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How to cite: Paul P, Mukhopadhyay A. Optimization of Process Parameters Based on Machine Learning and Determination of Relative Importance of Process Variables on Jute Ply Yarn Breaking Extension. Textile & Leather Review. 2024; 7:421-432. <https://doi.org/10.31881/TLR.2023.206>

How to link: <https://doi.org/10.31881/TLR.2023.206>

Published: 17 March 2024



Optimization of Process Parameters Based on Machine Learning and Determination of Relative Importance of Process Variables on Jute Ply Yarn Breaking Extension

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Article

<https://doi.org/10.31881/TLR.2023.206>

Received 20 December 2023; Accepted 6 March 2024; Published 17 March 2024

ABSTRACT

The breaking extension of jute ply yarn is comparatively low and ordinarily varies from 1.5 – 3.5% depending upon the process parameters like number of plies, single yarn twist factor and ply to single yarn twist ratio. To achieve various levels of jute ply yarn breaking extension within the above range, optimization of the three process variables was done in this study using a machine learning-based decision tree. For such optimization, twenty-seven different types of jute ply yarns were produced using three levels of singles' twist factor, number of ply and ply-to-single twist ratio. A total of 216 observed breaking extension values of these yarns were used for regression-based machine learning wherein 67% of test data were used to train the model and the remaining 33% of test data were used for validation. An 8-node decision tree thus achieved from the model was used for the optimization process. A boxplot vs. terminal node graph was also used for classified optimization of ply breaking extension for various levels. The study conducted in this work reveals that the breaking extension of jute ply yarn varies directly with the number of plies, where 4-ply jute yarn produces maximum breaking extension and 2-ply produces the minimum. It was also observed that the decision tree was useful for the judicious selection of process parameters to achieve various levels of jute ply yarn breaking extension, wherein, it was found that the critical values for ply to single yarn twist ratio and single yarn twist factor were 0.80 and 26. The study also shows that apart from the individual influence of the variables on the breaking extension of ply yarns, interactions between variables also influence the breaking extension of jute ply yarn.

KEYWORDS

optimization, machine learning, jute ply yarn, breaking extension

INTRODUCTION

Jute is a lingo-cellulosic fibre which possesses high tensile strength, low extensibility, high modulus and high surface friction [1-2]. Apart from its traditional use in the field of flexible packaging for centuries, jute is now being used in composites and other industrial applications due to its favourable properties like high specific modulus and low breaking extension [3]. It is a well-known fact that single yarns made of staple fibres are hairy, less resistant to abrasion, more uneven, and, most importantly, have lower specific strength and elongation. Despite these shortcomings, single yarns are still used for the majority of textile products are made from single yarns. However, plied or folded yarns are used in some cases

to obtain unique qualities in yarn and/or fabric that cannot be obtained through any other means. Research indicates that plying several single yarns enhances important yarn characteristics such as strength, elongation, evenness, hairiness, and abrasion resistance [4-5]. Elongation at break is one of the prime quality attributes of any spun yarn. Optimum elongation at break is important for the processability of the yarn in the downstream processing like weaving and knitting as well as the properties of the end products made with the yarn [6]. Researchers also observed that controlled extension is one of the key parameters for the satisfactory performance of sewing thread [7].

Significant research findings are available where researchers have studied the extension behaviour of ply yarns made out of various textile fibres. According to Palaniswamy & Mohamed's observation, the degree of twist in a cotton ply is directly correlated with the breaking elongation of the yarn [4]. According to Omerglu's research, the breaking elongation of cotton plied yarn is statistically influenced by both the ply and single yarn twist levels, with the effect of single twist being more pronounced in finer yarns [8]. Twist multiplier and twist direction's effects on acrylic-viscose plied yarn breaking elongation were reported by Tarafdar [9].

Although plenty of studies are available for other textile materials, the same for jute has not yet been reported. As jute has distinctive properties like low extension at break, this necessitates an independent study to understand the influence of individual process variables like number of plies, single yarn twist factor, ply to single twist ratio and single yarn breaking extension as well as their interactions on the breaking extension of jute ply yarn. As low extension of jute yarn is sometimes detrimental to its performance in sewing [10], it is also important to optimise the above parameters to achieve the desired level of ply-breaking extension.

