Comparison of Regression Models to Study Effect of Turning Parameters on the Surface Roughness

Ravindra Thamma, Central Connecticut State University

Abstract

Critical quality measure, Surface roughness (Ra) in mechanical parts depends on turning parameters during the turning process. Researchers have predicted and devloped various models for the optimum turning parameters for required surface roughness. This study focuses on comparing multiple regression models by collecting data pertaining to depth of cuts, nose radii, feed rates, surface roughness, and cutting speeds during the turning operation for an Aluminium 6061 workpieces. The conducted analysis show the behaviour of turning parameters and high accuracy levels of the models to predicted surface.

Introduction

Design engineers and product designers are determined to design machines that are efficient, have longer lives, and operate precisely as desired. Today's advanced machine requirements demand design allowances for higher loads and speeds which have led to radical change in the design of bearings, seals, shafts, machine ways, and gears. To satisfy the advanced requirements, machine parts should be dimensionally and geometrically accurate. The quality of a machined surface manifests the accuracy of the process in relation to the dimensions specified by the designer.

Machining operations tend to leave characteristic evidence on the machined surface. They usually leave finely spaced micro-irregularities that form a pattern known as surface finish or surface roughness. The quality of the finished product, on the other hand, relies on the process parameters; surface roughness is therefore a critical quality measure in many mechanical products [1].

A considerable number of studies have investigated the general effects of speed, feed, depth of cut, and nose radius. Receiving serious attention for many years, surface roughness has formulated an important design feature in many situations such as parts subject to fatigue load, precision fit, fastener hole, and aesthetic requirements. In addition to tolerances, surface roughness imposes one of the most critical constraints for the selection of machines and cutting parameters in process planning. A larger point angle in combination with softer materials yields a smoother surface. A relatively large depth of cut can produce a smoother surface as well [2].

Previous studies proved the significant impact of DOC, machining speed and rake angles on surface roughness. The few studies that have studied nose radius as a factor have failed to eliminate the effect of built-up edge. But very few researchers have studied the interaction effect of nose radius. The material will be defined when a larger nose radius was used, and the chip had a thickness value greater than the minimum thickness value [3].

The combination of both of these factors suggests a significant weight in the relationship. All the previous studies on predicting surface roughness have not included nose radius as a major factor that affects surface roughness.

Factors Affecting Surface Roughness

Nose Radius

Nose radius is a major factor that affects surface roughness [4]. A larger nose radius produces a smoother surface at lower feed rates and a higher cutting speed [5]. However, a larger nose radius reduces damping at higher cutting speeds thereby contributing to a rougher surface. The material side flow can be better defined when using a large nose radius [6]. Again this can be explained by studying the effect of the nose radius on the chip formation. During cutting with a tool having a large nose radius, a large part of the chip will have a chip thickness less than the minimum chip thickness value. In addition, increasing the nose radius has a direct effect on cutting forces leading to a significant increase in the ploughing effect in the cutting zone. Increasing the ploughing effect leads to more material side flow on the machined surface. In general, increasing the nose radius increases the level of tool flank wear. Cutting with a large nose radius results in a higher value of cutting forces due to the thrust force component. On the other hand, cutting with a small nose radius prolongs tool life, which can be explained by the reduction in the ploughing force.

Edge preparation has an effect on the surface roughness. Although the chamfered tool is recommended to prevent the chipping of the cutting edge, there is no significant difference in the rate of tool wear. The surface finish generally degrades with cutting time due to tool wear development. Large nose radius tools have, along the whole cutting period, slightly better surface finish than small nose radius tools. Tool wear development with cutting time showed, after high initial wear rate, that flank wear-land width increases in a linear way. The tool nose radii in the range of 0.8–2.4 mm seem to have no effect on the tool wear process, showing comparable wear rate and similar tool life [7].

Feed Rate

Feed rate is another major factor that has a direct impact on surface roughness [5]. Surfaces roughness is directly proportional to the feed rate. The feed rate produces effective results when combined with a larger nose radius, higher cutting speed, and a smaller cutting edge angle [1]. The work piece machined with a smaller feed rate, the machined surface shows that extensive material side plastic flow existed [3]. This explains the better surface finish obtained at lower feed rates. A lower feed rate increased the area in which the chip thickness was lower than the minimum chip thickness, (tmin). Hence, instead of cutting, a large part of the material was ploughed which led to material side flow.

