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Comparative Optimisation of the Cutting Parameters for Surface Quality and Energy Efficiency during the Machining Manufacturing of Teak, Saligna and Pine Wood Materials

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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ABSTRACT

The rapid increase in electricity demand has resulted in the nation and state governments enforcing and implementing various forms of energy conservation conversations as well as seeking alternative energy sources in order to meet demand of the production sector. Manufacturing Industries of wood materials, in modern day trends, are principally focused on the achievement of highest quality products and quality planed surface generation at minimum input factor of resources

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such as machining energy. In wood artifacts manufacturing practice, the appropriateness of the cost-quality-time matrix normally depend on supreme selection of cutting parameters for the operation. Machining response factors, such as generation of smooth wood surface roughness is a vital metric of the product quality, granted it significantly influence the performance of machined wood parts, affects how the machined component will interact with the environment as well as impacting on the artifact production costs. Energy use optimisation, in order to continue and enhance competitiveness in business operations, is a prime priority concern for the modern day wood machining manufacturing industry. The challenges of ever increasing energy prices, against mounting demand for more energy demanding machinery, increasing pressure from environmentalists and increasing nation state legislation, for reduced energy generation prompted environmental pollution, mean that manufacturers are expected to pay more money and attention towards energy use reduction. Thus, it is imperative, during machining process planning of wood materials, to determine the optimum cutting parameters combination which fosters easy and economical machining which simultaneously deliver good surface quality at reduced energy consumption. This Taguchi design of experiment study analysed and comparatively optimised the cutting parameters of three wood species in order to realise consistent surface quality at minimum energy use during the planing machining of Pine, Saligna and Teak materials. Analysis of variance showed the dominant factors influencing the respective response parameters whilst the optimum cutting conditions were established with the aid of the main effects plot of the signal to noise ratio.

Keywords: Optimisation; energy efficiency; machining; surface quality; HSC/HSM.

1. INTRODUCTION

Wood manufacturing represent an important industrial economic activity as well as a pivotal engine driving growth in many nation states, [1]. Wood have broad range of applications, including - typically - for domestic and industrial furniture, construction, and transportation and paper industries. Machining - an energy use intense process - is an important industrial production operation, used for manufacturing wood components. It allows the creation of complex-shaped items for many applications. It forms one of the oldest industrial processes and it is the most frequently used process in the manufacture of discrete industrial workpieces and components such as wood and timber artefacts. Planing is a primary cutting method used in the wood machining industry, [2]. Modern manufacturing facilities are faced with a myriad of challenges, such as rapidly growing demand for products with greater flexibility in diversity of form and quality standards, and must be produced resource efficiently in minimum time. Furthermore, manufacturers must also address increasing requirements for sustainability in the efficient use of key resources such as energy as well as minimising emissions from their manufacturing operations, including complying with legislation, leading to the development of more efficient processes and systems, [3]. Approximately 15% of the total value of all mechanical components manufactured globally emanate from a machining process [4]. Being a major manufacturing process machining, thus, contributes significantly to the products' overall cost [5], especially those of wood materials. Accordingly machining is one of the main cost-determining factors where machining is the main activity of the manufacturing process. Generally, Furthermore, the machining manufacturing industry- of wood like most other manufacturing industries - are faced with the challenge of how to meet the demands of low operational costs as well as addressing the social forces requiring that manufacturing be more environmentally friendly, as well the constraining demands placed on them by national governments legislation, [6].

Surface roughness is an important parameter of product quality. It seriously influence the performance of Mechanical parts as well as production cost. Surface quality of wood is fundamentally concerned with the geometric irregularities of the surface of a material and is pronounced in terms of surface roughness, lay, lacerations, flaws and waviness. Surface roughness is constituted of the irregularities in the surface texture, [7]. Roughness plays a general role in exhibiting how the object will interrelate with the environment. It forms one of the most important parameters which determine the quality standard of machined wood products, [8]. The complex mechanisms accounting for the formation of surface quality on the machined components are very dynamic and process parameters dependent. Some of the several parameters which affect the texture and smoothness of the surface quality, of machined wood, include spindle speed, feed rate, depth of cut, number of cutting points on the cutting tool, etc., [9].

In today's globally competitive business environment, wood products processing industries require the manufacturing of stumpy cost, high surface quality products, generated at minimum energy consumption. Energy use and surface quality are two important performance measurement parameters, to which significant attention is paid during the machining of wood materials such as teak, saligna and pine, by the planing machine operation process. The surface quality of a machined product determines its acceptability by the customer as well as the performance behaviour of the product in use. Thus, it is important to evaluate and determine the variable input machining parameter levels which optimise energy use and achievement of the best surface quality of the wood, before the machining is carried out. This knowhow will be useful in the wood artefacts production operations as it minimises the manufacturing costs at the desired quality standard. Being able to tell, in advance, the optimum machining conditions which brings forth determinate outcomes of surface quality and energy use outcomes will be a good advantage to the wood machining industries of teak, saligna and pine wood materials. Good surface quality and minimum energy use, of the machining process, are desirable for better performance of the machining process. Research literature on the optimisation of cutting parameters for better achievement of good wood surface quality and energy use consumption minimisation, is not abundantly published from previous researchers.