The Classification and Regression Tree (CART) is one of the simplest predictive algorithms used in machine learning for such optimization of variables to achieve a desired output. CART is a powerful and popular algorithm due to its interpretability and its ability to capture non-linear relationships between features and the target variable. The algorithm works by recursively partitioning training data into smaller subsets based on threshold values of decisive features. Decision trees with several terminal nodes are created using the CART algorithm, allowing for parameter optimization [11, 12]. While machine learning for textile optimization is still relatively new, a few recent researches have documented using it to optimize textile processes and materials [13-17]. Gültekin et al. used the decision tree regression method for the prediction of static tear strength performance from woven fabric physical parameters [13]. Thakur et al. used various machine-learning approaches to classify fabric defects like holes, knots, slubs and stains on solid woven fabrics [14]. The least-square support vector regression method of machine learning was used by Pervez et al. for optimization exhaustion percentage, fixation rate, total fixation efficiency and colour strength in reactive cotton dyeing process [15].

Efforts have been made in this study to optimize the important parameters quantitatively that influence jute plied yarn breaking extension using the CART regression module. The relative importance of those parameters in determining jute plied yarn extension as well as the variable interactions have also been studied in this work.

EXPERIMENTAL

2, 3, and 4-ply jute yarns of 930 tex resultant count were prepared from 465 tex, 310 tex, and 233 tex single jute yarns, respectively, using raw jute of TD4 quality [18]. Machine parameters were set to achieve Z-twisted single yarns with three levels of twist factor of 24, 26 and 28 in the tpc-tex unit. The singles were then used to prepare S over Z twisted ply yarns using three levels of ply-to-single twist ratio (0.5, 0.7 and 0.9). A total of 27 different types of plied yarns, thus prepared, were used for the investigation, taking into account three levels of ply number, three levels of single yarn twist factor [TF(S)], and three levels of ply to single twist ratio [P:S]. The details of machine parameters used in spinning single yarns and twisting of ply yarns are given in Table 1. To achieve the desired level of twist in the single as well as ply yarns, draft change pinions were used accordingly.

Table 1. Process parameters of spinning and twisting

Parameters	Single yarn spinning	Ply yarn twisting
Spinning machine type	4 ¼" spindle pitch slip draft 2-legged flyer jute spinning machine	Flyer twisting machine
Flyer rpm	3450	1720
Draft constant	600	-
Twist constant	180	127
Twist direction	Z	S over Z

Table 2 below shows the yarn parameters used for the preparation of 27 different types of experimental samples.

Table 2. Single and ply yarn parameters

Plied yarn count (tex)	930			930			930		
No. of ply x single yarn count (tex)	4 x 233			3 x 310			2 x 465		
Single yarn twist factor (in tpc - tex unit)	24	26	28	24	26	28	24	26	28
Single yarn twist level (turns per cm)	1.54	1.61	1.77	1.38	1.46	1.57	1.10	1.18	1.32
	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Ply to single twist ratio (P:S)	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7
	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9

For the regression model, a total of three variables (predictors) were taken into account: the number of plies, the single yarn twist factor, and the ply-to-single twist ratio.

While the single and ply yarns' twist levels (tpc) were evaluated in accordance with ASTM D1423, the yarns' breaking extension was tested in Instron UTM in accordance with ASTM D2256 and ten observations of breaking extension for each quality were recorded. As jute fibre possesses inherent variability in length and thickness, the properties of jute yarn vary widely for a particular quality [19]. The same variations in the breaking extension of jute ply yarn were also observed in this case, and accordingly, the Symmetric Trimming methodology was used with the removal of the top and bottom 10% of the test data [20,21].

Minitab® 21.4.2 statistical software was used for the CART regression algorithm to get regression decision trees. In the model, 67% of test data was used to train the machine while the remaining 33% of data was used for testing the model. The decision tree that lies within 1 standard error and has a maximum coefficient of determination (R^2) was considered an optimal tree for decision-making.