Depth of Cut

The depth of cut has a proven effect on tool life and cutting forces, it has no significant effect on surface roughness except when a small tool is used. Therefore a larger depth of cut can be used to save machining time when machining small quantities of work pieces. On the other hand, combining a low depth of cut with a higher cutting speed prevents the formation of a built-up edge, thereby aiding the process by yielding a better surface finish [8].

Cutting Speed

Cutting speed has no major impact on surface roughness. It affects the surface roughness when operating at lower feed rates which leads to the formation of a built-up edge. Higher speeds are important in yielding accurate results. At speeds higher than 300 ft/sec actual surface roughness comes closer to the calculated value of surface roughness [9].

Built-Up Edge (BUE)

A BUE usually forms at the tip of the tool cutting edge during machining. As the BUE becomes larger, it becomes unstable and eventually breaks up. The BUE is partly carried away by the chip; the rest is deposited on the work surface. The process of BUE formation is continuous and destruction is continuous. It is one of the factors that adversely affect surface roughness. Although a thin stable BUE that protects the tool's surface is desirable, BUE is generally undesirable. BUE does not form at higher cutting speeds, low depth of cuts, and higher rake angles [6].

Material Side Flow

One of the factors that deteriorate the machined surface is the material side flow. It is defined as the displacement of a work piece material in a direction opposite to the feed direction such that burrs form on the feed mark ridges [10]. Workpiece material in the cutting zone is subjected to a high enough temperature and pressure to cause a complete plastification of the work piece material. It has been observed chip material flow in a direction perpendicular to that of the usual chip flow during the machining of hardened steel. This material sticks on the new machined surface and causes a deterioration of the machined surface quality even if the surface roughness is kept within the desired tolerance. In addition, the adhered material is hard and abrasive, such that it wears on any surface that comes into contact with the machined surface.The surface deterioration is mainly attributed to material side flow that existed on the machined surface when machining with a worn tool. In addition, the cutting speed has a significant influence on material side flow. The high temperature generated during high speed machining facilitates the material plastifiction and therefore causes a tendency for more material side flow [6].

Chip Morphology

An increase in the nose radius increases the chip edge serration; the chip edge serration can be explained by the reduction in the actual chip thickness near the trailing edge. Since the chip formation takes place mainly along the nose radius, it is expected that the chip thickness varies along the cutting edge. Due to the nose radius, the chip thickness is decreased gradually to zero causing high pressure at the trailing edge [6]. Thus, the material at the trailing edge of the tool, where the chip thickness is a minimum, is subjected to high stress which causes tearing on the weakest edge of the chip. In addition, the variation in the chip velocity facilitates the non-uniform displacement along the chip width which leads to chip edge serration [11]. The existence of the chip edge serration facilitates trailing edge wear. Grooves are worn in the tool at the positions where the chip edge moves over the tool. These grooves deteriorate the surface roughness and in turn reduce the tool life.

Purpose of Study

Based on the above analysis, this study was to set up a statistical model that was capable of predicting the in-process surface roughness of a machined work piece using turning parameters. The model was expected to have the following features:

1. Use machining parameters, such as feed rate, depth of cut, and cutting speed as predictors.
2. Apply nose radius information as another predictor.
3. The prediction accuracy is high to above 95%.

Parameters' Selection for Experiment

Feed rate was selected in a range that magnifies the difference between two levels, Table 1. The spindle speeds selected were 1300 rpm and 1900 rpm. High speeds of machining were chosen to reduce the effect of built-up edge on surface roughness. The effect of BUE is nullified at speeds higher than 1300 rpm since the BUE becomes too fragile to withstand forces at such high speeds [4].

Table 1. Levels of Independent Parameters

Level	Fr	DOC	RPM	Nr
-1	0.004 mm/rev	0.1mm	1300rpm	1/64 inch
1	0.005 mm/rev	0.2mm	1900rpm	1/32 inch

The two levels of nose radii were significantly apart from each other fixed at 0.819 mm (1/32") and 0.409 mm (1/64") with a variable depth of cut equal to the nose radius. It has been proved that surface roughness causes drastically greater deterioration of the workpiece at feed rates higher than 0.3 mm; therefore feed rates of less than 0.3 mm were chosen to minimize the conditions that affect surface roughness. Cutting edge and rake angles were kept constant in all the experiments.

