operations, as assessed by productivity, total manufacturing cost per component or some other suitable criterion. Manufacturing industries have long depended on the skill and experience of shop-floor machine-tool operators for optimal selection of cutting conditions and cutting tools. Considerable efforts are still in progress on the use of handbook based conservative cutting conditions and cutting tool selection at the process planning level. The most adverse effect of such a not-very scientific practice is decreased productivity due to sub-optimal use of machining capability. Hence, the need for selecting and implementing optimal machining conditions in order to achieve the required cutting performances on work-piece such as surface roughness, cutting forces, cutting temperature, material removal rate (MRR), power consumption, specific cutting pressure, and tool wear (Tanveer & Imtiaz, 2014; Sujit, 2014).

Bala *et al.* (2013) investigated the effect and optimization of machining parameters on cutting force and surface finish in turning of mild steel and aluminum. They asserted that productivity and the quality of the machined parts are the main challenges of metal cutting industry during turning process, therefore cutting parameters must be chosen and optimize in such a way that the required surface quality can be controlled. They went further stating that statistical design of experiments (DOE) and statistical/mathematical model are used extensively to optimize. Their investigation was carried out for effect of cutting parameters (cutting speed, depth of cut and feed) in turning off mild steel and aluminum to achieve better surface finish and to reduce power requirement by reducing the cutting forces involved in machining. The experimental layout was designed based on the 2^k factorial techniques and analysis of variance (ANOVA) was performed to identify the effect of cutting parameters on surface finish and cutting forces are developed by using multiple regression analysis. The coefficients were calculated by using regression analysis and the model is constructed. The model is tested for its adequacy by using 95% confidence level. By using the mathematical model the main and interaction effects of various process parameters on turning was studied.

Khalaf *et al.* (2018) analysed finite element modelling and optimization of estimated cutting forces during machining of Inconel 718. In their study, the effect of different cutting parameters (cutting speed, feed rate, and depth of cut) on cutting force under dry hard turning of Inconel 718 was investigated. 3D- Finite element modelling of orthogonal machining-based Taguchi L9 design was used to obtain the results. The obtained results of simulation were verified with previous study and it was showed a good agreement. The effects of feed rate, cutting speed and depth of cut on cutting force were analysed based on. Analysis of Variance (ANOVA) was performed to understand the percentage influence of all the cutting parameters. The Taguchi L9 orthogonal array was selected to determine optimal values of cutting parameters. The results showed that the cutting force increases significantly with increase of depth of cut.

Tanveer and Imtiaz (2014), in optimization of cutting parameters in turning process, predicting the main cutting force during turning is of great importance as it helps in setting the appropriate cutting parameters before machining starts and again, optimization of cutting parameters is one of the most important elements in any process planning of metal parts as economy of machining operation plays a key role in gaining competitive advantage. Their study presented an experimental study of main cutting force in turning of AISI 1040 steel and developing a model of the main cutting force during turning using Response surface Methodology (RSM) as well as optimization of machining parameters using Genetic Algorithm (GA). The second order empirical model of the main cutting force in terms of machining parameters was developed based on experimental results. The experimentation was carried out considering three machining parameters: cutting speed, feed rate and depth of cut as independent variables and the main cutting force as the response variable. The formulated model was validated against new set of experimental values using Mean Absolute Percent Error (MAPE) method. The Genetic Algorithm approach was also used to optimize the cutting parameters to keep the main cutting force to a minimum.

The aim of this study is to optimize the machining parameters in CNC lathe turning operation of grey cast iron work-piece using ANSYS. The objectives of this study include:

i. To investigate the impact of the cast iron work-piece depth of cut by the turning operation on its material removal rate and surface roughness.
ii. To analyse the effect of the amount of cast iron fed into the turning operation on the material removal rate and surface roughness of the cast iron.
iii. To evaluate the impact of the turning operation spindle speed on the cast iron material removal rate and surface roughness of the cast iron.
iv. To determine an optimal machining parameter for the turning operation that enhances the productivity and quality of the cast iron.