In an effort to foster production of wood parts of desired surface quality at minimal energy use, appropriate machining parameters (depth of cut and number of cutting knives), must be selected. In this experimental research, the effect of cutting parameters on energy use and surface quality improvement was studied with the intention to determine the optimum settings desirable in order to achieve optimum energy utilisation and good surface quality, at process planning stage of the machining operation. The research aims included establishing the most dominant cutting parameter which affect the machining energy use and the quality of surface generated on the workpiece, as manifested by the pitch (cutter) marks per given unit area. Also the study aimed to determine the optimum set of cutting parameters for which minimum energy use and smooth surface roughness are realized. Then lastly regression analysis based mathematical models of the planning process were developed to further aid the cutting optimization process for energy use efficiency and surface quality improvement during the machining of the three timber species. In other words, the aim of the research is to experimentally establish the cutting parameters which optimises the achievement of minimum energy use and desirable surface quality. The objectives of the study included determining the cutting parameter levels (depth of cut and number of cutting knives) which optimise surface finish of work piece and also varying the cutting parameters in order to determine the input parameters combination which minimize energy use during machining to attain the desired surface finish. Some research work had been carried out regarding the optimisation of machining processes of wood. For example, Nasir & Cool, in a review study of wood machining and optimisation characterisation of factors which impact cutting power and surface quality, among other factors, concluded that factors such as feed rate, tool wear and saw accuracy have impact on the response factors of the machining process. According to Belleville attaining effective wood surface machining requires rigorous knowledge of the workpiece material as well as the implications of the cutting conditions used to prepare the wooden artifact surface. Wood is a heterogeneous material which is also anisotropic. As such, it is vital to understand its machining properties and characteristics in an endeavor to ensure that each manufacturing process will materialise into the production of the desired quality output standard. The quality of the final wooden product derive significantly from the quality of the machining conditions such that there is no compensation feasible for the performance malfunction of a component machined from badly planned cutting conditions [10]. Wood species in their diversity significantly affect wood machining characteristics of each respectively as regards the output response of the variation of the machining input factors [11].

Wood machining could be explained as the cutting tool action on wood material, which result in chips being separated, by effect of the cutting action, from the main piece and in the process generating the desired topological profile and geometrical architecture intended on the cut component, [12]. Being a material of biological origin the machining of wood is characterised with a lot of unpredictable variability attributed to its anatomical and physical properties, [13]. Mechanical machining is a multifarious stress-failure process in which, force is transmitted onto the wood - of inherent physical and mechanical properties – by a cutting tool of specific geometry, in a machine configuration defining the direction and orientation of the controlled force in conformity with the design of the machine tool. The machine tool configuration will determine the manner in which the stresses evolve at the cutting tool/wood material interface point and how the cutting or wood failure progresses. The cutting tool edge geometry as well as the condition of the wood material (dryness state and nature of defects, etc.) are some of the factors which affect how the machining process evolve, [2]. It is vital, therefore, that the wood profiling process variable parameters be managed in order to obtain the desired quality and productivity standards sustainably, [14]. In concurrence with this observation, Zhu, et al., [15] posits that enhancing energy use efficiency through improvement of efficiency during machining production operation helps to realise green manufacturing by industrial factories. Mallakpour, Sirous, & Hussain, [16] suggested achieving wood revitalisation and manufacturing sustainability through recovering sawdust from machined wood as a remediation effort.

Surface quality, fundamentally, have principal sway on the visual outlook of machined wood artifacts, as well as some other effects. The visibility of, machined wood, original colour becomes more enhanced by bright smooth surface finishes and devoid of irregularities. The durability of undamaged machined wood surfaces is superior compared to that of damaged processed surfaces, [12]. The quality of wood surface bonding with other surfaces is also a function of the surface finish quality which affect the mechanical and chemical properties of the wood. Such that wood whose surface is vastly shattered or crushed cannot form a strong bond regardless whether the adhesive makes a strong bond with the surface.