RESULTS AND DISCUSSION

Out of 216 test data of plied yarn tenacity considered for the model after the removal of 10% top and bottom outliers from 270 observations, 146 random observations were used for training the CART regression model and the remaining 70 observations were used for testing the model accuracy. The response information received after training and testing the model is given in Table 3.

Table 3. Model response information

Data Set	Number	% of total	Breaking extension of ply yarns						
			Mean	SD	Min	Q1	Median	Q3	Max
Training	146	67.6	2.10	0.40	1.58	1.85	1.95	2.21	3.50
Test	70	32.4	2.06	0.36	1.67	1.85	1.92	2.20	3.21

Model Validity and Accuracy of Prediction:

The accuracy of the model was analysed from the output coefficient of determination (R^2), mean absolute per cent error (MAPE) as well as scatter plots of response fits vs. actual values for both training and test data (Figure 1). From the model summary given in Table 4, it can be seen that the regression model has a high coefficient of determination (R^2) level of 0.95 for training data, thus showing the high accuracy of the model. Moreover, the R^2 value of 2 for test data signifies that the model is efficient enough to predict response for new yarn parameters. Also, MAPE values show that

the training and test data have only a 3% and 4% ratio between the fitted error and the actual value across all cases.

Table 4. Model summary

Statistics	Training	Test
R-squared	0.95	0.92
Mean absolute per cent error (MAPE)	0.03	0.04

Moreover, as can be seen from the scatter plot in Figure 1, both the test and training data points are relatively close to the calculated line, which denotes an equal amount of actual value and response value. Furthermore, identical scattering patterns between the training and test sets imply that the tree's performance on fresh data is comparable to its performance on training data.

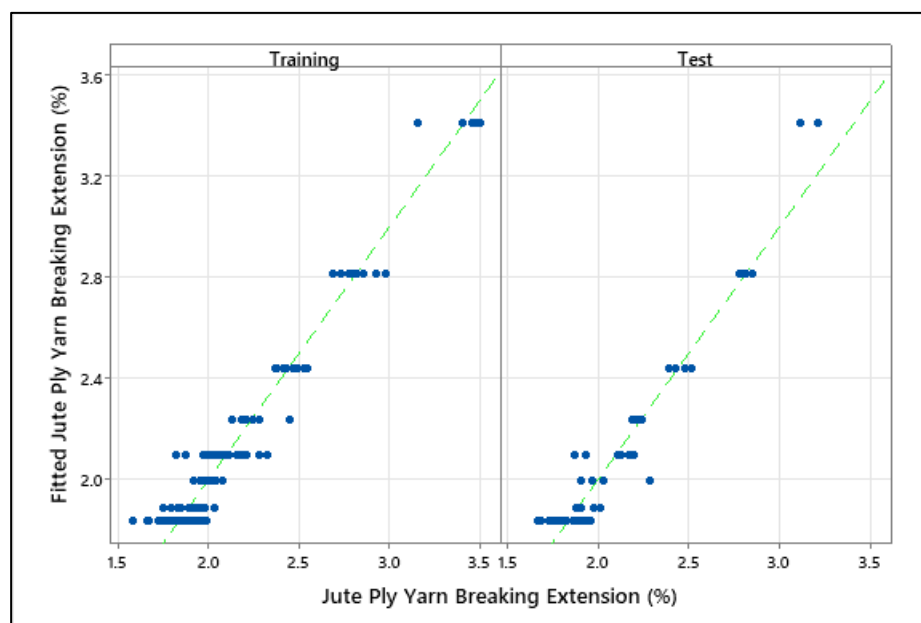


Figure1. Scatterplot of response fits vs. actual values

Selection of Optimal Decision Tree:

The model output shows many decision trees with varied numbers of terminal nodes ranging from 2 to 25. Graph showing the number of terminal nodes vs. coefficient of determination (R^2) is given in Figure 2, of which the decision tree with eight terminal nodes shows the maximum coefficient of determination within 1 standard error. Accordingly the same was considered for optimizing the three predictors.