2. MATERIALS AND METHODS

The materials used in this research work were data of the chemical, physical, thermal and mechanical characteristics of work-piece and the machining tool specifications as well as MATLAB computer program and a finite element modeling (FEM) and simulation software known as ANSYS.

Table 1: Chemical Composition of the Grey Cast Iron Work-piece

Element	Content
Carbon, C	2.5 – 4.0%
Silicon , Si	1.0 – 3.0%
Manganese, Mn	0.2 – 1.0%
Phosphorus, P	0.02 – 1.0%
Sulfur, S	0.02 – 0.2%

(Source: Mustafa & Emre, 2013)

The physical, mechanical and thermal properties of the grey cast iron work-piece material are presented in Table 2:

Table 2: Physical, Mechanical and Thermal Properties of the Grey Cast Iron Work-piece

Physical, Mechanical and Thermal Properties	Value
Density	$7200kg/m^3$ $(0.284lb/in^3)$
Specific Gravity	7.34
Specific Heat	447J/Kg.C
Young Modulus	110GPa
Fatigue Resistance	110Mpa
Thermal Conductivity	$52W/m^oC$
Bulk Modulus	83333Mpa

Tensile Strength	250MPa
Hardness	179 – 202HB
Poisson Ratio	0.28
Specific Heat	447J/KgK

(Source: Ansys Workbench Engineering Data)

Table 3: Geometric Variables of the Machining Tool

Geometric Variables	**Specification**
Rake angle, α	7^0
Nose radius (mm)	1.2
Relief angle	50^0
Cutting edge angle	150^0
Type of Coating	PVD

(Source: Mustafa &Emre, 2013)

The chemical compositions of the cutting tool used are given in Table 4.

Table 4: Chemical Composition of HSS (M Series Grade)

Elements	**Weight**
Molybdenum, Mo	5 – 10%
Tungsten, W	1.5 – 10%
Vanadium, V	1 – 4%
Chromium, Cr	4%
Cobalt, Co	5 – 10%
Iron, Fe	5%

(Source: Mustafa &Emre, 2013)

The thermal and mechanical properties of the cutting tool used are given in Table 5

Table 5: Thermal and Mechanical Properties of HSS (M Series Grade)

Thermal and Mechanical Properties	**Value**
Elastic Modulus, E (GPa)	800
Poisson's Ratio	0.2
Thermal Expansion (10^{-6}/K)	4.7
Density (Kg/m^3)	15000

(Source: Mustafa & Emre, 2013)

The average surface roughness is the integral absolute value of the height of the roughness profile over the evaluation length (L) and was represented by (Mohan & Kiran, 2017):

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

where
L = length taken for the formula
Y = ordinate of the profile curve.

This parameter strongly influences the finishing grade of the work piece.

$$MRR = \frac{(W_b - W_a)}{(t \ x \ q)} \ x \ 1000 \ (\text{mm}^3/\text{min}) \quad (2a)$$

where

Wb = Weight of the workpiece before machining (grams).

Wa = Weight of the workpiece after machining (grams).

t = Machining time period (minutes).

q = Density of work piece material (grams/cm^3)

The material removal rate (MRR) can also be determined using (Abhishek & Ramandeep, 2013):

$$MRR = \frac{1000 \ x \ v \ x \ f \ x \ d}{60} \quad (2b)$$

where

v = cutting speed (rpm),

f = feed rate (mm/min),

d = depth of cut (mm).

They cutting force can be estimated using (Peta & Ramesh, 2018):

$$\text{Cutting Force} = \frac{(\text{Ne x 60 x } 10^3 \text{ x Coeffcient of Efficiency})}{(\text{Depth x Feed x Spindle Cutting Speed})} \quad (3)$$

where

Ne = Power of machine (4.65kW)

Coefficient of Efficiency = 0.8

Nominal is the best:

$$\frac{S}{N_T} = 10 \log\left(\frac{\bar{y}}{s^2}\right) \quad (4)$$

Larger is the best (maximize):

$$\frac{S}{N_L} = -10 \log \frac{1}{y} \sum_{i=1}^{n} \frac{1}{y^{i2}} \quad (5)$$