The overall surface roughness of machined wood can be segmented into, respectively, the roughness component deriving from machining, and the roughness component due to the internal anatomical structure of the wood. In the current era of sophisticated machining technology, the problematic roughness on machined components is that which originates from the internal anatomical structure of the wood material. The roughness due to machining can be manipulated by manipulating the cutting conditions, such as cutting speed which when increased causes reduction of surface roughness of the wood, as long as the profile of the cutting tool edge is maintained sharp, [11]. The roughness which develops during machining have two major components, viz machining caused roughness as well as roughness caused by the internal structure of wood. The roughness due to machining usually derive from a number of factors which, inter alia, include cutting speed, rake angle of the tool, chip thickness (depth of cut), machining direction relative to the grain, tool edge sharpness (tool edge radius) and vibration amplitude of the workpiece. The brittle fracture of wood material combined with its low tensile strength perpendicular to the grain, account for the existence of machining-caused surface roughness of machined wood. According to Belleville [17], the brittle fracture tendency of wood cannot be eliminated although it can at most be limited by controlling other factors influencing the machining process. However, little has been done on wood planing, specifically on the machine tool level where one wants to obtain the optimum parameters for energy efficient machining as well as achieving desirable surface quality on the machined components.

2. EXPERIMENTAL SET-UP AND DESIGN

In this Taguchi Design of experiments (DOE) study, efforts were made to comparatively establish the optimum cutting parameters combination which yield minimum energy use and improved surface quality during the planing machining of Pine, Saligna and Teak wood species. Cutter (pitch) marks measurement was the technique used to reflect the quality of surface generated during the planing operation of the wood species, whilst the Lutron DW-6092 three phase digital power meter (Fig. 1) was used to measure the machining energy. The experiment machine station is shown in Fig. 2. Empirical experiments were conducted in order to establish the effect and outcome response trends of input parameters adjustment in depth of cut and number of cutting knives on the surface quality and energy consumption of the planing process. The experiment design plan based on the Taguchi L9 orthogonal array was utilised to evaluate the interactive relationship of the various factors, respectively, for the three species of wood. Minitab 22 statistical package, Analysis of Variance (ANOVA) was used to show the input parameters which have more influential effect on the response parameters (surface quality and energy use) of the wood machining. The Signal-to-noise (S/N) ratio main effects plot data analysis procedure was utilised to establish the optimum input parameters combination to engage in order to achieve the desired machined artefacts quality (surface roughness – pitch marks count) at minimum energy use. According to Mahendra & Neeraj [18], the optimum cutting input parameters are identified by selecting the parameters which give the highest values of the S/N ratio. These points offer the best statistical performance measures used to best control the effect of uncontrollable noise factors on the cutting process, [19]. In this research, best performance is realised by achieving minimisation of surface quality of the planed wood (reflected as minimum spacing of pitch marks) as well as the energy use requirement of the cutting process.

Fig. 1. Lutron 3 Phase digital Power Analyser/meter

Fig. 2. Set-up, tools and the experimental rig

Table 1.The planing machine features and specifications

Characteristic feature	Specification
Table length	2700 mm
Table width	430 mm
Planer head diameter	120 mm
Maximum depth of cutting	8 mm
Spindle speed	5000 rpm
Motor power rating	4 kW
Maximum number of cutters carried on the block	4

The cutting blades were HW-03F material type Tungsten carbide 5906 blade with 165 mm x 16 mm x 1.5 mm dimensions and of 22 micro-hardness number.

The 95% confidence interval, reflecting a significance level of 0.05 ($p < 0.05$), was the statistical analysis used, [20].

The research, in assessment, studied the trio types of Sub-Saharan furniture and construction wood material in Zimbabwe timber forests. The sample specimens images are presented in Table 2a.

The dimensions of each specimen were respectively, 450 mm x 114 mm x 50 mm. Characteristics of the wood material used in the research were as presented in Table 2b.

The test procedure involved a total of 27 sample specimens which were worked on during the 27 Planing study experiments, premising on the feasible cutting parameters combination plan determined by the L9 orthogonal array (Table 3).

The experiment process involved taking a fixed number (6) of planing passes on a single side of each specimen. The constant 6 passes was utilised as the experiment change-over criterion at the end of which stage the surface of the machined side of the timber was examined. At this experiment change over point, new set of knives would also be mounted after removing the previous experiment set of knives. Visibility of the cuttermarks, during assessment and measurement of the surface roughness, was enhanced or amplified with the aid of a magnifying glass set at a fixed height from the top surface of the machined timber block specimens. The cuttermarks, which were existent within a 25 mm square area, were counted and measured using a Vertex stainless steel hardened digital Vernier calipers with an accuracy of +/- 0.05 mm. 15 measurements were recorded, at 3 respective positions along the length of the machined timber block specimen, and an average value would be recorded as the roughness value of the surface roughness on that machining parameter setting.

Table 2a. Teak, Saligna and Pine wood types used

Wood Type Image	Wood name
	Teak
	Saligna
	Pine

Table 2b. Specimens hardness and moisture measurements

Sample Name	Hardness scale	Moisture percent content
Saligna	1250N	12.0
Teak	1000N	15.0
Pine	420N	8.6

Table 3. Cutting parameter combination and level control factors

Factor control level	Depth of cut (mm)	Number of cutting knives
1	1	2
2	2	3
3	3	4

3. RESULTS AND DISCUSSION

A summary of the experiment results are presented in Table 4.