Experimental Setup

Aluminum 6061(Al 6061) was used as the work piece material due to its high machinability index and commercial availability. Aluminium 6061 is an alloy of aluminium (98%), chromium (0.35%), copper (0.4%), iron (0.7), manganese (0.15%), magnesium (0.12%) and silicon in small quantities. A unique combination of properties makes aluminium and its alloys one of the most versatile engineering and construction material. The workpieces were 3.5 inches and 1 inch in diameter. The ends were faced to reduce the wobbling effect that arises due to the uneven edges. The longer the workpiece, the higher are the chances of wobbling. Therefore, care was taken when selecting the work piece. The workpiece's experimental length was less than three times its diameter.

A Cummins lathe was chosen to turn the work piece because of its capability to run at speeds higher than 1300 rpm. It runs on plastic gears which means lesser forces pass on to the work piece and the cutting tool. All of this translates into longer tool life and better surface roughness. Since the wear on plastic gears is less than metallic gears, vibrations resulting from back lash reduce significantly. The feed rate was selected from the available set of gear ratios for this particular lathe. For the two levels of the feed rates, two different gear ratios were used. For the lower level of the feed rate, the gear ratio was 20:50:20:80 while for the higher level of the feed rate, it was 20:60:20:80.

A digital laser non-contact tachometer (model number DT -6234) was used to measure the rotational speed of the spindle because measurements can be done with very high accuracy and also because the device, as the name suggests, is a non-contact type. This non-contact type is useful because any contact with the rotating parts of the system tends to produce unquantifiable changes in the system.

For measurement of the surface roughness, a Mitutoyo profilometer (SJ 201) was used because of its high reliability and capability to provide the user with precise surface measurements. This portable device operates on the inductive principle to measure the roughness. This instruments measurement head fits with a retractable diamond stylus sensor (5μm / 0.2mils radius) and a working load of 4mN. The roughness profiles are determined by the motorized travel of the sensor over the surface to be tested. Each unit is supplied with roughness reference standard, case, tools and main adaptor.

A non-ferrous grade, carbide tipped, cutting tool was used to turn the work piece material. The carbide tipped tools have a multiphase coating with Ti (C, N), AL2O3, and TiN (Carboloy grade TP200). The length of the tool shank is three and half inches.

Several trials were done on the lathe to test its performance at required high speeds. The amount of wobble in the workpiece while taking a cut was checked using a dial indicator. The wobble was later reduced by pre-adjusting the chuck. For each run different levels of parameters were chosen and were run with a different combination. Three tools of each of the two different nose radii were randomly used during the entire experiment. The work piece was turned to a length of one and half inch.

The data was collected randomly to eliminate bias in the results. Surface roughness was measured from three areas of the workpiece and an average value was used to reduce the error.

Experimental Design

The two levels of the factors were designated as either high or low or as -1 or 1. To keep the experimental design simple two levels of factors were chosen. In a typical factorial design, the number of treatment combinations is denoted by 2^n, where n is on the number of independent variables. Therefore, 2^4=16 treatment combinations given in table 2, were used corresponding to n=4. Table 2 shows the sixteen treatment combinations.

Table 2. Factorial Design for Four Independent Parameters

Run	Speed (RPM)	Depth of Cut (DOC)	Feed Rate (Fr)	Nose Radius (Nr)	Rep 1	Rep 2	Rep ..	Y
1	-1	1	-1	-1				
2	-1	-1	-1	-1				
3	-1	-1	-1	1				
4	-1	-1	-1	1				
5	1	-1	-1	-1				
6	1	1	-1	-1				
7	1	1	-1	1				
8	1	-1	-1	1				
9	-1	-1	1	-1				
10	-1	1	1	-1				
11	-1	1	1	1				
12	-1	-1	1	1				
13	1	1	1	-1				
14	1	-1	1	-1				
15	1	-1	1	1				
16	1	1	1	1				

The full factorial experiment was replicated ten times, to reduce the effect of the error. The order in which the trials were performed was random. In this full factorial experiment all of the main effects and interactions were tested to check for their effect on surface roughness. The surface roughness values measured from the 16 combinations were first analyzed for individual effects. The extent of the effect of each turning parameter was then estimated. Then the data was used to find out the existence of interactions and their effects.

