as in Table 1; the rule base for the FLC uses OR and AND conjunctions and the consequents are singletons (since Sugeno type FIS is used).

The output from the controller is connected to a variable frequency drive (VFD) which is used to control the grinding wheel speed. The variable speed drive has a control terminal which takes voltages between 0 V and 10 V that are used to control the motor speed. The VFD is connected to a three phase input power, and, gives a three phase output power to the motor.

4. Experimental setup

In order to test the effectiveness of the proposed controller, measurement of vibration in cylindrical plunge grinding process was carried out with and without the controller for two different materials, i.e., mild steel (0.2% carbon) and EN9 steel (0.5% carbon). The focus was on the amplitudes of the vibrations, with the root mean square (rms) values of work piece displacements being taken as indicative for the vibrations.

The experimental setup involved a universal HIGH-GLOSS 450-H grinding machine. The machine has a spindle rotational speed of 1430 rpm and a work piece rotational speed that can be adjusted to either 55 rpm, 130 rpm, 215 rpm or 295 rpm. It has a provision for feeding in two orthogonal axes, that is X and Y, and can be automatically fed in the X direction only. The minimum in-feed attainable is 0.01 mm. A B126 Cubic Boron Nitride (CBN) wheel with a grit density of 9.5/mm^2, outer diameter of 405 mm, inner diameter of 203 mm and thickness of 75 mm was used. A contact type displacement sensor, DT-10D, with a range of 10 mm and a piezoelectric dynamometer (AST-MH) were used for displacement and force measurements, respectively. The experimental setup was as shown in Figure 5.

The parameters that were used are shown in Table II where the coefficient of grinding, µ, was determined experimentally and the grit shape factor assumed to be of uniform grit.

5. Results and discussion

Figure 6 is an example waveforms of the vibration amplitudes from which the rms values were obtained.

The results for various work piece speeds and in-feed were recorded as shown in Figures 7 through 10.

Figure 7 shows the relationship between the work piece speed and the rms values when grinding mild steel. It can be seen in this figure that when grinding without a controller, the rms values of the vibrations vary between 0.2 µm and 0.25 µm for the cases considered. However, when grinding under the control of the FLC, the rms values are much lower and vary within a narrow range of 0.015 µm and 0.018 µm. This shows that the controller is able to maintain low vibration amplitudes regardless of the value of speed of work piece. This is a very desirable characteristic of the ANFIS based FLC.

Similar result can be seen Figure 8, for machining of EN9 steel, whereby the rms values of vibration amplitude vary in the 0.30 µm and 0.47 µm range for the uncontrolled case, and 0.018 µm and 0.023 µm range for the uncontrolled case.

Figure 9 and 10 show the variation of the rms values with in-feed for the two materials, i.e., mild steel and EN9. From Figure 9, it can be seen that, variation of the rms values with the in-feed range from 0.113 µm to 0.225 µm when grinding without controller. With the FLC, the rms values range between 0.013 µm and 0.019 µm. This shows that, the rms values are maintained low and in a very narrow range by the FLC, regardless of the in-feed.

Comparing the rms values of the amplitudes of vibration for both non-controlled grinding, and the Fuzzy Logic Controlled grinding processes, it can be inferred that;

- The amplitudes of the vibrations when grinding under no control are in the order of 10^{-1} µm, while the amplitudes for grinding under the control of the FLC are in the order of 10^{-2} µm. This shows a significant reduction in the vibration amplitudes.
- The vibration amplitudes remain in the 10^{-2} range irrespective of the in-feed, wheel or work piece speeds in the controlled process.

5. Conclusion

In this study, an ANFIS based controller was developed and used to control the vibrations in cylindrical grinding process. The controller was tuned using data obtained from the dynamic model of the cylindrical plunge grinding process. Results showed that the ANFIS based fuzzy logic controller reduced the vibration amplitudes from a 10^{-1} µm to a 10^{-2} µm range.

References

Albizuri J., Fernandes M., Garitaonandia I., Sabalza X., Uribe-Etxeberria R. and Hernandez J., (2007), An active system of reduction of vibrations in a center-less grinding machine using piezoelectric actuators, *International Journal of Machine Tools and Manufacture*, 47, 1607–1614.

