Chapter 4. Cutting Force Modeling for SSM

Machining Process Modeling for Intelligent Rough Machining of Sculptured Parts

Sorin I. Pop
Parametric Technology Corporation
Vancouver, BC, Canada

Geoffrey W. Vickers and Zuomin Dong (zdong@me.uvic.ca)
Department of Mechanical Engineering
University of Victoria
Victoria, BC, Canada V8W3P6

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Abstract: Rough machining removes the excess part material and dominates the machining time of a sculptured part. Maximization of the material removal rate using optimized cutting parameters for rough machining can considerably improve productivity. This work focuses on the identification, improvement and testing of a machining process model that is generally applicable to various cutting geometry, as well as model parameters that cover a broad range of cutting conditions. A method for acquiring machining parameters of various 2 ½ D milling operations for a generic cutting force model is proposed. The improved cutting force model requires few cutting tests, provides fast and accurate predictions, and supports future upgrading. Testing has shown a good agreement between predicted and measured cutting forces. A considerable saving of machining time can be achieved.

1. BACKGROUND AND MOTIVATION

In recent years, applications of sculptured parts increased significantly due to their unique functional and aesthetic properties, as well as the advances of new thermosetting materials and wide use of plastic materials. Machining of sculptured parts is usually completed in two stages: rough machining and finish machining. Depending on the shape of the stock and part, sometimes as much as 80 percent of the machining time is allocated to the roughing operation. A reduction of the machining time at this stage would considerably reduce machining time and consequently lower the costs of production. This objective can be accomplished by the maximization of the Material Removal Rate (MRR) and appropriate selection of cutters and cutting parameters.

At present most tool path planning and programming programs for sculptured part machining focus on the accurate production of the curved surfaces. Modest attention is given to the optimization of the machining parameters to achieve the maximum productivity. This is partially due to the complex nature of the sculptured part tool path planning and programming task. Different from the cases of simple rotational and prismatic parts, rough machining of sculptured parts has to deal with constantly changing cutting volume due to the varying difference between a stock of regular shape and a part with sculptured surfaces. It is very often that conservative machining parameters are used through out the rough machining process to avoid a sudden deep cut due to the curvature change of the part to avoid any damage to the cutter, the machine and the part. This approach considerably slows down the machining and lowers productivity. In principle, this problem can be solved using the adaptive machining

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scheme that senses the cutting force at each instance and adjusts the machining parameters (especially the feed rate) on line. However, the approach is seldom used due to the constant delay between a change of cutting force and the response of the control system, as well as the limited reliability of a complex sensing, data acquisition and control system.

To overcome this difficulty, a computer model based, sculpture part machining planning and programming method was introduced [3,5,6]. The method is based upon computer modeling of a sculptured part, the stock, and the machining process, as well as the optimization of machining productivity using an intelligent system and numerical optimization. The approach calculates the instantaneous cutting volume during sculptured part rough machining based upon the computer models of the part and the stock, given different tool path and machining parameters. Using an empirical data based machining process model, the method accurately predicts the cutting forces based upon the calculated instantaneous cutting volume. Incorporating various machining constraints, such as tool breakage and chatter, the maximum instantaneous cutting volume is maintained through out the machining process with the optimal machining parameters. The considered machining parameters include the tool path pattern, depth of cut, cross cutting depth, and feed rate [3-6]. The approach can significantly improve the productivity of sculptured part machining, ranging from 15-45 percent.

To effectively incorporate manufacturing knowledge into the machining parameter planning stage, a generally applicable and accurate machining process model that associates the instantaneous cutting volume with the cutting force becomes essential. However, most of the existing machining process models were introduced to model a specific machining operation and tested using a few cutting parameters with limited general applicability. A machining process model that is generally applicable to various cutting geometry, as well as model parameters that cover a broad range of materials and cutting conditions needs to be identified and tested. The work reported in this paper focused on these issues.

Based on the specific requirements of intelligent rough machining and the published mechanistic force models, a method for acquiring machining parameters of various 2 ½ D milling operations for a generic cutting force model is introduced. A combination of dependency testing and surface generation procedures are employed to generate the model. The improved model and obtained parameters are used to plan the feed rates required to maintain a productive feed rate and to reduce the total machining time. The improved cutting force model is easy to customize, requires few cutting tests to develop, is fast and produces accurate predictions, as well as contains provisions for future upgrading. Testing has shown a good agreement between predictions and actual cutting data. A considerable saving of machining time is achieved.