The analysis of variance (ANOVA) result of Total cutting energy (TCE) for Saligna wood, shown in Table 5 denote that both parameters (cutting knives and depth of cut) have positive influence on the response parameter. Both input factors have significant effect on the TCE for Saligna wood as shown by their p-values which are less than 0.05. However, for Saligna, TCE is influenced more by depth of cut than by number of cutting knives as confirmed by the Taguchi analysis response results shown in Table 6, where the depth of cut ranks higher than number of cutting knives. Thus, improvement for more efficient performance would require that depth of cut be adjusted before *the* number of cutting knives is accordingly addressed.

The main effects plot results for Saligna total cutting energy shown in Fig. 3 denotes that the optimum cutting conditions are attainable on input parameter setting with 2 cutting knives and depth of cut of 1 mm.

The Regression model, expressing the mathematical relationship of how total cutting energy (TCE) is connected to the input parameters, cutting knives and depth of cut, is shown in equation Eq1. The r^2 value of 94.6%, shown in the model summary (Table 7) shows a strong representativeness of the model to the data represented.

Saligna, TCE = 0.522 + 0.1658 Cutting knives + 0.2349 Depth of cut *Eq. 1*

Table 4. Summary of Experiment results for three types of wood machining

Number of Cutting knives	**Depth of cut (mm)**	**Saligna, TCE (kWh)**	**Pine, TCE (kWh)**	**Teak, TCE (kWh)**	**Saligna Cutter marks (mm)**	**Pine Cutter marks (mm)**	**Teak Cutter marks (mm)**
2	1	0.9977	0.6412	1.48	1.4	2.32	1.48
2	2	1.4322	1.0783	1.32	3.05	1.25	1.32
2	3	1.4853	1.1658	1.7	2.13	3.07	1.7
3	1	1.3043	1.0675	3.88	1.84	2.51	3.88
3	2	1.5392	1.3443	3.34	1.93	1.35	3.34
3	3	1.7377	1.2827	2.6	3.02	1.46	2.6
4	1	1.4245	1.0905	3.75	2	1.94	3.75
4	2	1.5725	1.3258	2.79	1.31	1.21	2.79
4	3	1.9132	1.5103	1.96	2.75	1.27	1.96

TCE – Total cutting energy

Table 5. Analysis of Variance for Saligna, TCE

Source	**DF**	**SS**	**MS**	**F**	**P**
Cutting knives	2	0.17131	0.085657	11.88	0.021
Depth of cut	2	0.33401	0.167003	23.17	0.006
Error	4	0.02883	0.007208	-	-
Total	8	0.53415	-	-	-

Table 6. Taguchi Analysis of Response for Saligna, TCE

Response Table for Signal to Noise Ratios (Smaller is better)			**Response Table for Means**		
Level	**Cutting knives**	**Depth of cut**	**Level**	**Cutting knives**	**Depth of cut**
1	-2.179	-1.787	1	1.305	1.242
2	-3.618	-3.599	2	1.527	1.515
3	-4.213	-4.624	3	1.637	1.712
Delta	2.035	2.837	Delta	0.332	0.470
Rank	2	1	Rank	2	1

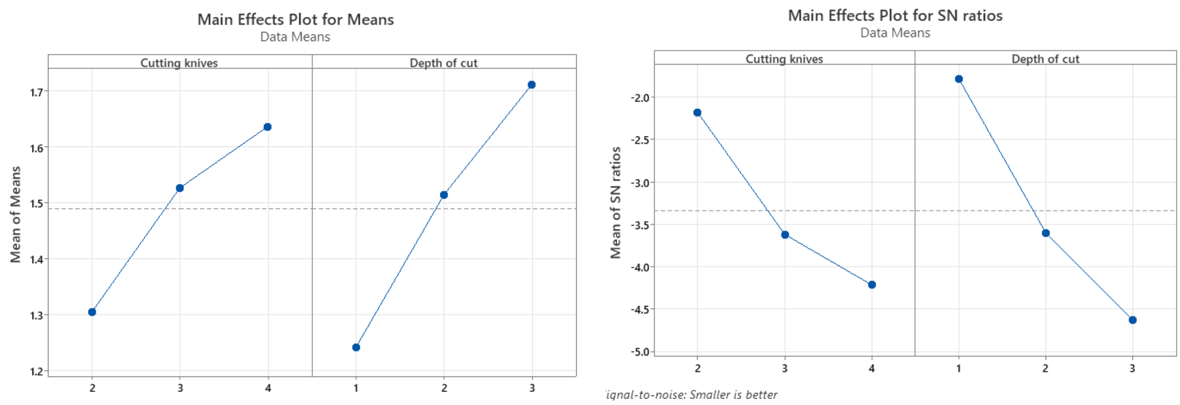

Fig. 3. Main Effects Plot for S/N Ratios on Data Means: Saligna Total Cuttiing energy

Table 7. Saligna TCE Model Summary

S	R-sq	R-sq(adj)
0.0849008	94.60%	89.20%

The significant positive influence, of the input cutting parameters, on the response parameter – TCE – is apparent on the ANOVA of pine wood shown in Table 8. Both cutting knives and depth of cut have p-value less than 0.05. The p-values of 0.022 for cutting knives and 0.014 for depth of cut shows therefore that the total cutting energy response for pine wood is more strongly influenced by the input factor depth of cut than cutting knives. The Taguchi analysis, of the response for pine TCE, presented in Table 9 further confirm the dominance of depth of cut over cutting knives in positively impacting on the response parameter as shown by the delta ranking order of scores.