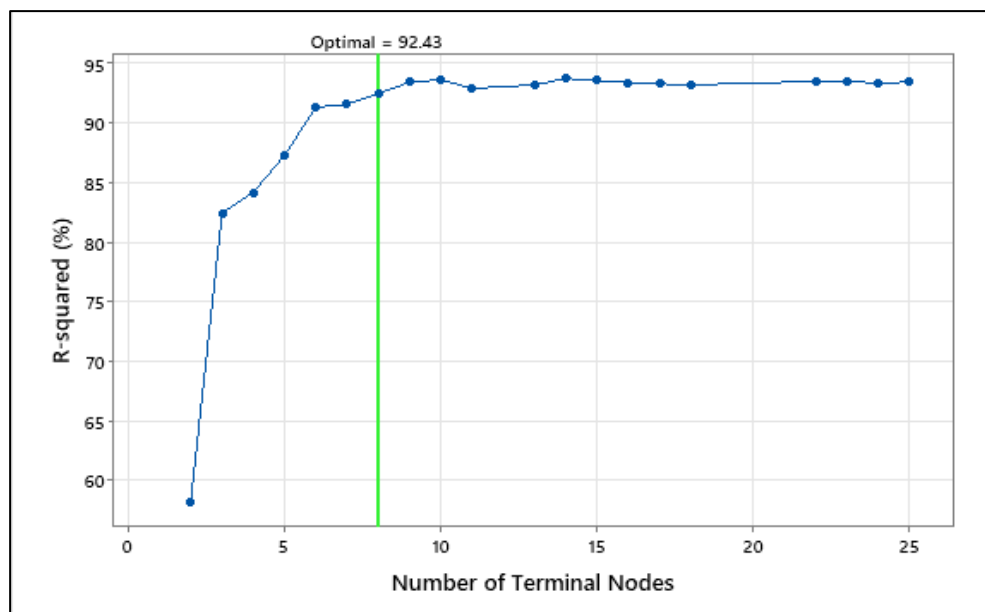


Figure 2. Coefficient of determination vs. number for terminal nodes

Variable Influence and Optimization of Jute Ply Yarn Breaking Extension:

Figure 3 shows the output 8-node regression-based decision tree. The root node N1 shows the average breaking extension of all the 146 training data and branched into N2 and N4 nodes according to the decision rule of many plies in the yarn. These nodes are then again sub-branched into various nodes and terminal nodes based on the decision rule of many plies, ply to single twist ratio, and single yarn twist factor.

From the decision tree, it can be seen that the average value of breaking extension for 2 and 3-ply yarn is 1.90 (node N2) and the same for 4-ply yarn is 2.50 (node N4). Again when node N2 is divided downstream according to many ply, it provides terminal nodes TN2 for 2 ply yarn and TN3 for 3 ply yarn which show average breaking extension values of 1.89 and 2.10 respectively. Thus, when TN2, TN3 and N4 are compared, it is evident that the average breaking extension of 2-ply, 3-ply and 4-ply jute yarns are 1.89%, 2.10% and 2.50% respectively. These indicate that the breaking extension of jute ply yarns increases with the increase in the number of plies.

When ply to single yarn twist ratio is considered as a predictor, it can be seen from TN1, N3, N5 and N7 of the decision tree that P:S of 0.80 is a decisive value; breaking extension of jute ply yarns becomes significantly low below that P:S and significantly high above it. This may be due to the higher obliquity of single yarns in the ply due to the higher ply to single twist ratio which may contribute to higher breaking extension of the ply yarn. The same is also evident from the breaking extension values in the terminal nodes TN4 and TN5.

From N6, TN6, TN7 and TN8, which are branched based on the decision rule of single yarn twist factor, it can be seen that a single yarn twist factor of 26 is a decisive figure. Jute ply yarns made out of higher singles' twist factor show high ply breaking extension.