2. ACQUISITION OF MACHINING DATA

2.1 Cutting Force Measurement System

In order to measure the tangential and radial cutting forces in end milling, a dynamometer was built [6]. The unit consists of a tubular section onto which semiconductor strain gauges are bonded, as shown in Figure 1. Electrical signals produced by the strain gauges are collected and transmitted through slip rings and brushes to a data acquisition system, as shown in Figure 2. This tubular section is installed into a rotary tool holder adapter that is inserted in the milling machine's spindle. At the other end a tool adapter provides the connection between the milling cutter and the dynamometer. The dynamometer is reliable for measuring tangential and radial cutting forces in end milling, although it is more flexible and prone to chatter at large depths of cut, compared to a commercial table-mounted dynamometer. The cutting force data are acquired using a *LabVIEW* Lab-NB Multifunction 12-bit A/D board and processed using virtual instrument application programs, running under *LabVIEW* on a PC.

2.2 Calibration of the Dynamometer

Both static and dynamic calibrations of the discussed dynamometer were performed. The static calibration was performed on a Materials Testing System (MTS) machine. In order to reproduce the actual load conditions of a cutting process, a jig was built. This jig provided adequate fixation and support for the dynamometer. The strain gauges that measure the cutting force components were alternatively subjected to loads that varied from 0 to 600 *lbs.* in 50 *lbs.* increments. A multimeter was used for voltage readings.

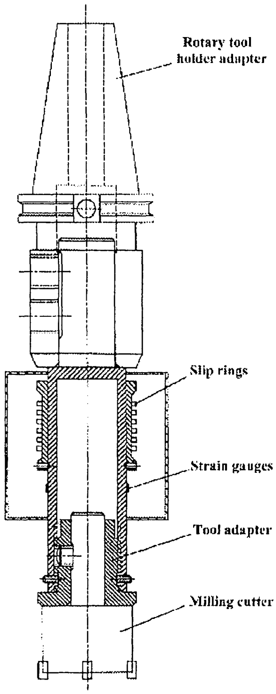

Figure 1 .Schematic diagram of the dynamometer

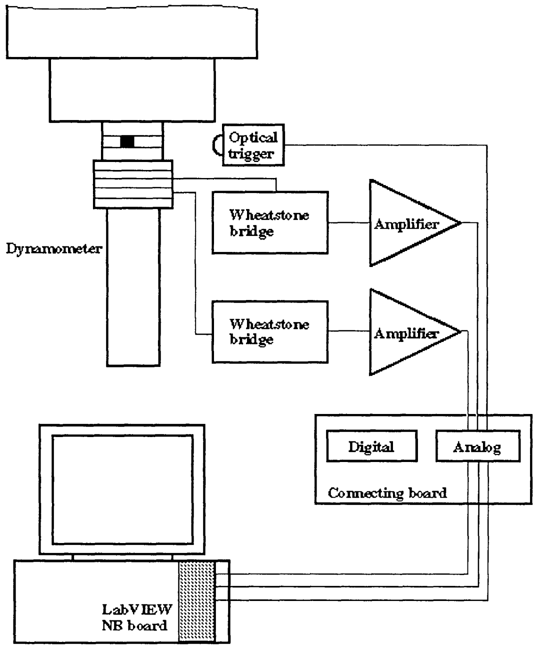

Figure 2 .Schematic of the data acquisition system

The calibration assessed against a known commercial dynamometer from Prof. Y. Altintas at the University of British Columbia (UBC). The newly built dynamometer from UVic was installed on the spindle of a milling machine, while the commercial unit was fixed on the machine's table. Adjustment of the dynamometer for aligning each pair of strain gauges to the compression loads created by the relative movement of the two dynamometers was carried out.

In the dynamic calibration, a constant load was applied to the rotating dynamometer through a ball bearing, which eliminated the friction between the reference load cell and the dynamometer. The load was increased in increments of 25 *lbs*, from 50 to 300 *lbs*. The LabVIEW data acquisition and processing system was used to acquire the output of the strain gauges. Since the magnitudes of the output signals from the two pairs of strain gauges are different, two sensitivity factors have to be calculated. A line was fitted through the data points that were obtained by plotting load vs. output voltage, thus producing a mathematical correlation between load and strain gauges' output. Using the sensitivity calibration constant, the output voltages obtained during the tests were transformed into forces. The result of this conversion is illustrated in Figure 3.