The data is used to create two multiple regression models that determines the strength of the relationship between the turning parameters and surface roughness which in turn, is then used to predict the theoretical value of surface roughness. With and without the depth of cut as main effect made the difference in the models.

Developed multiple regression models were checked for accuracy. Predicted surface roughness values are calculated using the developed regression equation. The difference between the surface roughness values of measured data and predicted data is used to calculate the error percentage. The error percentage is then used to calculate accuracy of the predicted model [12].

The predicted surface roughness values by both models were tested using a t-test for independent samples to find if significant different exist.

Multiple Regression Modeling

A statistical software program, Minitab version 14, a statistical software and Microsoft Excel, was employed in model training. The goal of the multiple regression analysis was to determine the dependency of surface roughness to selected machining parameters. In addition to the main effects of these variables, effects of the interactions of them were included in the analysis. The significance level for both the models was set at 0.05 (α = 0.05). For the involvement of the interactive predictor variables, a total of 13 and12 predictor variables were used in the training of the model, as shown in Equation 1 and 2.

First regression model (Depth of Cut as main effect) was expressed as:

$$
\begin{aligned}
R_{a1} &= K_0 + K_1 V + K_2 F_r + K_3 D + K_4 N_r + \\
& K_5 VD + \mathrm{K}_6 \mathrm{VF_r} + \mathrm{K}_7 \mathrm{VN_r} + \mathrm{K}_8 \mathrm{DF_r} + \mathrm{K}_9 \mathrm{DN_r} \\
& + \mathrm{K}_{10} \mathrm{F_r Nr} + \mathrm{K}_{11} \mathrm{VDF_r} + \mathrm{K}_{12} \mathrm{VDN_r} + \mathrm{K}_{13} \mathrm{VF_r N_r} \\
& + \mathrm{K}_{14} \mathrm{DF_r N_r}
\end{aligned}
\tag{1}
$$

Where,
R_a -Observed Surface roughness,
F_r - Feed Rate,
V- Cutting speed,
D - Depth of Cut,
N_r -Nose Radius, and
K- Linear Constants, Coefficients

Second regression model (without Depth of Cut as main effect) were expressed as:

$$R_{a2} = K_0 + K_1 V + K_2 F_r + K3N_r + K_4 VD + \mathrm{K}_5 \mathrm{VF}_r + \mathrm{K}_6 \mathrm{VN}_r + \mathrm{K}_7 \mathrm{DF}_r + \mathrm{K}_8 \mathrm{DN}_r + \mathrm{K}_9 \mathrm{F}_r \mathrm{Nr} + \mathrm{K}_{10} \mathrm{VDF}_r + \mathrm{K}_{11} \mathrm{VDN}_r + \mathrm{K}_{12} \mathrm{VF}_r \mathrm{N}_r + \mathrm{K}_{13} \mathrm{DF}_r \mathrm{N}_r \quad (2)$$

The null and alternative hypothesis for the models was:

$$H_{O1} : K_0 = K_1 = K_2 = K_3 = K_4 = K_5 = \mathrm{K}_6 = \mathrm{K}_7 = \mathrm{K}_8 = \mathrm{K}_9 = \mathrm{K}_{10} = \mathrm{K}_{11} = \mathrm{K}_{12} = \mathrm{K}_s = 0$$

H_a : At least one of the K does not equal to Zero.

The measured t-values of independent variables are populated in table 3. A t-test performed on the data from the experimental design showed that except for depth of cut, all the turning parameters have a significant effect on surface roughness. The measured t-value of depth of cut, 1.56, is less than the critical t-value of 1.96, whereas the measured t -values of nose radius, feed rate, and cutting speed, 7.84, 10.21, and 10.77 respectively are greater than the critical value of 1.96 indicating that these variables significantly affect surface roughness. To validate this outcome second model was developed without depth of cut as main effect. The t-values of interactions with depth of cut are higher than the critical t-value of 1.96.

Table 3. Coefficients of the First Model

Predictor Variable	Coefficients	T-values
Constant	39.529	9.00
V	-0.027	-10.77
Fr	-9963.9	-10.21
D	33.94	1.56
Nr	-429.33	-7.84
VD	0.004	0.38
VFr	7.077	12.63
VNr	0.325	10.96
DFr	-1496	-0.31
DNr	766.7	-4.06
FrNr	113989	9.46
VDFr	-4.344	-1.69
VDNr	0.126	2.66
VFrNr	-83.771	-12.94
DFrNr	119194	3.07

Showing depth of cut has a significant impact on surface roughness in an interaction. Cutting speed has the highest t-value of 10.73 implying its strong impact on surface roughness. Interaction involving cutting speed and feed rate, with a t-value of 12.63, has greater impact on surface roughness than other independent variables.

