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# Prediction of Polyester/Cotton Ring Spun Yarn Unevenness Using Adaptive Neuro Fuzzy Inference System

Samson Rwawiire, Allan Kasedde, Ildephonse Nibikora, George Wandera
Textile and Ginning Engineering
Busitema University
Uganda
rsammy@eng.busitema.ac.ug

**ABSTRACT**

*Yarn produced from a series of experiments carried out at Southern Range Nyanza Limited (SRNL) in Jinja – Uganda was used in developing an Adaptive Neuro-Fuzzy Inference System (ANFIS) model to probe the yarn unevenness of a polyester/cotton (65:35) blend. Blending was carried out at the draw frame. Parameters which are functions of yarn unevenness such as yarn count, spindle speeds and yarn twist were used as inputs for the ANFIS model. Coefficient of Variation (CV%) was used as a measure of yarn unevenness, the output of the model. The model had an R-square (R2) of 0.86, Root mean square error (RMSE) of 0.65 and SSE of 10.86, therefore rendering the ANFIS model a success and superior to linear regression methods in predicting polyester/cotton yarn unevenness.*

*Keywords: Prediction, Polyester/cotton, Ring spun, Yarn unevenness, ANFIS*



## 1. Introduction

Uganda is one of the leading cotton growing countries in Africa with a growing textile industry which has been existent since 1920s (John Baffes, 2009) The Ugandan textile industry produces both fabrics and yarns which are exported worldwide including the United States of America through the Africa Growth Opportunities Act (AGOA). Due to the increasing market of Ugandan textile products because of the quality of her cotton, spinners are obliged to produce fabrics and yarns which meet international standards majorly the European Union and United States of America.

Besides the agronomic factors which can’t be directly controlled by the industry, the industry related inputs which affect the quality of the produced yarn or fabric are supposed to be optimized. Blending of fibrous materials is a common phenomenon whereby spinners blend different fibers according to a specific blend ratio for the purpose of harnessing robust appearance, comfort and mechanical properties. The most widely used blend in the Ugandan textile industry is of Polyester/Cotton (PC) (Kotb, 2012).

Depending on the end product, yarn obtained from the spinning process may undergo knitting or weaving; due to the complicated nature of fabric production processes, production of a faultless yarn desires the afore-knowledge of the factors influencing production of a perfect fabric. One of the defects in spinning which go on into post spinning processes is yarn unevenness which is a function of fiber strength, fineness, twist, count etc.

### 1.1 Yarn unevenness

The yarn quality is majorly influenced by the yarn structure (yarn count and twist), unevenness (neps, hairiness), physical and mechanical properties (strength and elongation) (Kotb, 2012; Admuthe et al., 2010). Due to the nature of natural fibrous textile materials, there is variability in terms of diameter along the fiber length; this therefore contributes to the variability of yarn fineness. The variability along the yarn is known as yarn unevenness. During weaving and knitting processes, the yarn produced by a spinner undergoes a series of mechanical processes, which require the yarn to bear the different loading conditions it is subjected to; therefore, yarn unevenness can have adverse effects in production such as yarn breakage, fabric faults, uneven dye penetration etc. Statistical methods are used to probe yarn unevenness, therefore irregularity percentage (U%), which is the materials percentage deviation in mass of unit length and the coefficient of mass variation percentage (CV%) calculated as shown in equation (1) are widely accepted.

$$\mathrm{C.V\%} = \frac{\mathrm{StandardDeviation}}{\mathrm{Average}} \mathrm{x}100 \qquad (1)$$

### 1.2 Soft Computing

Modeling textile properties using soft computing techniques such as fuzzy logic in combination with Neuro-computing and genetic algorithms has attracted a lot of research and are the front seat drivers for soft computing (Babay et al., 2005; Demiryurek & Koc, 2009; Majumdar, 2010; Admuthe et al., 2010). Majumdar, 2010 showed that Artificial Nueral Networks (ANNs) had a problem of black boxing; they do not create a relationship between input and output parameters. Jang (1993) indicated that Fuzzy logic had no standard way for transforming human knowledge or experience into the rule base of a Fuzzy Inference System (FIS). There is therefore a need to map Membership Functions (MFs) to minimize output errors and measure or maximize the performance index. ANFIS serves as a basis for constructing Fuzzy If-then rules with appropriate membership functions to generate a stipulated input-output. N.A. Kotb, 2012 developed a linear regression model for polyester/cotton from fiber types and yarn structures. However, like other researchers predicted (El Mogahzy et al., 1990; Chanselme et al., 1997) linear regression performance is lower than that of ANFIS models. Ke-Zhang & Ning, 2000; Cyniak et al., 2006 studied the influence of several parameters, drafting system, roving hank, Break draft, traveler weight, on yarn unevenness, fiber properties on yarn unevenness. Assad & Muhammad, 2012; Jerzy & Tadeusz, 2006 showed that yarn count and twist have a great influence on unevenness whereas EL, 2009 and Chaudhuri, 2003 suggested the significant influence of spindle speed on yarn unevenness.