3. MACHINING PARAMETER SELECTION

3.1 Previous Approach and Improvements

In present practice, machining parameters are determined as follows. First, the spindle speed is selected based upon recommendations of machining handbooks. The axial depth and radial width of cut are determined based upon part geometry and cutter diameter. At last, feed rates are determined by various constraints imposed on the machining process, such as tooth breakage, chatter and dimensional surface error. The maximum feed rate that will probably satisfy all of these constraints will be used in the machining. However, in sculptured part machining, this estimation can only be made based upon the worst case scenario, which results in a constant, very conservative feed rate throughout the entire machining process.

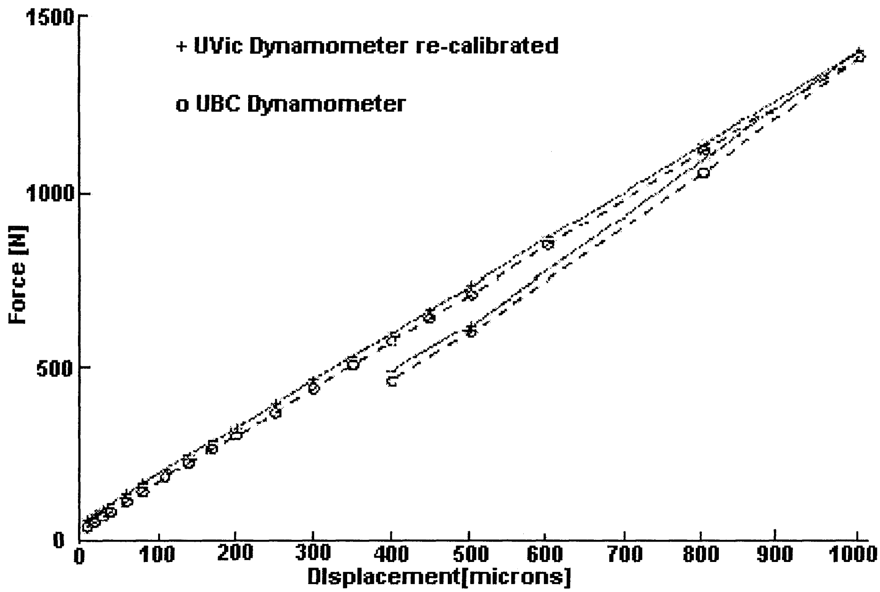

Figure 3. Output comparison after the dynamic re-calibration

A method for planning more efficient machining parameters was introduced by Altintas and Spence [1]. The method applies a solid modeler based process simulation scheme, which takes part and stock geometry and predicts the milling forces of the cutting process. The mechanistic model developed by Tlusty and MacNeil was used.

$$F_t = K_t \cdot b \cdot s_t \cdot \sin(\phi) \tag{1}$$

$$F_r = K_r \cdot F_t \tag{2}$$

$$F = \sqrt{(F_t^2 + F_r^2)} \tag{3}$$

where, F_t is the tangential component of the cutting force for one tooth, K_t, is a constant called specific cutting pressure, b is the width of cut (measured parallel to the axis of the cutter), s_t is the feed rate per tooth, ϕ is the immersion angle, F_r is the radial component of the cutting force, K_r is the tangential/radial force ratio, and F is the resultant cutting force.

Their approach produces simulation results with a good agreement with the measured milling forces. However, a number of improvements need to be made in order to incorporate this approach into the Intelligent Rough Machining of Sculptured Parts.

First, the Constructive Solid Geometry (CSG) based graphical simulation system that Altintas and Spence used has limited capability in modeling complex sculptured parts and requires extensive computation to calculate the instant cutting volume. For this reason a meshed surface representation, supporting a higher degree of part complexity, and a dedicated intersection calculation algorithm were developed. Then, the determination of the instantaneous and average forces requires extensive calculations. In this work, feed rate is directly calculated from the model without the need to determine the instantaneous cutting forces, so the computational effort is reduced. Finally, in their approach Altintas and Spence, calculate the values of the cutting coefficients, K_t and K_r, based on four constants, M_t, M_r, P_t and P_r, that need to be determined through cutting tests.