As shown in Table 4, both MR1 and MR2 models had low S, estimate of the variance values (0.0567and 0.074, respectively) after the linear relationship between the response and the predictor has been taken into account. This show both the equations predicts the response with low error. The square values of the regression coefficients were 99.8 and 99.4, respectively, which indicated high association of the regression coefficients with variances in the predictor values. The adjusted square values of the regression coefficients were 97.50 and 95.7. This indicates accounted variance is high, making the models stronger.

The results of analysis of variance (ANOVA) of the models also supported strong linear relationships in the models (Table 5 and 6). The obtained F values of regression were 42.98 and 26.83 for MR1 and MR2, respectively. These high F values indicated a great significance for models in not rejecting the alterative hypothesis, at least one of these coefficients did not equal to zero. Therefore, the linear relationship between the predicted variable (R) and predictor variables significantly existed.

Table 4: First Model Summaries

Model	S	r-sq	r-sq (adj)
MR1	0.0567	99.80	97.50
MR2	0.074	99.4	95.7

Table 5. The ANOVA Table of the First Regression Models (MR1)

Item	SS	DF	Mean Square	F	Sig.
Regre	1.937	14	0.138	42.98	0.119
Resid-ual	0.003	1	0.003		
Total	1.941	15			

Table 6. The ANOVA Table of the Second Regression Models

Item	SS	DF	Mean Square	F	Sig.
Regre	1.930	13	0.148	26.83	0.036
Residu-al	0.011	2	0.005		
Total	1.941	15			

The coefficients of all predictor variables and the constants of the model are listed in Table 3 and 7. According to these coefficients, the multiple regression models are built as shown in Equations 3 and 4 for MR1 and MR, respectively.

First Model (MR1):

$$R_a = 39.5 - 0.0272V - 9964F_r + 33.9D - 429N_r + 0.0044VD + 7.08\mathrm{VF_r} + 0.325\mathrm{VN_r} - 1496\mathrm{DF_r} - 767\mathrm{DN_r} + 113989\mathrm{F_rNr} - 4.34\mathrm{VDF_r} + 0.127\mathrm{VDN_r} - 83.8\mathrm{VF_rN_r} + 119194\mathrm{DF_rN_r} \tag{3}$$

Second Model (MR2):

$$R_{a2} = 44.6 - 0.296V - 11055F_r - 452.20N_r + 0.0204VD + 7.582\mathrm{VF_r} + 0.327\mathrm{VN_r} + 5777\mathrm{DF_r} - 614\mathrm{DN_r} + 118279\mathrm{F_rNr} - 7.71\mathrm{VDF_r} + 0.111\mathrm{VDN_r} - 83.8\mathrm{VF_rN_r} + 90594\mathrm{DF_rN_r} \tag{4}$$

Table 7. Coefficients of the Second Model

Predictor Variable	Coefficients	T-Values
Constant	44.620	11.57
V	-0.296	-11.24
Fr	-11054.8	-12.39
Nr	-452.20	-6.54
VD	0.020	2.65
VFr	7.582	12.64
VNr	0.327	8.43
DFr	5777	4.12
DNr	-614.3	-2.90
FrNr	1118279	7.69
VDFr	-7.707	-4.20
VDNr	0.111	1.82
VFrNr	-83.771	-9.87
DFrNr	90594	2.02

Model Accuracy

Average error in the models is the average of ratio difference of predicted and measured surface roughness to measured surface roughness expressed in percentage. As given in equation 5 and 6. Model accuracy added to average error, value should be very close to 100.

$$\delta i = \frac{|R_{ap} - R_a|}{R_a} \times 100\% \tag{5}$$

$$\Delta = \frac{1}{n}\sum_i^n \delta i \tag{6}$$

Where,

δ_i - Percentage error in data

R_{ap} - Surface roughness predicted using the developed regression model

R_a - Observed surface roughness value

Δ - Average error in surface roughness prediction.

n - Number of experiments

(100- Δ)% - Accuracy of the model

Difference between the Models

The models have an accuracy of 99.37% and 99.09% as reported in table 9 with average error of 0.622 and 0.908 respectively. The mean values in table 8 suggest that there is little difference between the two regression models (-0.350, 0.350).The t-value strengthens the fact that there is no significant difference between the models. As measured at 99% confidence level t-value (0.00) is less than the critical t -value value of 2.75, there is no significant difference between the two models.