Ding N., Zhang D. and Liu X., (2007) Neural fuzzy prediction control of an industrial grinding process, *IEEE*, 1, 221–224.

Fernandes M.H., Garitaonandia I., Albizuri J., Hernandez J. M. and Barrenetxea D., (2009), Simulation of an active vibration control system in a center-less grinding machine using a reduced updated FE model, *International Journal of Machine Tools and Manufacture,* 49, 239–245.

Hodge E. J. and Thomas R. K., (1999), Adaptive pole-zero cancellation in grinding force control, *IEEE Transactions on control systems technology*, 7, 363–370.

Hongqi L. and Shin Y. C., (2007) A study on chatter boundaries of cylindrical plunge grinding with process condition dependent dynamics, *International journal of machine tools and manufacture*, 47, 1563–1572.

Inasaki I., Karpuschewski B. and Lee H., (1999) Grinding Chatter - Origin and suppression, *Journal of machine tools and manufacture*, 4,, 25–32.

Ioan D. M., Mike H., Eckart U., Rowe W.B. and Ichiro I., (2007), *Handbook of machining with grinding wheels.* CRC Press, Taylor and Francis Group.

Jae S. K. and Song J. B., (2001), Trouble diagnosis of the grinding process by using acoustic emission signals, *International Journal of Machine Tools and Manufacture*, 41, 235-241.

Janez G., Andreas B., Edvard G., Fritz K. and Igor G., (2003), Automatic chatter detection in grinding," *International Journal of Machine Tools & Manufacture*, 1, 1397–1403.

Jang J.S., Sun C.T. and Mizutani E., (1997), *Neuro-Fuzzy and Soft Computing: A computational approach to learning and machine intelligence*, Prentice-Hall, Inc., Upper Saddle River, New Jersey.

Jason Braden, Rogelio Hecker, (2005), Cylindrical grinding open architecture and feed rate control by power feedback. *Georgia Institute of Technology.*

Junkar M., Filipic B., (2001), Grinding process control through monitoring and machine learning, *IEEE*, 4, 77–80.

Lee E. and Kim N., (2001), A study on the machining characteristics in the external plunge grinding using the current signal of the spindle motor, *International Journal of Machine Tools and Manufacture*, 41, 937–951.

Mohammad A., (2006), ANFIS based soft-starting and speed control of AC voltage controller fed induction motor, *IEEE*, 3, 106–110.

Orynski F. and Pawlowski W., (1999), The influence of grinding process on forced vibration damping in headstock of grinding wheel of cylindrical grinder, *International Journal of Machine Tools and Manufacture*, 39, 229–235.

Saravanan R., Asokan P., Sachidanandam M., (2002), A multi-objective genetic algorithm (GA) approach for optimization of surface grinding operations, *International Journal of Machine Tools and Manufacture*, 42, 1327–1334.

Shaw B. A., Evans J.T., Wojtas A.S., Suominen L., (1997), Grinding process control using the magnetic Barkhausen noise method, in Electromagnetic Non-Destructive Evaluation II, *Proceedings of the 3rd International Workshop on E'NDE*, Reggio Calabria, Italy, IOS Press–Amsterdam, 82–87.