$$K_t = M_t \cdot \overline{h}^{-P_t} \tag{4}$$

$$K_r = M_r \cdot \overline{h}^{-P_r} \tag{5}$$

where, $\overline{h}$ is the average chip thickness. No explicit correlation between these constants and the cutting data is produced during the cutting tests. It means that every time a new cutter, part material, or cutting condition is introduced, a new set of tests has to be carried out. In this work a systematic examination of the model under different cutting conditions is carried out and the test results are built into a comprehensive machining database. Ideally, the database will contain as many combinations of cutting conditions as feasible. A good approach from an industrial perspective would be to narrow down the variation of cutting conditions to those that are used in 80 to 90% of cases in a machine shop. Specifically, this research intends to

- create a database of cutting force coefficients, K_t and K_r under a variety of cutting conditions. K_t and K_r values, under different cutting conditions based upon experiment data.
- offer a better solution for the feed rate scheduling. The Intelligent Rough Machining scheme requires that the immersion intervals and cutting force to be calculated quickly.
- increase the accuracy of the milling process simulator.
- implement the adapted machine process model into the Intelligent Rough Machining planning and programming.

3.2 Cutting Experiments and Obtained Model Parameters

A broad range of cutting tests was carried out in this work to cover various cutting conditions and to identify the valid ranges of machining parameters. The parameters examined in the tests are feed rate, cutting speed, depth of cut, entry angle, exit angle and type of milling cutter. The initial ranges for the cutting speed, depth of cut, and feed rate were selected based on machining standards to identify the cutting parameters that produced the least chatter. The tested ranges were:

- cutting speed: 30 to 60 m/min
- feed rate: 0.19 to 0.64 mm/tooth/rev
- depth of cut: 0.5 to 7 mm
- entry angle: 0 to 90 degrees, and
- exit angle: 120, 160 and 180 degrees

To study the behavior of K_t, K_r, and their value change according to a wide range of feed rate, s_t, the axial depth of cut, d, cutting speed, and entry angle were studied.

4. THE MODIFIED MACHINING PROCESS MODEL FOR THE SCULPTURED PART INTELLIGENT ROUGH MACHINING

Variation trends for the specific cutting pressure K_t, tangential/radial force ratio K_r and cutting force F can be extracted from force measurements. By using Equations 6 and 7, it was possible to calculate K_t and K_r from cutting data obtained from parameter varying cutting tests. where, F_t is the tangential component of the cutting force (measured), F_r represents the radial component of the cutting force (measured), K_t and K_r are the cutting force coefficients

$$K_t = \frac{F_t}{d \cdot s_t \cdot \sin(\phi)} \tag{6}$$

$$K_r = \frac{F_r}{F_t} \tag{7}$$

(calculated), d is the axial depth of cut (varied according to the test plan), s_t is the feed rate (varied but not simultaneously with d), and φ is the immersion angle. K_t and K_r have a flat response with the variation of the immersion angle, φ, in the range 45 to 135 degrees. The average value of the cutting coefficients has been defined over this flat response interval. In this work, K_t, K_r, F_t, and F_r represent the averaged values.

The analysis of cutting tests showed that the magnitude of the specific cutting pressure is inversely proportional to the feed rate. Tests conducted with different end mills have led to the same conclusion. Also, the tangential/radial force ratio shows a decrease with the increase in feed rate. Other cutting parameters, such as cutting speed and entry angle, showed little influence over the magnitudes of the cutting force coefficients. Limited tests with cutters presenting tool wear were conducted and led to believe that cutter wear and geometry might also affect the values of the coefficients.

An example relation that illustrates the compounded effects of the cutting parameters (feed rate and axial depth of cut) to the model parameter, K_t, is illustrated in Figure 4. When the effect of a third parameter is investigated, the meshed surface transforms into a solid representation.

To verify the accuracy of predictions, two milling cutters were used and the cutting tests carried out were identical for both tools. Graphical representations of the differences between the test data and predicted values for the new tool are presented in Figure 5.

5. IMPLEMENTATION OF THE MACHINING PROCESS MODEL

The obtained cutting force model was incorporated into the automated planning and programming program for sculptured part rough machining. Based on the workpiece geometry and the cutting model the cutting force is predicted. The feedrate of the cutting process is calculated to ensure that the maximum allowed cutting force is used through out the cutting process to achieve the maximum productivity. The inputs to the feedrate planning program include:

- θ_{en}, entry angle calculated based on the geometry of the part and stock
- surface models of the workpiece
- d, the depth of cut calculated using the method discussed in [6]

- $F_{t\ max}$, the desired cutting force to be maintained throughout the machining process. The limits of cutting force are based on toolmaker's recommendations and/or experimental data.