Smaller is better (minimize):

$$\frac{S}{N_S} = -10 \log \frac{1}{\bar{y}} \sum_{i=1}^{n} y^{i2} \qquad (6)$$

where

$\bar{y}$ = average of observed data
S = variance of y
y = observed data

Mathematically, one way-ANOVA F-test statistic is given by:

$$F = \frac{\text{explained variance}}{\text{Unexplained variance}} \qquad (7)$$

The explained variance is given by:

$$\text{Explained variance} = \frac{\sum_{i=1}^{K} n_i \left(\bar{x}_i - \bar{x}\right)^2}{(K-1)} \qquad (8)$$

where

$\bar{x}_i$ = sample mean value in the *i*-th group
n_i = number of observations in the *i*-th group
$\bar{x}$ = overall mean value of the data
K = number of groups

The unexplained variance is given by:

$$\text{Unexplained variance} = \frac{\sum_{i=1}^{K} n_i \sum_{j=1}^{n_i} \left(x_{ij} - \bar{x}_i\right)^2}{(N-K)} \qquad (9)$$

where

x_{ij} = the *j*th observation in the *i*th out of K groups
N = overall sample size

The arithmetic mean of the values is given by:

$$\text{Arithmetic mean } (\bar{x}) = \frac{\sum_{i=1}^{n} x_i}{n} \tag{10}$$

where

n = number of values

$\sum_{i=1}^{n} x_i$ = Sum of the individual values

The standard deviation of the values is given by:

$$\text{Standard deviation (s)} = \sqrt{\frac{\sum\left(x-\bar{x}\right)^2}{n-1}} \tag{11}$$

where

x = individual value

$\bar{x}$ = mean value

The degree of freedom is determined using (Mohan & Kiran, 2017):

$$Degree\ of\ \ Freedom\ (DOF) = [(L-1)x\ P] + 1 \tag{12}$$

where

L = number of levels for each parameter

P = number of parameters

3. RESULTS AND DISCUSSION

Nine 3D simulation models were performed using the selected machining parameters on the base of Taguchi L9 design. In L9 orthogonal array, 9 experimental runs are conducted and the corresponding outputs were evaluated by Taguchi optimization technique. In Taguchi method, the analysis of variation is performed using Signal-to-Noise ratio (S/N). There are three S/N ratio criteria approaches of common interest for optimization but for this work, the objective is to optimize cutting force machinability response, so larger is better was chosen for the response, as material removal was requested to be high and surface roughness requested to be low. Appendix II, IV and VII shows the MATLAB algorithm for material removal rate (MRR), the cutting force on the workpiece and the analysis and simulation results of the cutting force on the work-piece, the material removal rate (MRR) and surface roughness due to stress developed along with S/N ratio.

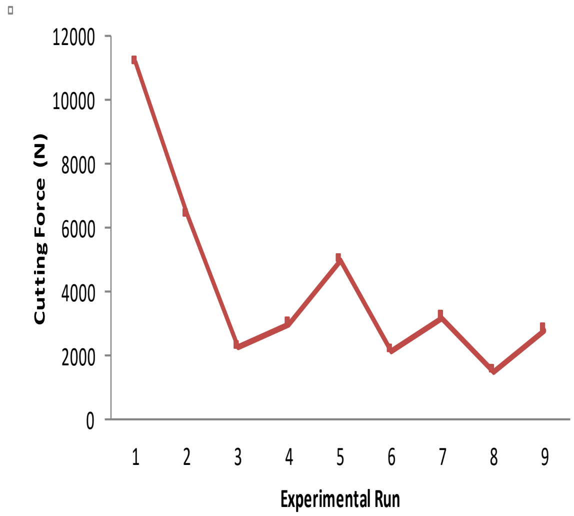

Figure 1: Cutting Force at different Experiment Runs

Figure 1 reveals the results of the cutting force on the work-piece for the nine (9) runs of experiments. The figure showed that the 1st experiment (speed at 200 rpm, feed rate at 0.10mm/min. and depth of cut at 1.0mm) produced the greatest cutting force at 11190N while the 8th experiment had the lowest cutting force at 1488N with machining parameters (speed at 500rpm, feed rate at 0.15mm/min. and depth of cut at 2.0mm) on work piece. The objective is to maximize cutting force response, and since the largest cutting force (11190N) was obtained using feed rate (0.10mm/min) and depth of cut (1.0mm), so larger is better was chosen for the response. This result correlates with results gotten from previous studies (Tanveer & Imtiaz, 2014; Khalaf *et al.*, 2018; Olodu, 2018).

