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Mathematical Modelling of Shear Cutting Process of Grain Oriented Electrical Steels Using Regression Modelling

Nihat ÇELİK [*1], Alaaddin TOKTAŞ[1]

Abstract

This article proposes a regression model for the shear-cutting process of grain-oriented electrical steel magnetic cores of transformers made from different gages and magnetic properties of steels. In the experimental runs, 3 levels for thickness (230, 270, and 300 µm) and 4 levels for magnetic features of electrical steels are considered. Core steels are supplied as foils and slit to designed lengths in slitting machinery along the rolling direction of coils. The best magnetic features rely on the rolling direction of the coil and the transverse direction of the coil is subject to the shear-cutting process. The result of cutting operations, discontinuities, and degradations in magnetic properties may occur because of deterioration in crystallography and strain gradation on laminated sheets. Shear-cutting process factors have a strong influence on magnetic degradation even the magnitude of the no-load loss of the transformer core. In this study, the mathematical relation between shear cutting factors sheet thickness *ST*, counts of hits *CH*, and the response burr length *BL* is determined using regression modeling. For this purpose, the process parameters of GEORG TBA 400 cut-to-length machinery in use core production is studied. The calculated coefficient of determination is close to almost 1.00 i.e., R^2 = 0.9896 which means the factors are sufficient to model the response, and the model is obtained with a good prediction performance. The aim of the present study is building up a useful process control tool for the machinery and raise a discussion alike process in industry.

Keywords: Shearing, regression, burr, deformation, modelling

1. INTRODUCTION

The cut-to-length process is an important part of the core manufacturing of transformers because of plastic deformations and discontinuities that emerged along the transverse direction (TD) of steel. Length of burrs *BL* can indicate that plastic deformation occurred during shear cutting. *BL* levels of the cutting process are subject to be under a limited level. Such that, no-load losses, EDDY and stray loses can be kept under the desired level for stacked cores regarding IEC 60604-02. No-load losses are an important part of the total operation cost calculation of a transformer during at least 30 years life span, especially operated in partly loading conditions of a transformer in a grid. Transformer cores are made by stacking grain-oriented electrical steel laminations,

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before stacking a few mechanical processes like slitting, and mitering must be applied. Advanced magnetic properties show up on the rolling (i.e., easy magnetization) direction of core steels because of the grain orientation pattern of laminations. Thicknesses are equal to or under 300 microns because of descending EDDY losses in AC magnetic field. The mitering process is very important because some of the magnetic features of steel are disappeared because of the mechanism of the cutting process and emerged plastic deformations on the near-cut surface. Some of the variances in the shearing process like cutting speed, diving angle of the upper tool, sharpness of tools, length of burr, thickness, hardness of sheet, cutting clearances, etc., have an influence on the deterioration magnetic properties of steel.

There are some published studies about statistical analysis and modeling of the shear-cutting process for transformer core steel. Wadi *et al*. [1] considered different blanking parameters such as neural network methodology and regression analysis in 1999. Baudion *et al.* [2] studied magnetic degradation on non-oriented electrical steels and blanking parameters in 2003. Peksoz *et al.*[3] proposed another experimental model for the degradation of magnetic properties of non-oriented electrical steels from the cutting line between grain size and silicon content of materials in 2008. Al-Momami *et al*. [4] created their statistical data from finite element modeling of the cutting process and implemented a neural network and multiple regression analysis in 2012. Multiple regression analysis was applied, and models were proposed [5] by Bashah *et al*. for die designers to estimate the spring-back effect in relation to design variables called die radius, punch radius, depth, and weight in 2012.