The optimum cutting parameter condition combination, for pine TCE is realised on setting both cutting knives and depth of cut at their minimum level ash shown on the main effects plot results in Fig. 4.

The Regression model expressing the relationship of the input factors to the response function (*Pine TCE*) is given by Eq2:

Pine, TCE = 0.260 + 0.1736 Cutting knives + 0.1933 Depth of cut *Eq. 2*

The coefficient of determination of 92.96% in the model summary (Table 10) shows the very strong representativeness of the data by the fitted regression model.

Table 8. ANOVA for Pine, TCE

Source	DF	SS	MS	F	P
Cutting knives	2	0.19923	0.099613	11.60	0.022
Depth of cut	2	0.25448	0.127239	14.82	0.014
Error	4	0.03434	0.008586	-	-
Total	8	0.48805		-	-

Table 9. Taguchi Analysis of Response for Pine, TCE

Response Table for Signal to Noise Ratios *(Smaller is better)*			Response Table for Means		
Level	**Cutting knives**	**Depth of cut**	**Level**	**Cutting knives**	**Depth of cut**
1	0.6243	0.8469	1	0.9618	0.9331
2	-1.7666	-1.8917	2	1.2315	1.2495
3	-2.2612	-2.3588	3	1.3089	1.3196
Delta	2.8855	3.2057	Delta	0.3471	0.3866
Rank	2	1	Rank	2	1

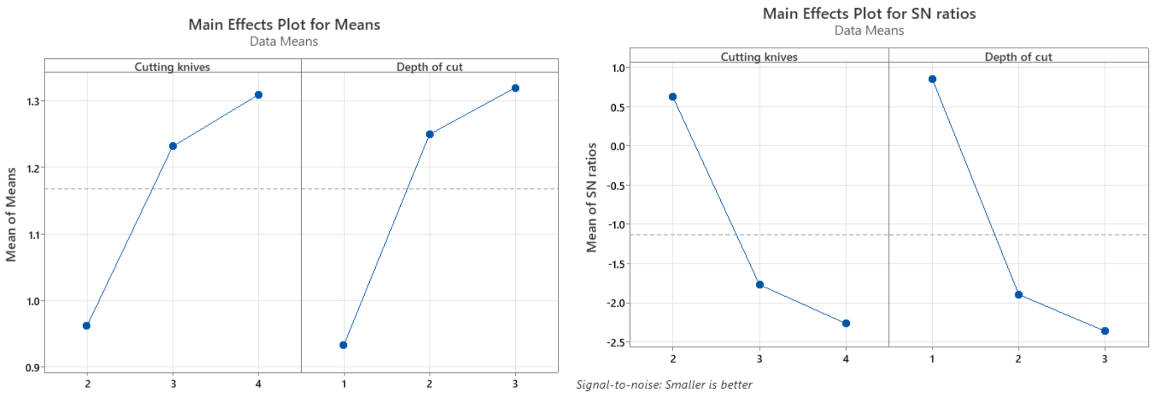

Fig. 4. Main Effects Plot for S/N Ratios on Data Means: Pine Total Cutting energy (TCE)

Table 10. Pine TCE Model Summary

S	R-sq	R-sq(adj)
0.0926601	92.96%	85.93%

The Teak TCE ANOVA results presented in Table 11 show that the input parameter, cutting knives, have more positive effect on the measured output parameter, TCE for Teak wood whilst the input parameter, depth of cut have less significant influence on TCE as shown by the p-value of 0.206. Input parameters effect confirmation assessment is presented on the Taguchi analysis response, for signal-to-noise ratios response table for means (Table 12) which was premised on the smaller is better criteria. Cutting knives had higher significant influence on TCE for Teak as confirmed by the delta ranking scores.

The optimum parameters setting for total cutting energy, for Teak, were 2 cutting knives and depth of cut of 3 as presented by the results of the signal-to-noise ratios main effects plot in Fig. 5.

Regression analysis was used to model the relationship explaining the connection of TCE, for machining Teak, with the two variable input parameters (cutting knives and depth of cut) is shown in equation Eq3.