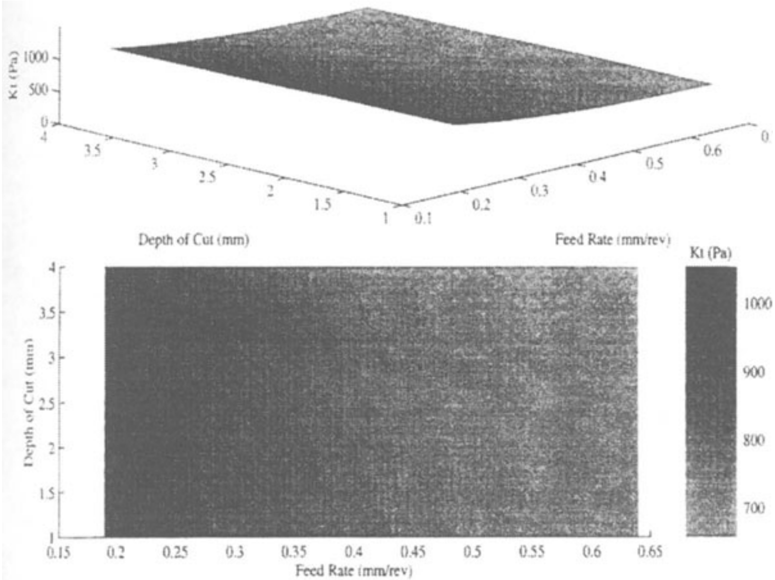

Figure 4. A 3D representation of a two parameter case

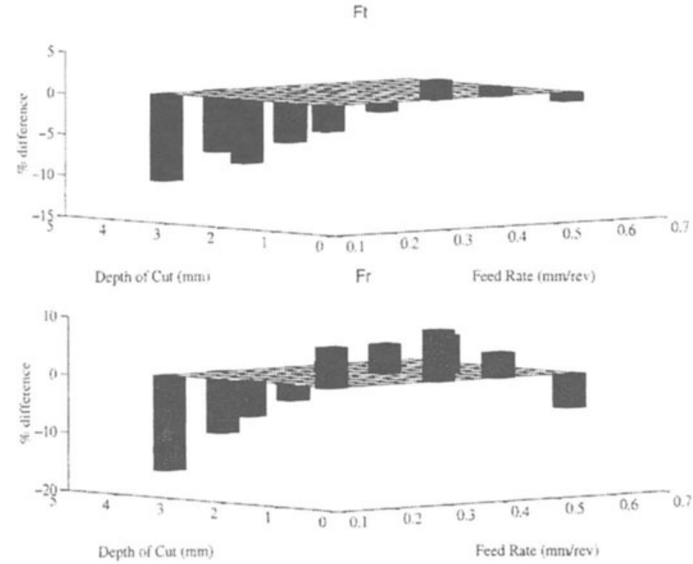

Figure 5. A comparison of predicated and measured cutting forces

The feedrate for a particular position of the cutter is calculated based on the following algorithm. First, the entry angle at that position is calculated from the part and workpiece geometry. Depending on the entry angle, depth of cut and $F_{t\ max}$, the feedrate, s_t, is then determined through interpolation.

The work of Vickers and Bradley [10] provided information regarding the time response of the Victor VM-5 four-axis machining center, equipped with a FANUC 6MB controller. They discovered that the shorter the table's advancement, the larger the waiting time/execution time ratio becomes. It is thus advantageous to combine short moves into longer steps. This principle was reflected in the feedrate planning to avoid unnecessarily large number of small moves with a small change on feedrate.

To verify the introduced machining process model parameters and their use in intelligent rough machining, a machining test was carried out. In this test a wedge-shaped workpiece was machined under a preset constant maximum cutting force. This limit on the cutting force was determined by the requirement of a chatterless cutting condition. To reduce the idle time between two successive instructions, a clustering of the table motion intervals was applied. The clustering is determined such that the predicted cutting force is within a preset range (i.e. 10 percent}. Consequently, a reduced number of NC instructions is achieved, resulting in more efficient machining. The output from the program is shown in Figures 6 and 7.