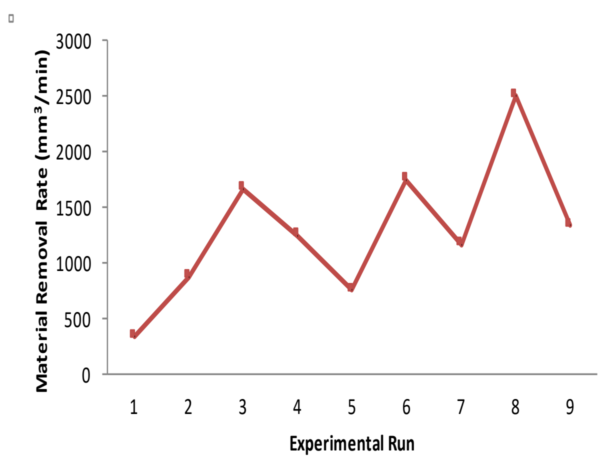

Figure 2: Material Removal Rate at different Experiment Runs

Figure 2 reveals the results of the material removal rate of the work-piece for the nine (9) runs of experiments. The figure showed that the 8th experiment (speed at 500rpm, feed at 0.15mm/min. and depth at 2.0mm) had the greatest material removal rate (MRR) at 2500mm^3/min while the 1st run of experiment had the lowest material removal rate at 333.34mm^3/min with machining parameters (speed at 200rpm, feed at 0.10mm/min. and depth at 1.0mm) on work piece.

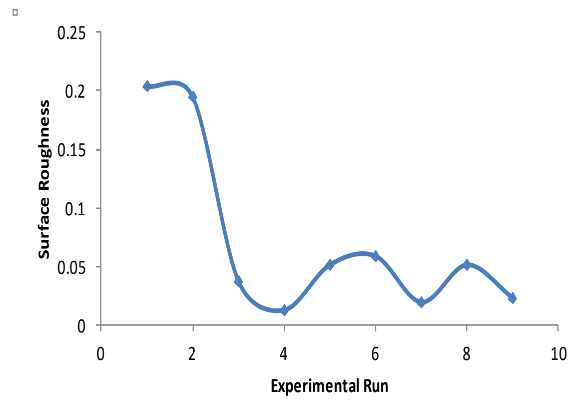

Figure 3: Surface Roughness at different Experiment Runs

Figure 3 reveals the results of the surface roughness due to stress on the
Work-piece for the nine (9) runs of experiments. The figure showed that the 1st experiment with machining parameters (speed at 200 rpm, feed rate at 0.10mm/min. and depth of cut at 1.0mm) on work piece produced the greatest surface roughness while the 4th experiment (speed at 500 rpm, feed rate at 0.10mm/min. and depth of cut at 1.5mm) produced the lowest surface roughness.

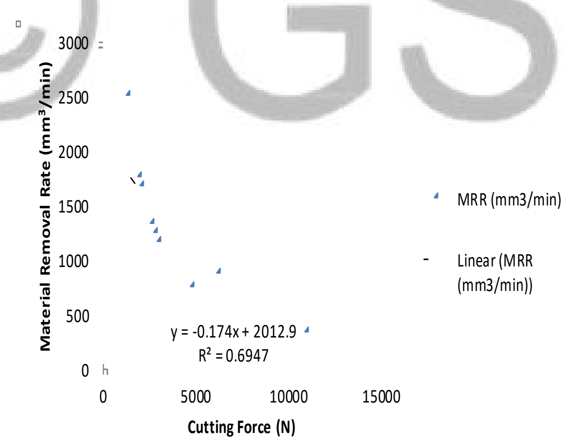

Figure 4: Material Removal Rate against Cutting Force at different Experiment Runs

Figure 4.4 reveals the results of the relationship between the material removal rate and the cutting force on the work-piece for the nine (9) runs of experiments. The figure showed that there is a strong positive relationship between material removal rate and cutting force on the work-piece for the nine (9) runs of experiments as with lesser cutting force, greater volume of grey cast iron material was removed from the workpiece and vice versa.