Teak, TCE = 1.49 + 0.667 Cutting knives - 0.475 Depth of cut Eq3

Table 11. Analysis of variance for teak, total cutting energy

Source	DF	SS	MS	F	P
Cutting knives	2	5.116	2.5580	9.00	0.033
Depth of cut	2	1.366	0.6830	2.40	0.206
Error	4	1.138	0.2844	-	-
Total	8	7.620	-	-	-

Table 12. Taguchi Analysis of Response for Teak, TCE

Response Table for Signal to Noise Ratios ***(smaller is better)***			Response Table for Means		
Level	**Cutting knives**	**Depth of cut**	**Level**	**Cutting knives**	**Depth of cut**
1	-3.475	-8.887	1	1.500	3.037
2	-10.184	-7.266	2	3.273	2.483
3	-8.746	-6.251	3	2.833	2.087
Delta	6.708	2.636	Delta	1.773	0.950
Rank	1	2	Rank	1	2

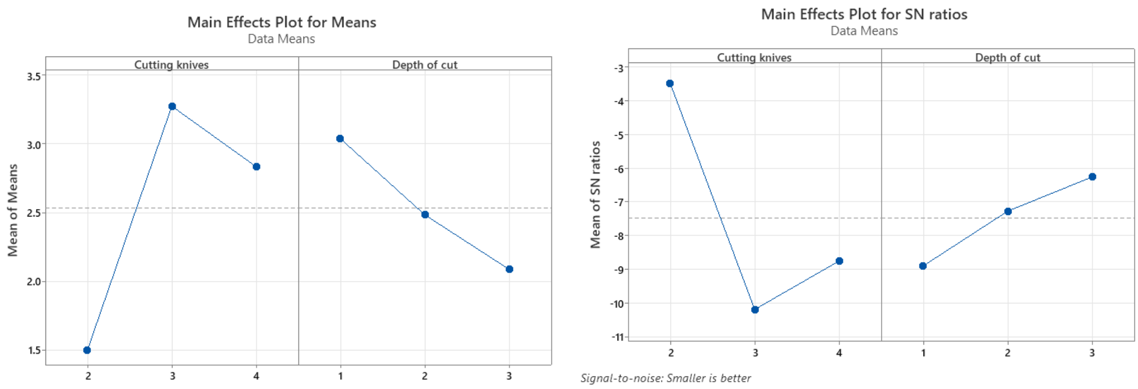

Fig. 5. Main Effects Plot for S/N Ratios on Data Means: Teak Total Cutting energy (TCE)

The coefficient of determination (R^2) of 85.05%, presented in the Teak TCE model summary (Table 13) confirms the significance of how well the regression model (equation Eq3) approximates the real data points projecting the relationship between the predictor variables (cutting knives and depth of cut) and the response parameter, Teak for TCE. A coefficient of determination, R^2 of value zero means that the dependant variable cannot be predicted from the independent variable.

In wood machining cutter marks count serve to indicate surface quality or surface roughness, [21]. In that regard in this study, reference to cutter or pitch marks imply surface roughness or surface quality of the machined artefacts.

The ANOVA results, of Saligna cutter marks, presented in Table 14, show the dominant positive influence of depth of cut, (p-value of 0.402) than cutting knives in impacting on the surface quality (cutter marks) of Saligna wood. The Taguchi analysis response Table for the S/N ratios results in Table 15 confirms the ranking order of the influence of input parameters on the Saligna cutter marks.

The optimum cutting conditions for Saligna cutter marks, according to the main effects plot in Fig. 6 is setting of cutting knives at 4 and a depth of cut of 1 mm.

Table 13. Teak TCE model summary

S	R-sq	R-sq(adj)
0.533271	85.07%	70.14%

Table 14. Analysis of variance for saligna, surface roughness

Source	DF	SS	MS	F	P
Cutting knives	2	0.09416	0.04708	0.09	0.915
Depth of cut	2	1.19669	0.59834	1.16	0.402
Error	4	2.07084	0.51771	-	-
Total	8	3.36169	-	-	-

Table 15. Taguchi analysis of response for saligna, surface roughness

Response Table for Signal to Noise Ratios *(Smaller is better)*			**Response Table for Means**		
Level	**Cutting knives**	**Depth of cut**	**Level**	**Cutting knives**	**Depth of cut**
1	-6.392	-4.747	1	2.193	1.747
2	-6.869	-5.914	2	2.263	2.097
3	-5.718	-8.318	3	2.020	2.633
Delta	1.152	3.572	Delta	0.243	0.887
Rank	2	1	Rank	2	1