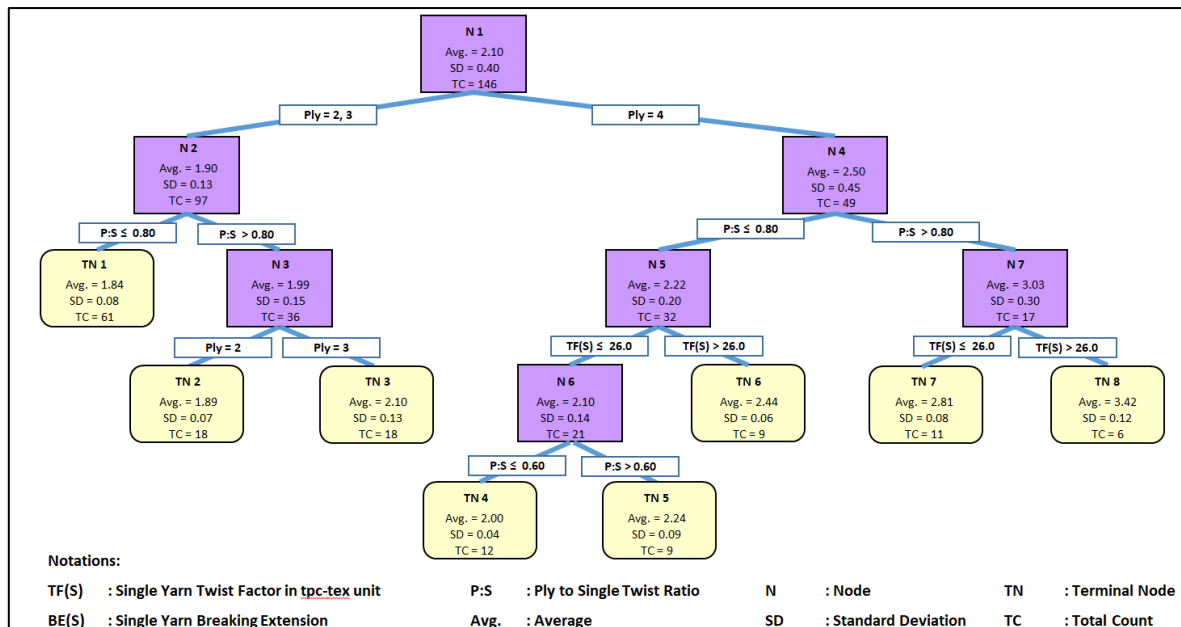


Figure 3. 8 node regression-based decision tree for optimization of jute ply yarn breaking

The boxplot shown in Figure 4 provides levels of breaking extension for each terminal node where terminal node ID 8 (i.e. TN8) provides the highest level of breaking extension among all experimental varieties and TN1 shows the least. Thus, this plot may be used to set machine and process parameters to achieve a desired level of breaking extension of jute ply yarn.

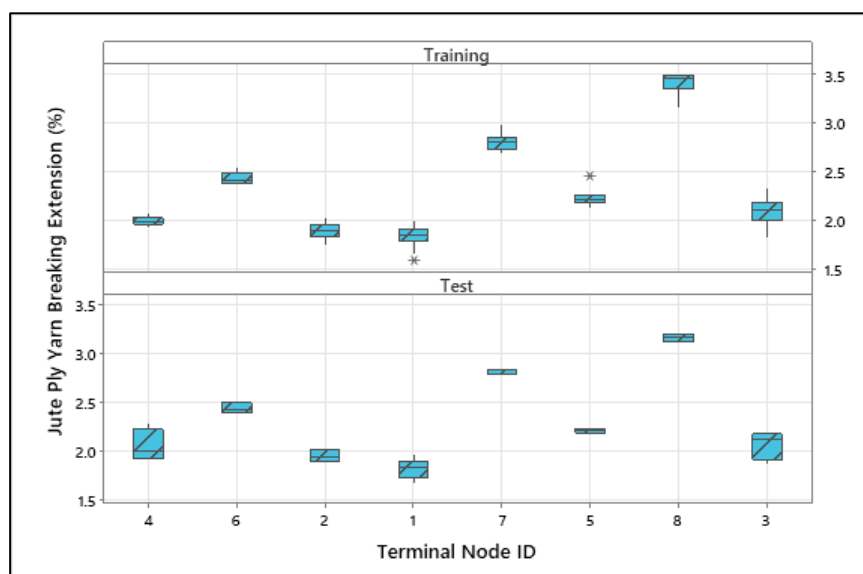


Figure 4. Boxplot of ply yarn breaking extension for each terminal node

Using the decision tree and the boxplot, the following optimizations are made for various ranges of ply-breaking extension –