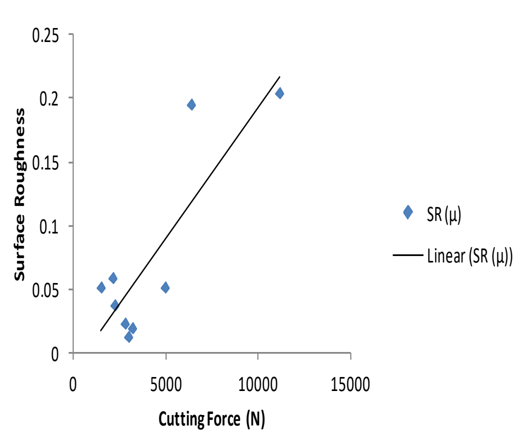

Figure 4: Surface Roughness against Cutting Force at different Experiment Runs

Figure 4 reveals the results of the relationship between the surface roughness and the cutting force on the work-piece for the nine (9) runs of experiments. The figure showed that there is a strong positive relationship between surface roughness and cutting force on the work-piece for the nine (9) runs of experiments as with lesser cutting force, lesser stress was imposed on the workpiece and vice versa.

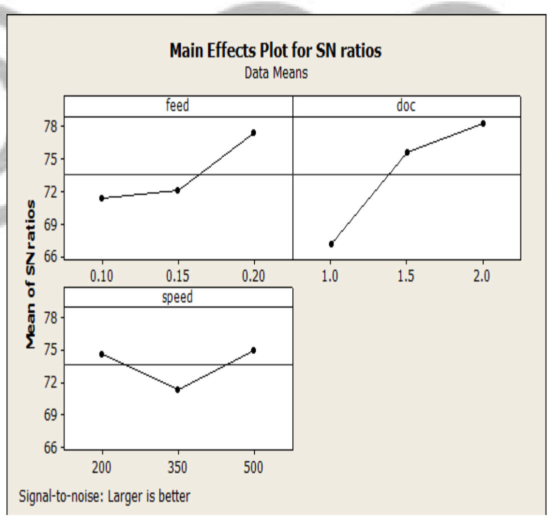

Figure 7: The S/N ratio for Surface Roughness

Figure 7 depicts the main effect plot for S/N ratio on the surface roughness. Based on the results observed in appendix vii and from the graphical plots for S/N ratio on the surface roughness, the optimal machining parameters that produce minimum value of surface roughness are D3F3V2 i.e. (depth of cut 2.0 mm, feed rate 0.20 mm/min and spindle cutting speed 350rpm).

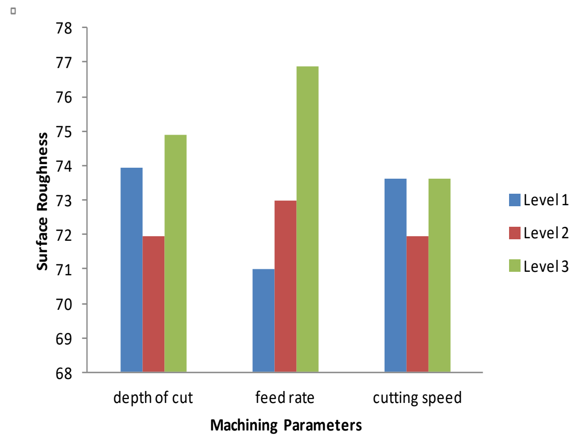

Figure. 8: Response Chart of Surface Roughness

The result of the mean S/N ratio for all nine models as illustrated in Figure 8 show that the feed rate of the grey cast iron workpiece is the machining parameter with the greatest contribution to surface roughness followed by the depth of cut while the spindle cutting speed machining parameter contributes the least to surface roughness.