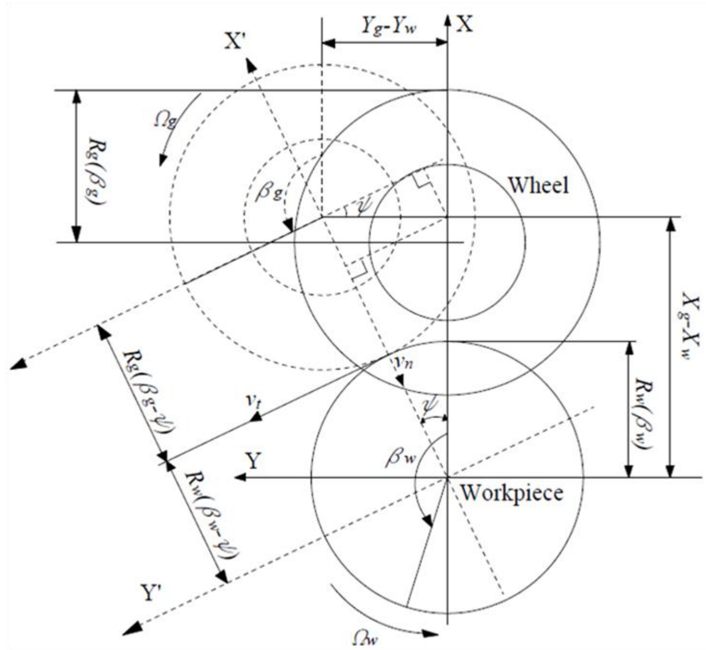


Figure 1: Kinematics of a plunge grinding process (Hongqi and Shin 2007)

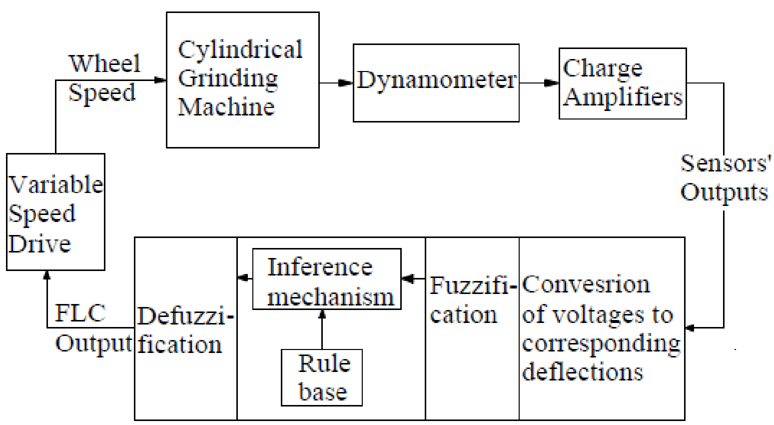


Figure 2: Schematic diagram for the control of cylindrical grinding process using FLC

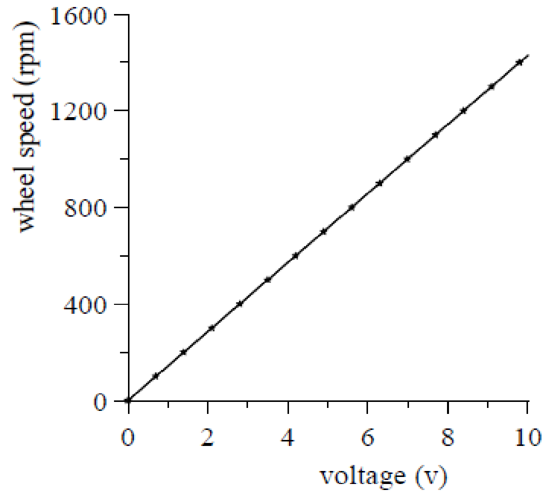


Figure 3: Controller calibration curve

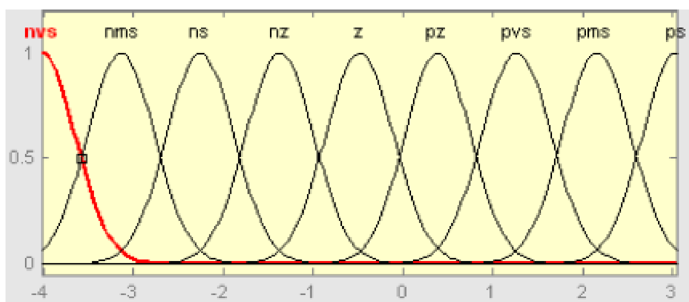


Figure 4: Membership functions of the inputs

Table 1: Membership functions' definitions

Membership functions	Definition
nvs	Negative very small
nms	Negative medium small
ns	Negative small
nz	Negative zero
z	Zero
pz	Positive zero
pvs	Positive very small
pms	Positive medium small
ps	Positive small