- A 2-ply jute yarn always shows a breaking extension of less than 2.0%, irrespective of other process parameters.
- When one desires to produce jute ply yarn having breaking extension between 2.0 to 2.25%, the same can be achieved from 3-ply jute yarn having P:S 0.80 – 0.90. The same range of breaking extension is also achievable by using 4-ply jute yarn, but in that case, the single yarns should have a twist factor below 26 and ply to single twist ratio should be kept within 0.50 – 0.80.
- Jute ply yarn with breaking extension in the range of 2.25 – 2.50% may be achieved in 4-ply yarn by using singles' having a twist factor more than 26 and twisted using a P:S between 0.50 – 0.80.
- If 4-ply jute yarn is made out of slightly low twisted singles ($TF < 26$) but ply to a single twist ratio above 0.80, the resultant ply yarn may show breaking extension in the range of 2.5 – 3.0%.
- When the higher breaking extension of jute ply yarns (more than 3.0%) is required, the same may be achieved by using high twisted singles ($TF > 26$) and a high level of P:S (> 0.80)

Relative Importance of the Predictors

Figure 5 obtained from the model shows the relative importance of all three predictors; No. of ply, single yarn twist factor and ply-to-single twist ratio. The figure illustrates that the number of ply is the most significant parameter (top predictor) of the breaking extension of jute plied yarn followed by ply to single twist ratio which contributes 69.2% concerning the top predictor in determining ply yarn breaking extension. On the other hand, the single yarn twist factor has a 26.5% impact on jute ply breaking extension.

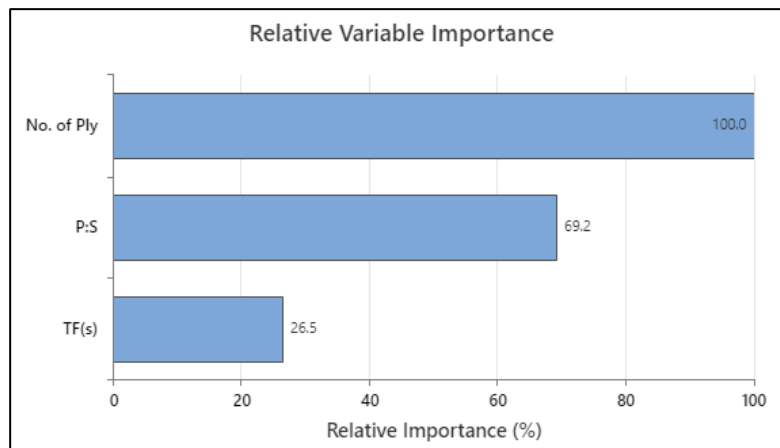


Figure 5. Relative variable importance

Interaction between the Predictors

To determine the interaction between the variables used for this study, multiple regression analysis with response optimisation was done and given in Fig. 6. It is observed that among the three variables considered in the study, the interaction between single yarn twist factor and No. of ply is significant, as the slope of each of the mean BE(P) lines is different from the other. Similar interaction has also been observed between ply to single twist ratio and No. of ply. However, no interaction between the single yarn twist factor and ply-to-single twist ratio has been observed.