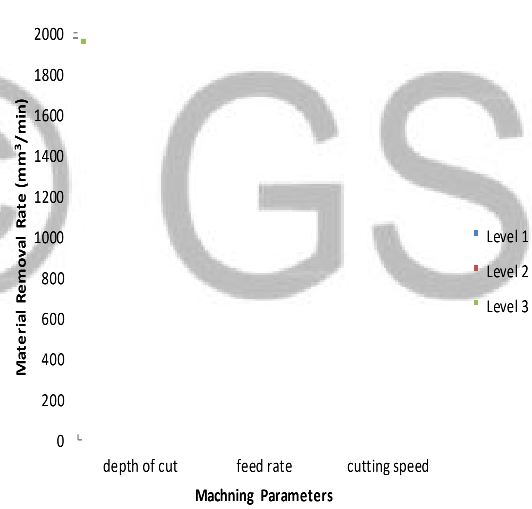

Figure. 9: Response Chart of Material Removal Rate (MRR)

The result of the mean MRR for all nine models as illustrated in Figure 9 show that the spindle cutting speed of the workpiece is the machining parameter with the greatest contribution to the workpiece MRR followed by the depth of cut while the feed rate of the workpiece is the machining parameter contributing the least to the workpiece MRR.

4. CONCLUSION

In this research, the machining parameters in CNC lathe turning operation of cast iron work-piece were modelled and optimized to enhance the productivity and quality of the cast iron work-piece. The first objective which was to investigate the impact of the cast iron work-piece depth of cut by the turning machine on its material removal rate and surface roughness was achieved from the ANSYS computer simulation as presented in Figure 1. It revealed that increasing the depth of cut in the work-piece will moderately increase the rate of material removal and surface roughness.

The second objective which was to analyse the effect of the amount of cast iron fed into the turning machine on the material removal rate and surface roughness of the cast iron was achieved from the ANSYS computer simulation as presented in Figure 2. It revealed that increasing the feed rate of the grey cast iron work-piece on the lathe turning machine, will increase the surface roughness of the workpiece but less significantly influence the rate of material removal.

The third objective of this study which was to evaluate the impact of the turning machine spindle speed on the cast iron material removal rate and surface roughness of the cast iron was achieved from the ANSYS computer simulation as presented in Figure 3. It revealed that increasing the spindle speed will increase the rate of grey cast iron material removal but it less significantly influence its surface roughness.

Ultimately, the fourth objective was to generate an optimal machining parameter for the CNC lathe turning operation that enhances the productivity and quality of the cast iron. Taguchi's robust design was used for optimizing turning parameters on grey cast iron. Experiments were conducted using L9 orthogonal array. For each experiment, surface roughness was measured, recorded and analysed using Taguchi S/N ratios. These ratios were calculated with consideration of performance characteristic: larger-the- better, as material removal was requested to be high and surface roughness is requested to be low. Based on the results observed as presented in Figure 6 the optimal machining parameters that produce minimum value of surface roughness are D3F3V2 i.e. (spindle cutting speed 350rpm, feed rate 0.20 mm/min and depth of cut 2.0 mm).

The results of the experimental study reveal that increase in the cutting parameters (spindle cutting speed, feed rate and depth of cut on the grey cast iron) work-piece will consequently increase the surface roughness and material removal rate of the work-piece. An increase in the depth of cut lead to increasing surface roughness and the energy required. ANSYS turning process and Johnson cook flow stress model was used to get the near possible simulation of the cutting forces, material removal rate and surface roughness due to stress during turning of grey cast iron. Surface roughness is mainly affected by feed rate of the grey cast iron work piece followed by depth of cut while spindle cutting speed is the machining parameter with the least influence on surface roughness. The spindle cutting speed of the workpiece is the machining parameter with the greatest contribution to the workpiece MRR followed by the depth of cut while the feed rate of the workpiece is the machining parameter contributing the least to the MRR of the workpiece.
FEM with Taguchi's robust design could yield a reduction in overall machining costs and saves time through an economic analysis by applying the simulation software to predict the machining response parameters of grey cast iron.

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