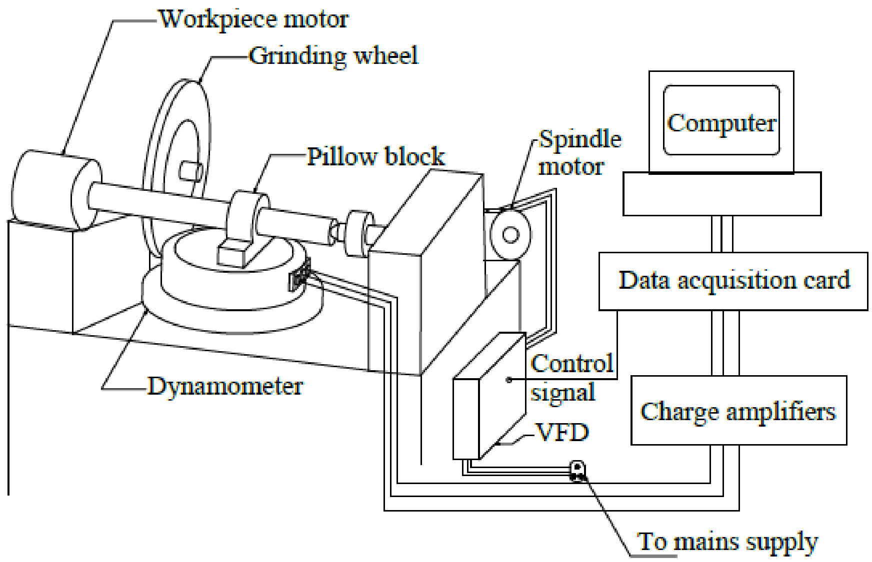
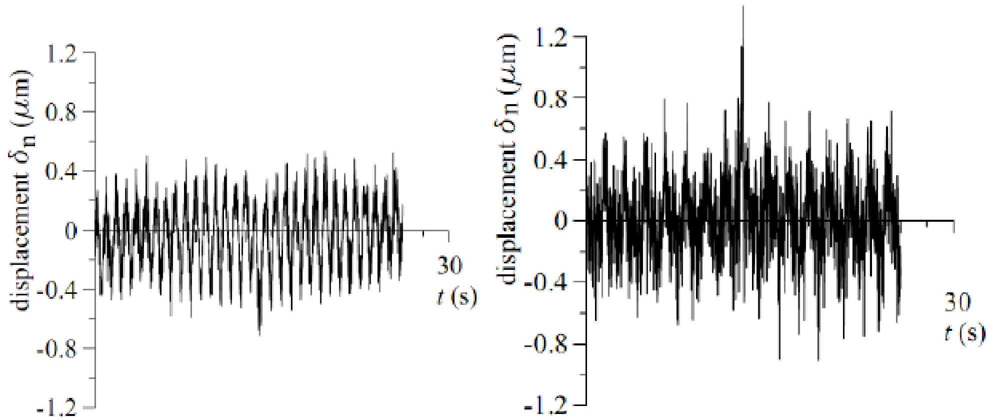


Figure 5: Experimental setup for control of grinding vibrations

Parameter	Value
Coefficient of grinding (μ)	0.5
Grit shape factor (r)	1
Grinding wheel diameter (d_g)	405 mm
Workpiece diameter (d_w)	30 mm

Table 2: Grinding parameters



(a) workpiece speed at 295 rpm: the rms value is 0.2199

(b) workpiece speed at 130 rpm: the rms value is 0.2344

Figure 6: Vibrations waveform for grinding mild steel (wheel speed, 1430 rpm)

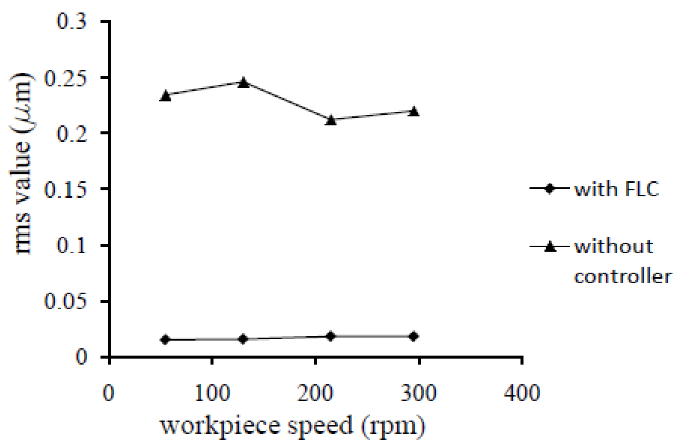


Figure 7: Variation of rms values of displacements with work piece speed in grinding mild steel