Models evaluated as capable to predict the spring-back response with high R^2 predicted values and supported by the results of the validation procedure. In another research for regression analysis and modeling, an adaptive response surface modeling was proposed by Karaoglan *et al.* [6] and regression coefficients were calculated by supporting of consonant process parameters based on an experimental setup in 2014. A regression model proposed in 2017 by Park *et al*. [7] for the reconfigurable cold-forming process of thin steel sheets. The effects of clearance, blanking forces, and sheet thickness on burr length were also studied, and a regression model by Cavusoglu *et al.* [8] was proposed in 2017. Multiple regression analysis and finite element simulation were studied by Badgujar *et al.* [9] for sheet forming in 2017, also Bohdal *et al.* [10] studied slitting process parameters and made graphical modeling between process parameters and magnetic properties in 2020.

Another research was issued by Zhao *et al*. [11] about the usage of nonlinear regression modeling between process parameters in the monitoring of the turning process in 2020. Neseli *et al*. [12] experienced DOE and RSM for surface roughness and vibration level optimization on cylindrical grinding machinery in 2012. Potanai *et al.* [13] predicted the temperature of human being buildings by MLR modeling in 2022 and Hanief *et al.* [14] researched the turning process by process parameters via MLR and ANN in 2016. Lee *et al.* [15] researched optimized CNC turning processes with DOE, RSM, and ANN tools. The authors presented several regression models for different machine types in 2010. Patel *et al.*, [16] established linear and non-linear multiple regression models on image processing systems to optimize the detection error of surface roughness in 2020.

Guided by previous research, to control the emerging of burr on the mitering process of grain-oriented electrical steels, a simply applicable regression model proposed for burr levels to keep under desired level for the aim of preventing magnetic degradation of electrical steels. Even, the supposed regression model can be useful in process control applications. The presented regression model in this research is useful for keeping burr length which is an indicator of plastic deformation level in the shear cutting process, to keep within limited length thus preventing excessing plastic deformation and magnetic degradation at lower degrees on mitered edges to produce more efficient magnetic cores of transformers. This paper is part of research about building lower no-load loss cores with decreasing shear cutting degradation and recurring them with annealing after cutting.

Materials and methods are presented in the next section, data acquiring methodology is expressed, a quadratic regression analysis is implemented with acquired data for the blanking process, and a model is proposed for process control activities as a conclusion.

2. MATERIALS AND METHODS

Author of this article improved a regression model for shear-cutting process like as some of referenced researcher have already done but only 2 of shear cutting process predictors included and left non-measurable and controllable process parameters out for this specific process.

Sample groups are defined as five different types of industrial GO codes as shown in Table 1. These codes are generic and used for manufacturing the transformer cores in BEST TRANSFORMER COMPANY.

Table 1 Main GOES types used in core production in BEST Transformer

Type Number	Nominal Thickness (μm)	Well-known descriptions
Type1	300	(M5 – 0.30)
Type2	230	(MoH – 0.23)
Type3	270	(NV27S)
Type4	270	(MoH – 0.27)
Type5	300	(M4 – 0.30 PH110)

It is seen in Table 1 that the most frequently consumed steel thickness are 0,23 and 0,30 mm. Additionally, the chemical composition of Fe-Si 3,09% is given in Table 2.

Table 2 Chemical composition of GO steels

Atom.	Si	C	Mn	S	Cu	P	Al	Fe
W%	3.09	0.054	0.072	0.018	0.075	0.015	0.010	Bal.

Typical GOES consist of at most 3.00 - 3.25 Si%, very little C, and other elements, and the rest is ferritic Fe. Typical mechanical properties of GOES blanked in this project are presented in Table 3.

Table 3 Mechanical properties of grain-oriented steel cut samples

Type	Thickness (μm)	Tensile Strength (MPa)	Yielding Strength (MPa)	Elongation (%)	Hardness (Hv1)
Type1	300	361	336	12	205
Type2	230	352	330	12	200
Type3	270	358	333	13	204
Type4	270	358	333	13	204
Type5	300	361	336	12	205

Grain-oriented electrical steel foils are provided as in Table 1 and slit to designed lengths. The slitting process is also very precious and valuable for plastic deformation evaluation and has an important influence on the magnetic properties of the stacked core. For the current study, slitting is not in scope. Slitted foils loaded to mitering machinery to get mitered laminations. Both ends of laminations are mitered such that α is 45° and symmetrically as shown in Figure 1. The dimensions of laminations are defined as L_1 = 300 mm, L_2 = 180 mm, and W = 60 mm. Because the diving angle of the upper blade changes about (2.0 ≈ 2.5°), thorough *W* emerged *BL* may show gradient. So, 3 different *BL* measuring points were selected for each cutting side and the maximum value was considered to represent the *BL* value of ends.