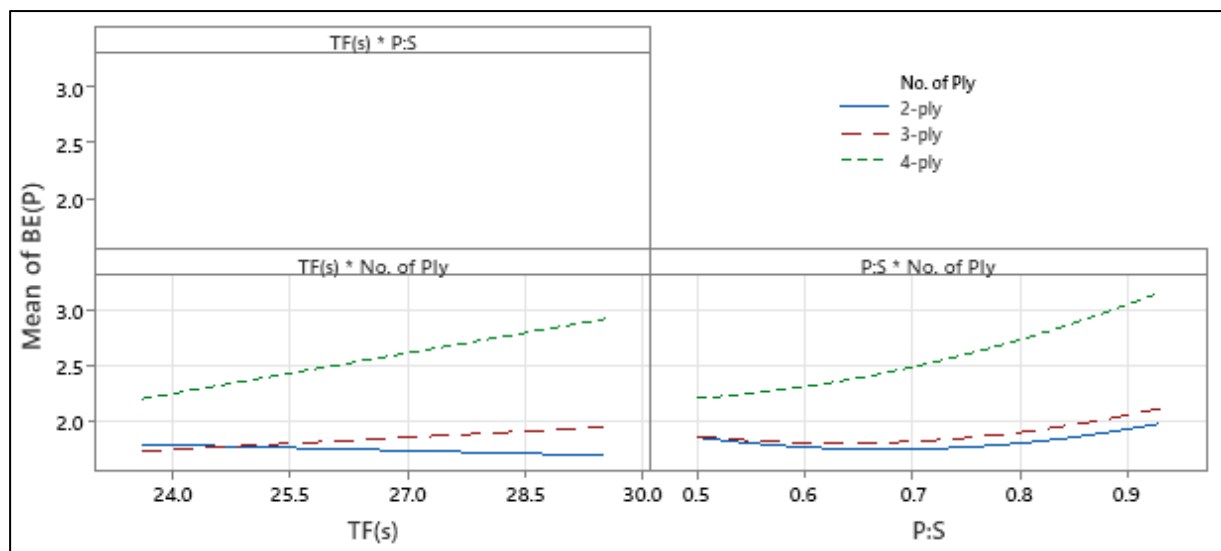


Figure 6. Variable interactions plot for ply yarn breaking extension

CONCLUSION

From this study, it can be concluded that the classification and regression tree (CART) based machine learning may be used to optimise jute ply yarn process parameters to achieve various levels of desired

breaking extension of the ply yarn. From the study, it is observed that the breaking extension of jute ply yarn is influenced by the number of plies used, single yarn twist factor and ply-to-single twist ratio, where the relative importance of many plies is the most followed by ply-to-single twist ratio. The study also shows that apart from the individual influence of the above variables, the breaking extension of jute ply yarn is significantly influenced by the interaction between the single yarn twist factor and many plies as well as the interaction between ply to single yarn twist ratio & number of ply.

The following optimised parameters were thus achieved from the study for various levels of jute ply yarn breaking extension:

- Breaking extension of less than 2.0% was achieved from 2-ply jute yarn, irrespective of other process parameters.
- Breaking extension between 2.0 to 2.25% was achieved in 3-ply jute yarn having ply to single twist ratio between 0.80 – 0.90. The same range of breaking extension was also observed in the case of - ply jute yarn when single yarns' having twist factor below 26 tpc-tex unit were used and ply to single twist ratio was kept within 0.50 – 0.80
- Jute ply yarn breaking extension in the range of 2.25 – 2.50% was achieved in 4-ply yarn having a twist factor of more than 26 and twisted using a P:S between 0.50 – 0.80.
- 4-ply jute yarn made out of slightly low twisted singles (TF < 26) but ply to single twist ratio above 0.80 showed breaking extension in the range of 2.5 – 3.0%.
- The maximum level of breaking extension of jute ply yarn was observed when the same was made out of high twisted singles (TF > 26) and a high level of P:S (>0.80).

Author Contributions

Conceptualization – Paul P; methodology – Paul P, Mukhopadhyay A; formal analysis – Paul P, Mukhopadhyay A; investigation – Paul P; resources – Paul P; writing-original draft preparation – Paul P, Mukhopadhyay A; writing-review and editing – Paul P; visualization – Paul P; supervision – Mukhopadhyay A. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

Funding

This research received no external funding.

Acknowledgements

The authors sincerely acknowledge the support of the Indian Jute Industries Research Association, Kolkata, India for providing a facility for sample preparation and testing.

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