Table 8. Model Accuracy

Model	Size	Average Er-	Model Accura-
MR1	16	0.622	99.37
MR2	16	0.908	99.09

Table 9. T-Test to check for Difference between the Models

Model	S	r-sq	r-sq (adj)
MR1	0.0567	99.80	97.50
MR2	0.074	99.4	95.7

Conclusions

Using the collected data, two multiple regression models have been developed to predict the surface roughness. With these data and results, one could conclude that:

1. The results show both regression models are valid at a high significance. Therefore, both models for surface roughness prediction can reasonably adapt.
2. Cutting speed, feed rate, and nose radius have a major impact on surface roughness. Smoother surface will be produced when machined with a higher cutting speed, smaller feed rate and nose radius.
3. Depth of cut has a significant impact on surface roughness only in an interaction with other factors.
4. The interactions of the cutting speed, nose radius, and feed rate also have more significant impact on surface roughness than the individuals.

Recommendations

Considering these conclusions, further research will be conducted to develop other prediction systems that could enhance the accuracy for surface roughness prediction.

1. Tool Temperature Vibrations, tool length, and tool material should be incorporated into roughness prediction model.
2. Effects of built-up edge should be studied.
3. Predict optimum cutting parameters that maximize surface smoothness.

Reference

[1] Groover, M.P. (1996). Fundamentals of modern manufacturing, Prentice Hall, New Jersey. Proceedings of The 2008 IAJC-IJME International Conference ISBN 978-1-60643-379-9

[2] Feng, X .C. (2001). "An experimental study of the impact of turning parameters on surface roughness." Proceedings of the 2001 Industrial Engineering Research Conference, paper no. 2036.

[3] Kishawy, H.A., and Elbestawi, M.A. (1997). International Journal of Machine Tools and Manufacture 39, (1997) 1017–1030.

[4] Beauchamp, Y. and Thomas, M. (2003). "Investigation of cutting parameter effects on surface roughness in lathe boring operation by use of a full factorial design." Computers and Industrial Engineering 31 (3–4), (1995) 645–651.

[5] Beauchamp, Y., Thomas, M., and Masounave, J. (1997). "An experimental design for surface roughness and built-up edge formation in lathe dry turning," International Journal of Quality Science 2 (3), (1997) 167–180.

[6] Kishawy, H.A., and Elbestawi, M.A. (1997b) "Effect of process parameters on chip morphology when machining hardened steel, MED, 6-2," Manufacturing Science and Technology, ASME (1997) 13–20.

[7] Chou, Y.K., and Song, H. (2004). "Tool nose radius effects on finish hard turning." Journal of Material Processing Technology, 148, 259–268.

[8] Kwon, W.T., and Choi, D. (2002). "Radial immersion angle estimation using cutting force and predetermined cutting force ration in face milling." International Journal of Machine Tool and Manufacture, 42, 1649–1655.

[9] Lambert, B. K. (1983). "Determination of metal removal rate with surface finish restriction." Carbide and Tool Journal, 23, 16–19.

[10] Tsai, Y., Chen, J.C., and Lou, M.S. (1999). "In-process surface recognition system based on neural networks in end milling operations." International Journal of Machine Tools and Manufacture, 39, 583–605.

[11] Sreejith, P.S. (2005) "Machining force studies on ductile machining of silicon nitride." Journal of Materials Processing Technology, 5, 2002—2007. Retrieved November 2007, www.elsevier.com/locate/jmatprotec.

[12] Huang, B., and Chen, J.C. (2001). "An in-process neural network-based surface roughness prediction (INN-SRP) system using a dynamometer in end milling operations." The International journal of Advanced Manufacturing Technology, 21, 339–347.

Biographies

RAVINDRA THAMMA is currently an associate professor of Manufacturing and Construction Management at the Department Engineering at Central Connecticut State University. Dr. Thamma received his phd from Iowa State University. His teaching and research interests are robotics, linear control systems, and intelligent systems.