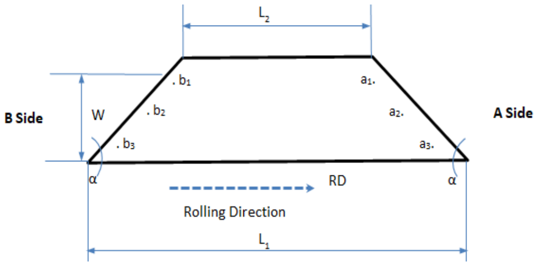

Figure 1 Main size of thin sheet GO lamination mitered at GEORG TBA400

The shear-cutting process executed in GEORG TBA 400 tried to be modeled with some of the process variances. Classical shear-cutting process parameters as the hardness of the steel sheet, the kinematic energy level of the upper blade (i.e., the velocity of upper blades), cutting forces occurring during diving of blades into the sheet, applied forces by upper blade holder, diving angle of upper blades, stroke of blades and a vertical clearance of blades are omitted in the model because of these process parameters are not possessing control ability or strictly kept as constant by machinery producer. Instead of these physical shear-cutting process parameters, direct or indirect process variables are chosen for modeling the critical output of the process.

BL is very critical in core building and expected that should be kept under crucial limits to ensure total no-load losses of the core as calculated level, this could be by minimizing of magnetic degradation of steel during mitering. Figure 2 shows how burr formed in shear cutting process.

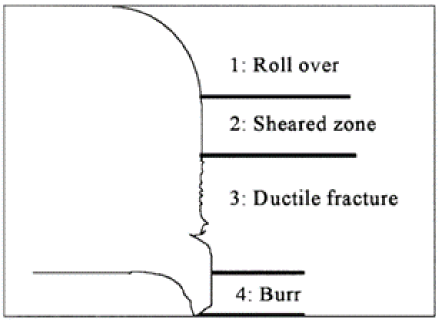

Figure 2 Surface profile after shear cutting process

Magnetic degradation is resulting from plastic deformation on mitered corners where flux movement is subject to change in vectorial direction in the core structure. Because of that, *BL* is considered a conclusive dependent variable of this special blanking process.

As shown in Figure 3 horizontal clearance of blades between the upper blade and lower blades is also another important parameter of the blanking process. In this case, as a main setting parameter of machinery, horizontal clearance of blades is always kept under limited values

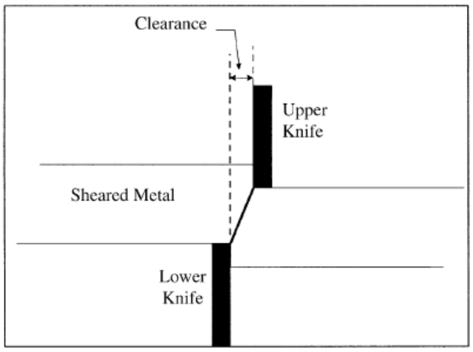

Figure 3 Simple presentation of horizontal clearance between blades

with Go & NoGo gages; preset values of the machine were 10 µm shims might be Go but 20 µm might be NoGo gages. Because of the very narrow adjustment gap and, not having any fine-tuning ability in the setup of machinery, horizontal clearance of blades is accepted as a constant parameter of the process. Although, the thickness of sheet lamination may vary regarding the chosen type of steel. As shown in Table 1, there are three different thicknesses of sample groups that show different effects regarding the horizontal clearance of blades. This means, all other conclusions accepted as immeasurable results of the process alike morphology of cut surface, plastic strains achieved during cutting, length of DAZ, and dislocation gradient near cut surface, all would be admissible that count on sheet thickness. Direct control of the horizontal clearance ratio of blades is not possible because of machinery stationary setup, but indirect effects can be representable by changing sheet thicknesses. Because of that, another independent variable of the shear-cutting process is chosen as Sheet Thickness *ST*.