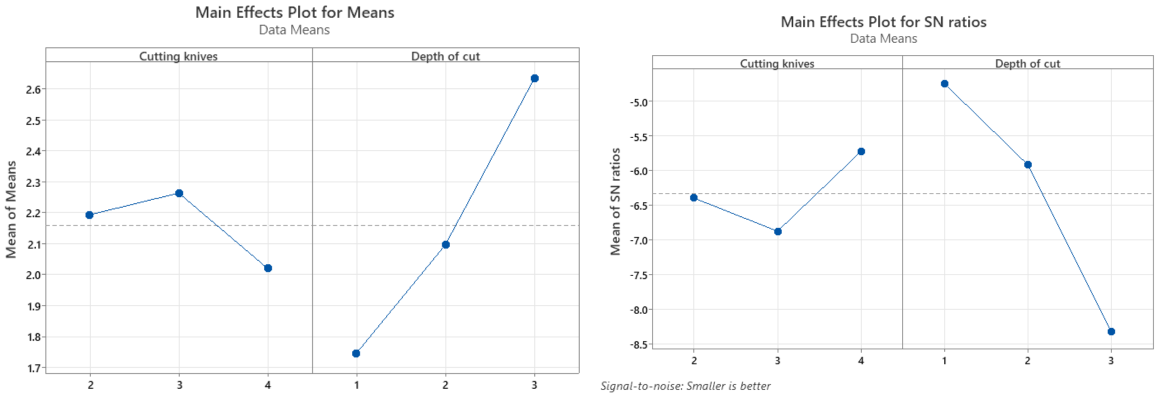

Fig. 6. Main Effects Plot for S/N Ratios on Data Means: Saligna Cutter marks

The regression equation modelling the relationship of input parameters and the response, Saligna surface quality is presented in equation Eq 4.

Saligna Cutter marks = 1.532 - 0.087 Cutting knives + 0.443 Depth of cut Eq 4.

The coefficient of determination of 92.89% (Table 16) show the strong representativeness of the data by the model.

The results presented in Table 17, show the ANOVA analysis of pine wood surface quality. It is apparent that the input factor depth of cut (p-value of 0.213) had a more significant influence on pine cutter marks than the number of cutting knives. The Taguchi analysis response table results, presented in Table 18, also confirm the dominance of depth of cut in influencing surface roughness than the number of cutting knives showing a ranking order delta position of 1 and 2 respectively for depth of cut and number of cutting knives.

The optimum cutting parameter combination for pine surface roughness, according to the main effects plot results presented in Fig. 7, is setting 4 cutting knives and 2 mm depth of cut.

Table 16. Saligna Surface roughness Model Summary

S	R-sq	R-sq(adj)
0.0795346	92.89%	90.53%

Table 17. ANOVA for Surface roughness of Pine

Source	DF	SS	MS	F	P
Cutting knives	2	0.8312	0.4156	1.28	0.373
Depth of cut	2	1.5181	0.7590	2.33	0.213
Error	4	1.3037	0.3259	-	-
Total	8	3.6530	-	-	-

Table 18. Taguchi Analysis of Response for Pine, Surface roughness

Response Table for Signal to Noise Ratios *(Smaller is better)*			Response Table for Means		
Level	**Cutting knives**	**Depth of cut**	**Level**	**Cutting knives**	**Depth of cut**
	-6.330	-7.020	1	2.213	2.257
2	-4.629	-2.067	2	1.773	1.270
3	-3.163	-5.035	3	1.473	1.933
Delta	3.168	4.953	Delta	0.740	0.987
Rank	2	1	Rank	2	1

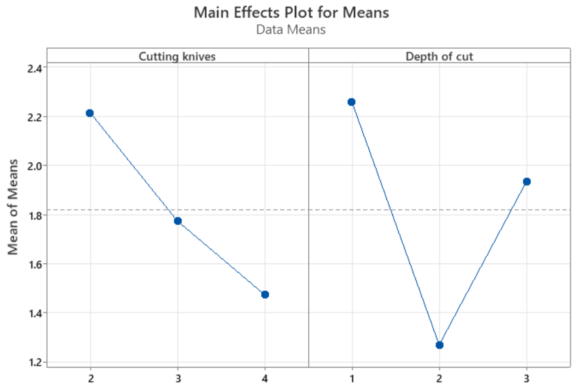

Fig. 7. Main Effects Plot for S/N Ratios on Data Means of Pine Surface quality

The Regression model relating the surface roughness response parameter to the input parameters is presented in equation Eq 5. The model summary (Table 19), show data representativeness of no less than 64% by the model.

Pine Cutter marks = 3.25 - 0.370 Cutting knives - 0.162 Depth of cut Eq 5.

The results presented in Table 20 is the Analysis of Variance (ANOVA) results for the surface quality of Teak wood, which show that both cutting knives as an input parameter have a more positive effect on the pine wood cutter marks than depth of cut. The significance of the influence of cutting knives is apparent from the fact that on the ANOVA have a p – value of 0.033 which is below the 0.05 threshold value. The Taguchi analysis response table for the S/N ratios results in Table 21 confirms the ranking order of the influence of input parameters on the teak surface roughness.

The signal-to-noise ratio main effects plot, for the teak wood surface quality, show the level of significance of the influence of input machining parameters (cutting knives and depth of cut) on the response parameter, cutter marks. The Signal to Noise Ratios plots were premised on smaller is better. The optimum cutting conditions according to Fig. 8 is achievable at 2 cutting knives and 3 mm depth of cut combination.