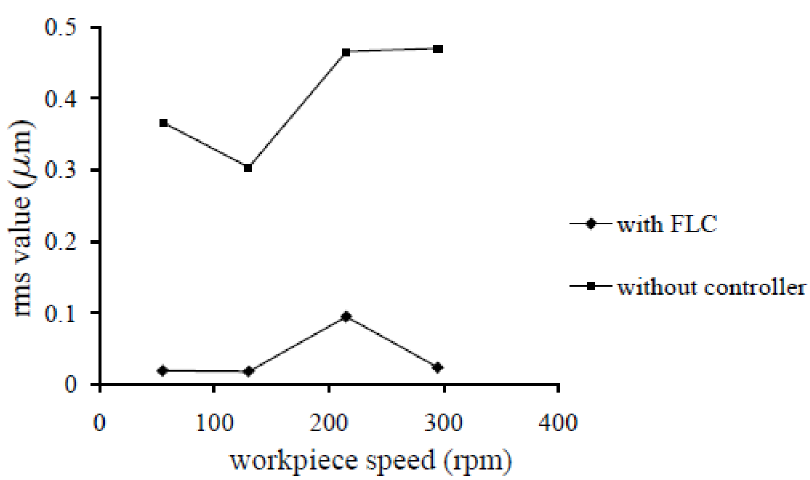


Figure 8: Variation of rms values of displacements with work piece speed in grinding EN9 steel

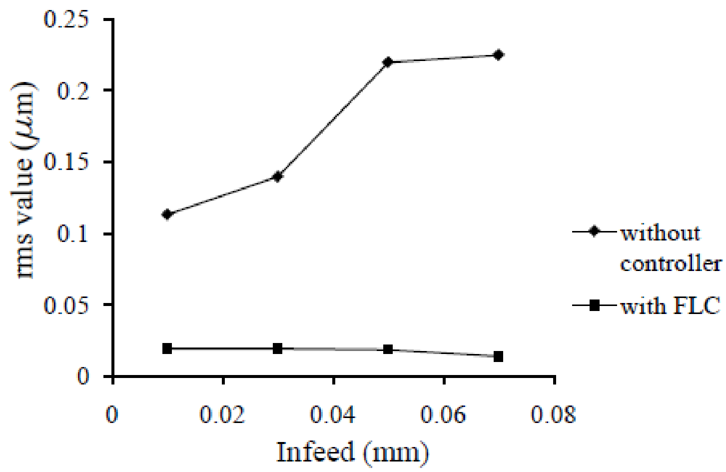


Figure 9: Variation of rms values of displacements with in-feed in grinding mild steel

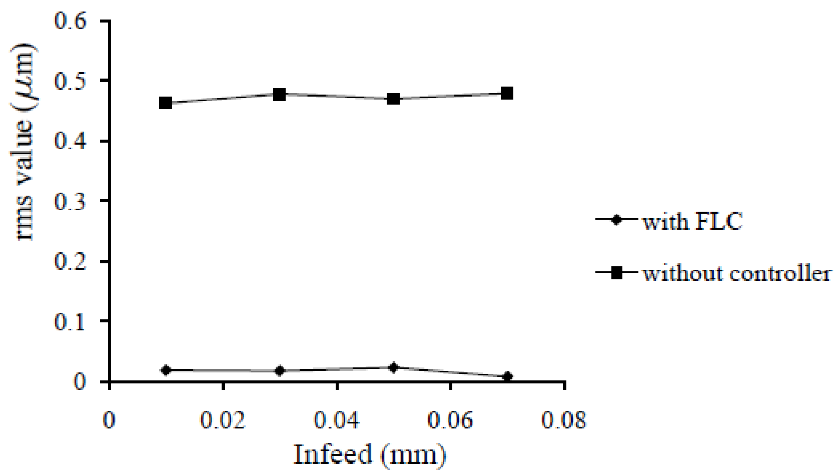


Figure 10: Variation of rms values of displacements with in-feed in grinding EN9 steel