The last independent variable would have been indicator of wearing oof blades. All blades are expected to have a sharp edge profile initially. By the time, after a working period, blades can get worn. During the process, there is no possibility for direct measuring of the blunting level of blades. When a sharpened or original blade is fixed to the blade holders, fixing dates are recorded and counts of hits can be recorded automatically. So, the researcher can get the count of hits *CH* to show the blunting level of blades till than initial fixing date to the measuring day. In this study, *CH* values represent the wearing level of blades and accepted an independent variable CH_A for A side blade and CH_B for B side of blades.

Mitered cut sample geometry is shown in Figure 1. Data of samples were collected as shown in Table 4 and Table 5, such that different *CH* values for different blades were collected to present different wearing levels of blades.

In a summary, the dependent variables of the blanking process are defined as burr length *BL*, as the first independent variable is sheet thickness *ST* and the second one is counts of hits *CH*. With these 3 variables, experimental runs are performed. The experimental runs are given in Table 5 and summarized in Table 6.
Different trades of grain-oriented electrical steels Type1 to Type5 were cut at 4 different dates with different counts of hits values of blades. 20 pieces produced from each type of grade at once. Both sides of the blades (A side and B side) were considered individually and *CH* values were recorded to represent the wearing level of the blades. Actual thickness values of samples were recorded as *ST* values by 3 points in each mitered edge along the width, *W*. Measurement of sheet thicknesses and *BL* of cut samples executed by a micrometer within 1 µm scale.

Table 4 Experimental setup; *CH* values of blades, dates, sample types and group numbers

Type Nu.	Counts of Hits *CH*		Fixing Date of Blades		Group Nu.
	A Side Blade CH_A	B Side Blade CH_B	A Side	B Side	
Type1	69520	586753	02.04.20	22.02.20	1
Type2	69542	586801	02.04.20	22.02.20	1
Type3	69563	586825	02.04.20	22.02.20	1
Type4	69586	586846	02.04.20	22.02.20	1
Type5	69607	686867	02.04.20	22.02.20	1
Type1	179132	668567	02.04.20	22.02.20	2
Type2	179154	668588	02.04.20	22.02.20	2
Type3	179176	668603	02.04.20	22.02.20	2
Type4	179198	668630	02.04.20	22.02.20	2
Type5	179220	668651	02.04.20	22.02.20	2
Type1	203727	642597	19.01.21	28.10.20	3
Type2	203751	641979	19.01.21	28.10.20	3
Type3	203775	642001	19.01.21	28.10.20	3
Type4	203779	642023	19.01.21	28.10.20	3
Type5	203823	642045	19.01.21	28.10.20	3
Type1	429935	90466	19.01.21	15.02.21	4
Type2	429958	90487	19.01.21	15.02.21	4
Type3	429980	90508	19.01.21	15.02.21	4
Type4	430002	90529	19.01.21	15.02.21	4
Type5	430024	90550	19.01.21	15.02.21	4