Table 19. Pine cutter marks Model Summary

S	R-sq	R-sq(adj)
0.570906	64.31%	\`28.62%

Table 20. ANOVA for Teak Cutter marks

Source	DF	SS	MS	F	P
Cutting knives	2	5.116	2.5580	9.00	0.033
Depth of cut	2	1.366	0.6830	2.40	0.206
Error	4	1.138	0.2844	-	-
Total	8	7.620	-	-	-

Table 21. Taguchi Analysis of Response for Teak, Surface roughness

Response Table for Signal to Noise Ratios *(Smaller is better)*			Response Table for Means		
Level	**Cutting knives**	**Depth of cut**	**Level**	**Cutting knives**	**Depth of cut**
1	-3.475	-8.887	1	1.500	3.037
2	-10.184	-7.266	2	3.273	2.483
3	-8.746	-6.251	3	2.833	2.087
Delta	6.708	2.636	Delta	1.773	0.950
Rank	1	2	Rank	1	2

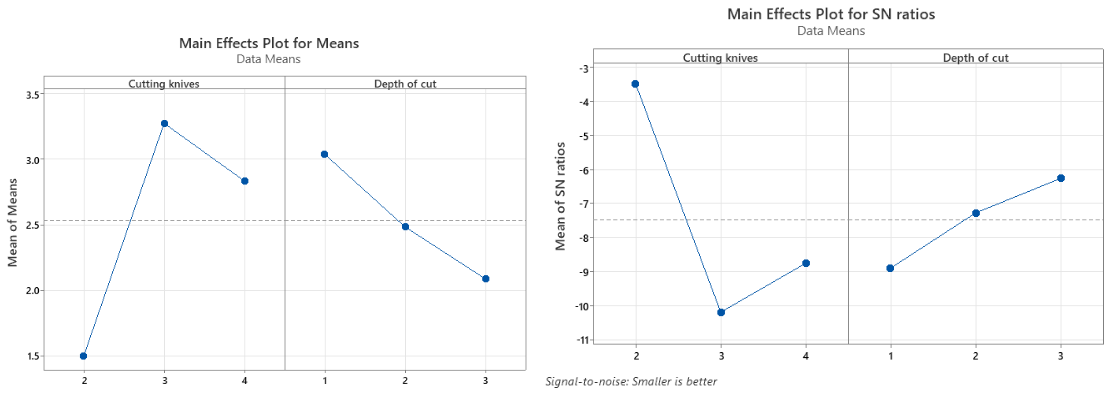

Fig. 8. Main Effects Plot for S/N Ratios on Data Means of Teak surface quality

Table 22. Teak cutter marks Model Summary

S	R-sq	R-sq(adj)
0.533271	85.07%	70.14%

Table 23. Summary of optimum cutting parameters for TCE

Wood type	Optimum cutting parameters settings	
	Number of Cutting knives	Depth of cut (mm)
Pine	2	1
Teak	2	3
Saligna	2	1

Table 24. Summary of optimum cutting parameters for surface quality/ pitch (cutter) marks

Wood type	Optimum cutting parameters setting	
	Number of Cutting knives	Depth of cut (mm)
Pine	4	2
Teak	2	3
Saligna	4	1

The Regression model relating the input parameters to the response factor (teak cutter marks) is given by equation Eq 6:

$$\text{Teak Cutter marks} = 1.49 + 0.667 \text{ Cutting knives} - 0.475 \text{ Depth of cut} \quad \text{Eq 6.}$$

The coefficient of determination, r^2, of 85.07% (in Table 22) show very strong representativeness of the data by the regression model.

3.1 Summary of the Optimization

This section present a summary of the determined optimum input cutting parameter settings for machining the three types of timber, respectively, for the Total cutting energy (TCE) in Table 23 and for the cutter marks or surface quality in Table 24.

4. CONCLUSION

The research set out to experimentally study and comparatively analyse the effect of cutting parameters on the response parameters (energy use and surface quality) during the machining of Pine, Saligna and Teak wood with the intention to determine the input parameters which optimise the response parameters. The Taguchi DOE technique was utilised to plan the planning experiments. The ANOVA and S/N ratio techniques had been used, respectively, to determine the impact of the input parameters on the response factors and optimisation. Deducing from the results and analysis of the experimental investigation, on the three different materials under the varied cutting parameters combination, conclusions were reached that; the input parameters (depth of cut and the number of cutting knives) have different levels of influence on the response parameters according to the type of wood being machined. Optimum cutting conditions were established for the three different types of wood and the mathematical models presented. According to the confirmation experiments run, by setting the model determined optimum condition on the machining experiment platform, the maximum variation of result between the experiment and optimisation model was 9% or less which showed the reliability of the optimisation platform utilised.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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