6. CONCLUSIONS

To facilitate intelligent rough machining, which incorporates a machining process model into the planning and programming of sculptured part machining to achieve maximum productivity, this study on machining process models and generally applicable machining parameters was carried out. A low-cost dynamometer for a milling machine was designed, built and calibrated. Various existing machining process models was studied. A large number of cutting tests were carried out to establish a general purpose machining parameter database.

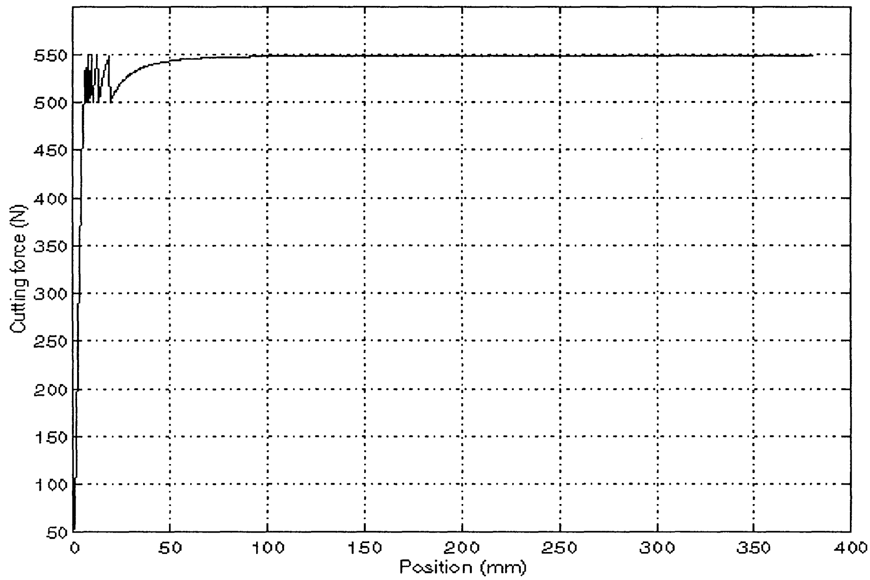

Figure 6 . Clustered and non-clustered feed rates

A procedure for directly calculating instant feed rate based upon workpiece geometry (without the extensive calculation of cutting forces) was introduced. Feed rate clustering was introduced to improve machining productivity. The use of the cutting force prediction model led to 4 to 16 percent reduction of machining time, which translated into increased productivity and better loading on the machine tool. An analysis of the machine process model showed that the cutting force model produces conservative results due to the preferred over prediction on cutting force. An addition of cutter wear consideration in the model can further improve its accuracy. The cutting test produced satisfactory results. Incorporation of the cutting force model into the planning of machining parameters will produce significant machining time reduction.

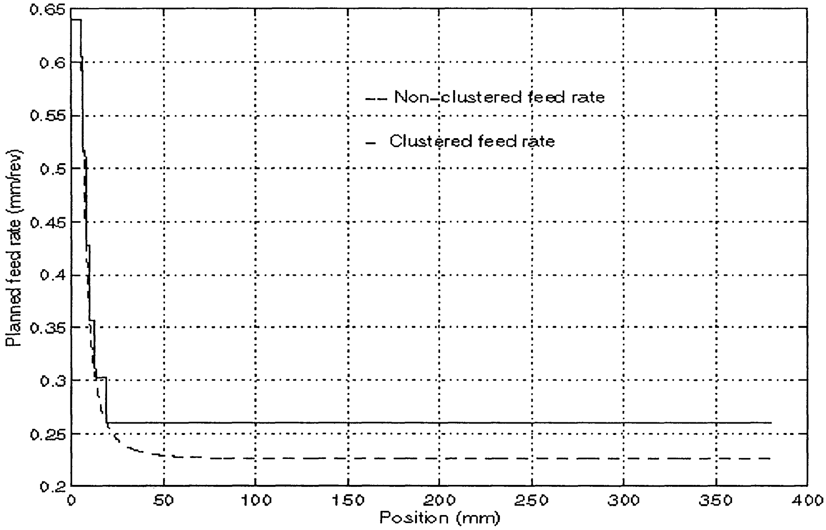

Figure 7. Measured cutting force of the test

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