Table 5 *BL* and *ST* Measuring from GEORG TBA 400

		A Side of blades								B Side of blades							
Number of samples		N_1				N_{20}				N_1				N_{20}			
Group	Type	*ST* values	$ST_{avg.}$	*BL* values	$BL_{max.}$	*ST* values	$ST_{avg.}$	*BL* values	$BL_{max.}$	*ST* values	$ST_{avg.}$	*BL* values	$BL_{max.}$	*ST* values	$ST_{avg.}$	*BL* values	$BL_{max.}$
		284		0		282		0		285		6		284		8	
	Type1	285	284	2	2	284	283	2	2	285	285	8	8	283	283	8	8
		282		1		282		1		284		1		282		1	
		224		1		225		3		224		7		224		12	
	Type2	225	223	1	1	224	224	3	3	224	224	11	11	223	224	11	12
		220		1		224		2		224		1		224		0	
		260		1		258		1		259		2		255		13	
Group 1	Type3	261	260	2	2	256	257	2	2	260	259	2	2	258	257	10	13
		259		1		257		1		257		1		258		1	
		265		5		263		2		266		7		264		8	
	Type4	265	266	2	5	264	264	1	2	267	267	5	7	264	264	6	8
		267		0		264		1		267		2		265		1	
		288		1		285		4		288		10		285		8	
	Type5	287	287	2	2	285	284	1	4	288	288	0	10	285	284	2	8
		286		2		283		2		287		2		283		1	
		288		6		289		0		288		10		289		11	
	Type1	287	286	0	6	288	288	1	1	287	287	10	10	288	288	8	11
		284		0		286		1		285		2		288		2	
		224		1		223		1		222		11		222		12	
	Type2	224	224	0	1	222	222	0	1	223	222	18	18	223	222	14	14
		223		1		222		0		222		2		222		2	
		256		3		260		1		257		13		257		11	
Group 2	Type3	256	256	1	3	257	258	1	1	259	258	3	13	256	256	11	11
		256		0		258		0		257		3		256		3	
		267		3		265		1		266		7		266		5	
	Type4	268	267	1	3	266	266	1	1	266	266	6	7	267	266	5	5
		267		1		266		0		265		1		266		2	
		287		1		284		2		287		13		288		12	
	Type5	287	287	1	1	286	285	1	2	286	286	9	13	287	287	6	12
		287		0		285		1		286		4		286		1	
		297		7		295		4		297		10		294		10	
	Type1	298	298	1	7	294	295	1	4	299	299	5	10	297	295	3	10
		300		2		297		3		301		1		295		5	
		227		6		227		7		224		11		226		6	
	Type2	224	225	4	6	228	227	4	7	224	224	14	14	227	227	10	10
		223		3		225		3		224		5		228		8	
		258		9		260		12		260		13		260		15	
Group 3	Type3	259	258	2	9	282	268	4	12	257	259	2	13	260	260	9	15
		258		1		262		1		260		7		261		2	
		259		10		261		9		261		16		260		10	
	Type4	258	259	2	10	261	260	7	9	258	259	1	16	260	260	3	10
		259		1		258		2		258		11		260		1	
		287		5		290		6		286		7		288		10	
	Type5	285	286	3	5	289	289	3	6	286	286	7	7	287	287	1	10
		285		2		289		2		287		2		287		1	
		290		1		293		2		287		1		291		1	
	Type1	288	287	1	4	290	290	3	3	286	286	1	1	287	287	1	1
		282		4		288		1		286		1		283		1	
		228		3		226		1		228		2		225		2	
	Type2	229	228	6	6	227	226	4	4	227	227	2	2	225	225	1	2
		227		1		226		2		226		1		224		1	
		259		3		259		3		254		4		260		2	
Group 4	Type3	256	257	3	3	260	260	5	5	253	254	1	4	260	260	2	3
		255		3		262		1		255		3		259		3	
		265		1		259		1		261		1		260		2	
	Type4	259	262	6	6	257	258	1	4	261	261	2	2	260	259	2	2
		261		3		257		4		261		2		258		2	
		289		1		288		4		289		2		292		1	
	Type5	287	287	1	2	289	288	1	4	289	289	1	2	290	290	2	2
		286		2		288		2		288		2		289		2	

As mentioned before, the maximum value of measuring is recorded to represent *BL* values in regression analysis. So, 240 different *BL* and 240 different *ST* measurements are recorded in Table 5. On the other hand, an average of 8 different *CH* values is recorded in Table 4.

This research was executed for exploring a regression model for defined process variances. For this purpose, the General Full Quadratic Regression model is applied as given in Equation (1) below. The β vector which is composed of the parameters of the regression mode is given in Equation (2). Finally, the calculation of the β vector and the definitions of Y and X matrices are given in Equations (3) and (4), respectively:

$$Y_u = \beta_0 + \sum_{i=1}^{n1} \beta_i X_{iu} + \sum_{i=1}^{n} \beta_{ii} X_{iu}^2 + \sum_{i<j}^{n} \beta_{ij} X_{iu} X_{ju} + e_u \quad (1)$$

$$\beta^T = [\beta_0, \beta_1, \beta_2, \dots, \beta_n] \quad (2)$$

$$\beta = (X^T X)^{-1}(X^T Y) \quad (3)$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ \dots \\ y_N \end{bmatrix} X = \begin{bmatrix} 1 & x_{11} & x_{21} & x_{11}^2 & x_{21}^2 & x_{11} x_{21} \\ 1 & x_{12} & x_{22} & x_{12}^2 & x_{22}^2 & x_{12} x_{22} \\ 1 & x_{13} & x_{23} & x_{13}^2 & x_{23}^2 & x_{13} x_{23} \\ & & & \dots & & \\ 1 & x_{1N} & x_{2N} & x_{1N}^2 & x_{2N}^2 & x_{1N} x_{2N} \end{bmatrix} \quad (4)$$

As described above, the variance of the shear-cutting process is defined as Sheet Thickness (*ST*) and Counts of Hits of blades (CH_A and CH_B.). Accepting with initial conditions of the blade are identic, and all other cutting parameters of blades are stationary, intact, and the only parameter that can be observed is the Count of Hits, values of CH_A and CH_B integrated as *CH*. Also, in the same manner, the researcher integrated BL_A and BL_B as if one variance *BL*.

For *ST* spot checks, an average of 3 points along mitered edge *W* is accepted to represent actual *ST* values as shown in Figure 1. All *BL* and *ST* checks were recorded from the first sample of N_1 and the last sample of N_{20} of the sample groups. Table 6 shows the combined measuring of variances produced by merging and simplifying of Tables 4 and 5. Some of the rows which have responded values very close to each other are extracted from main Table 6. So the modeled number of rows decreased to 17.

Table 6 Summarize of measurements

CH	*ST*	*BL*
179164	223.0	7
179208	266.5	3
203761	225.7	7
429945	288.5	4
429990	258.5	5
430012	259.7	6
430024	287.8	4
586763	283.8	8
586811	223.8	12
586856	265.5	8
668577	287.5	11
669613	257.0	13
642607	297.2	10
641989	225.5	14
642055	286.8	10
90518	256.8	4
90560	289.5	2

3. RESULTS AND DISCUSSIONS

By running the Equations (1-4) through the data presented in Table 6, the regression equation for *BL* is calculated. For this, the Minitab statistical package is used. The calculated model is presented in Equation (5):

$$BL = 72{,}0602852442791 - (0{,}000029801809832xCH) - (0{,}42722756659429xST) + (0{,}00000000004238\, xCH^2) + (0{,}00065412941627xST^2) + (0{,}00000004535513xSTx\, CH) \quad (5)$$

Equation (6) is used to calculate the R^2 value (which is used to determine if the factors are adequate to represent the change in the response):

$$R^2 = \frac{\beta^T X^T Y - n\overline{Y}^2}{Y^T Y - n\overline{Y}^2} \quad (6)$$

From the equation, R^2 is calculated as 0.9896 (which is very close to 1) and this means *CH* and *ST* is seems too sufficient to explain the variation at *BL* and cannot need to use additional blanking process parameters.

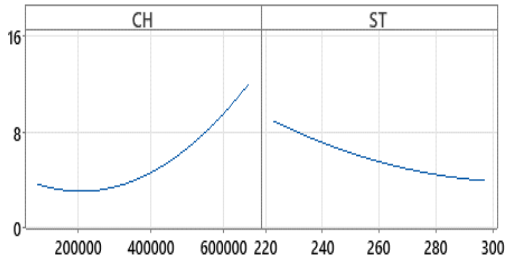

Figure 4 How *BL* changes one of *CH* and *ST*

Figure 4 shows that no multicollinearity effect on the model. Each variance varies response with different affection ratios.

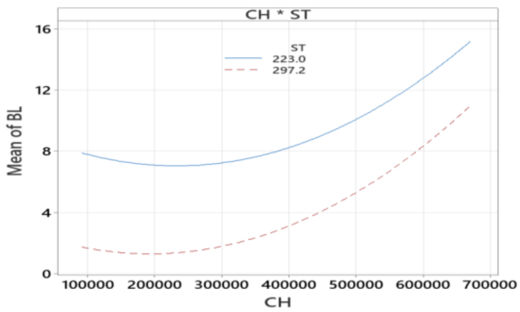

Figure 5 How *BL* changes with *CH*ST* and *ST*

Figure 5 shows how *BL* changes with the setting of *CH* separately and the interactions of *CH*ST*.

Figure 6, Residuals vs Fitted values scattering plots shows no clustering and heteroscedasticity on change of variance. No constant variance scattering plot was observed from residuals vs fitted values. Only one observation (Row 10) shows us a large residual. Scattering around zero seems random.

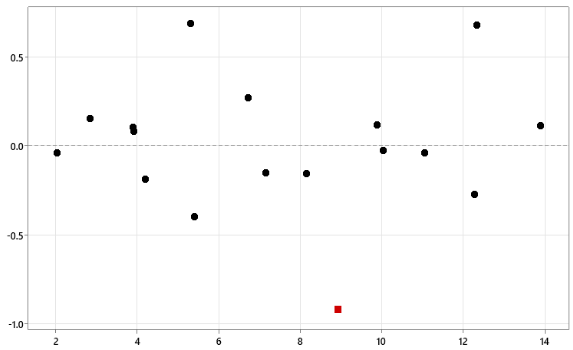

Figure 6 Residuals vs Fitted values

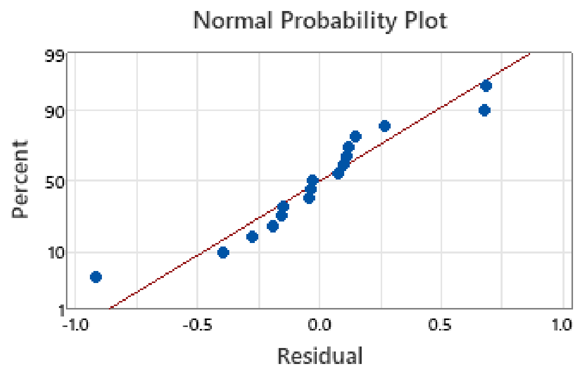

Figure 7 Normal probability plot

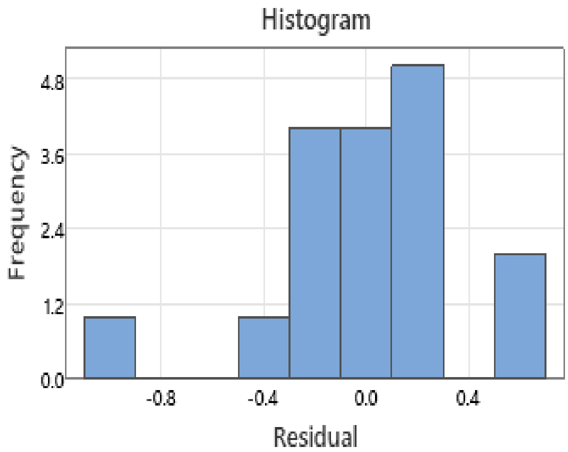

Figure 8 Histogram of residuals about normal

Figure 7 shows normal probability plot of residuals and Figure 8 shows the normal distribution of residuals. Finally, Analysis of Variance (ANOVA) is performed using Minitab. The ANOVA results are summarized in Table 7.

P value is found very smaller than (0.000<0.05) which means the model is significant at a 95% confidence level. Verification of calculated results with experimentally measured values is given in Table 7.

As is seen from Table 8, the maximum residual value is -0.91729937, and the maximum absolute deviation ratio is 12.9%. and the average percentage of residuals can be calculated as 3.35%.

Table 7 Analysis of Variance

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	5	212.006	42.401	209.25	0.000
Linear	2	159.066	79.533	392.50	0.000
CH	1	138.386	138.386	682.94	0.000
ST	1	42.287	42.287	208.69	0.000
Square	2	30.325	15.163	74.83	0.000
CH*CH	1	26.164	26.164	129.12	0.000
ST*ST	1	1.763	1.763	8.70	0.013
2-Way Interaction	1	0.918	0.918	4.53	0.057
CH*ST	1	0.918	0.918	4.53	0.057
Error	11	2.229	0.203		
Total	16	214.235			

Table 8 Matching of experimental and calculated results of the model

CH	*ST*	*BL*	Fitted *BL*	Residuals	Residuals (%)
179164	223.0	7	7.15110295	-0.15110295	-2.11%
179208	266.5	3	2.84861529	0.15138471	5.31%
203761	225.7	7	6.73000941	0.26999059	4.01%
429945	288.5	4	3.89818487	0.10181513	2.61%
429990	258.5	5	5.39656857	-0.39656857	-7.35%
430012	259.7	6	5.31446752	0.68553248	12.90%
430024	287.8	4	3.92126833	0.07873167	2.01%
586763	283.8	8	8.15850585	-0.15850585	-1.94%
586811	223.8	12	12.27467597	-0.27467597	-2.24%
586856	265.5	8	8.91729937	-0.91729937	-10.29%
668577	287.5	11	11.04108672	-0.04108672	-0.37%
669613	257.0	13	12.32334083	0.67665917	5.49%
642607	297.2	10	9.88155331	0.11844669	1.20%
641989	225.5	14	13.88728650	0.11271350	0.81%
642055	286.8	10	10.02789691	-0.02789691	-0.28%
90518	256.8	4	4.18961699	-0.18961699	-4.53%
90560	289.5	2	2.03852059	-0.03852059	-1.89%

When the model applies to process control of wearing level of blades can be predicted without any other measure and the burr length of mitered coils will have kept under the desired level.

4. CONCLUSION

The shear-cutting process is very a critical stage of the transformer core production process. Observations on GEORG TBA 400 model cut-to-length blanking machinery in BEST Transformer have been made and data recorded for optimizing burr length. As variable of burr length represents the plastic deformation level of mitered laminations. Burr lengths should be under control and limited range regarding IEC 60604-02. When a regression model occurred for the blanking process, dependent and independent variables process chosen as mentioned above, a meaningful model derived with R^2 = 0.9896 and model proposed for practice process control beneficial. For the next step of the study, the selection type of predictor variances and observation method of independent variables can be improved; wearing level of blades values can be derived by optical inspections. Further, for a more precious model, hardness and type of laminations can also join the observations. Hopefully, producing more efficient power transformer cores and reducing no-load losses of transformers in the grid will complement additional value and motivation to the next generations.

A mathematical process control model based on regression analysis can be raised to get useful and confidential process control activities for the traditional process shear-cutting process. Predictors observed physically and known experientially might be in the model.

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The Declaration of Conflict of Interest/ Common Interest
No conflict of interest or common interest has been declared by the authors.

The Declaration of Ethics Committee Approval

This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The authors of the paper declare that they comply with the scientific, ethical, and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification of the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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