Adaptive Neuro-Fuzzy Inference System (ANFIS) has shown superiority in modeling textile process as compared to its counterparts like Artificial Neural Networks (ANNs) and fuzzy logic. (Majumdar, Ciocoiu & Blaga, 2008).

The purpose of this research is therefore to create an Adaptive Neuro-Fuzzy Inference System (ANFIS) model to predict yarn unevenness for the first time using input data of spindle speed, yarn twist and yarn count.

## 2. Materials and Methods

A series of experiments were performed on various ring frame machines operating under various control parameters. Yarn was produced from polyester/cotton with a blend ratio 65:35. Yarn blending was carried out on the draw-frame. Roving was produced from a speed frame and resultant output tested. Draw-frame sliver and roving properties are presented in Table 1. Coefficient of Variation (CV) and Irregularity (U) tests were carried out on an Uster tester 3, v2.50.

**Table 1. Materials and their various properties used to produce yarn**

<table>
<tr><td rowspan="4"></td><td>Material</td><td>Hank</td><td>U%</td><td>CV%</td><td>COUNT</td><td>ΔU%</td><td>ΔCV%</td></tr>
<tr><td rowspan="3">ROVING</td><td>PC 65:35 (combed)</td><td>0.83</td><td>4.46</td><td>5.64</td><td>22</td><td>5.55</td><td>7.18</td></tr>
<tr><td>PC 65:35 (carded)</td><td>0.13</td><td>5.06</td><td>6.28</td><td>22</td><td>6.63</td><td>9</td></tr>
<tr><td>PC 65:35 (Combed)</td><td>0.12</td><td>1.47</td><td>1.86</td><td>0.83</td><td>2.99</td><td>3.78</td></tr>
<tr><td>DRAW FRAME</td><td>PC 65:35 (Carded)</td><td>0.12</td><td>2.36</td><td>2.95</td><td>0.13</td><td>2.1</td><td>3.33</td></tr>
</table>

A fractional factorial experiment design was used to obtain data for training and validating the ANFIS model. Experimental design was based on, Jiju and Nick (1998). Table 2 shows data obtained during the experimentation and testing process. Testing was carried out at room temperature 27ºC and pressure 76mm/Hg. Number of trails for the factorial experiment is given by N= $2^K$ where K is number of control parameters having two levels of interaction. Twenty-eight data sets were used for training the ANFIS. Table 2.shows the results from the experimentation.

**Table 2. Mean measured values**

| TRAIL NO. | COUNT | SPINDLES | TWIST | ACTUAL CV% |
|---|---|---|---|---|
| **1** | 15 | 10908 | 18.28 | 13.10 |
| **2** | 15 | 8294 | 18.28 | 13.21 |
| **3** | 15 | 10908 | 15.68 | 11.32 |
| **4** | 15 | 8294 | 16.12 | 12.60 |
| **5** | 15 | 8294 | 15.68 | 12.20 |
| **6** | 15 | 8294 | 15.68 | 13.39 |
| **7** | 20 | 10500 | 17.62 | 11.82 |
| **8** | 20 | 10500 | 17.62 | 11.84 |
| **9** | 22 | 11200 | 20.72 | 11.63 |
| **10** | 22 | 11200 | 18.28 | 11.5 |
| **11** | 22 | 13100 | 16.12 | 13.29 |
| **12** | 22 | 11200 | 16.12 | 15.23 |
| **13** | 22 | 13100 | 15.23 | 13.20 |
| **14** | 22 | 11200 | 15.23 | 12.82 |
| **15** | 27 | 8294 | 18.28 | 15.88 |
| **16** | 27 | 11500 | 18.28 | 12.91 |
| **17** | 27 | 11500 | 18.28 | 14.36 |
| **18** | 27 | 10500 | 18.28 | 13.51 |
| **19** | 27 | 8294 | 18.28 | 14.21 |

| | | | | |
|---|---|---|---|---|
| **20** | 27 | 12110 | 21.12 | 15.37 |
| **21** | 30 | 13100 | 20.72 | 19.13 |
| **22** | 30 | 10500 | 20.72 | 14.38 |
| **23** | 30 | 10500 | 20.72 | 15.28 |
| **24** | 30 | 8294 | 20.72 | 14.22 |
| **25** | 30 | 8294 | 18.68 | 13.38 |
| **26** | 30 | 8294 | 18.68 | 14.79 |
| **27** | 30 | 8294 | 18.68 | 16.21 |
| **28** | 30 | 13100 | 15.23 | 14.61 |

## 2.1 Fuzzy Inference System (FIS) properties

Fuzzy logic is based on the principle of fuzzy sets. A fuzzy set is one without a crisp, clearly defined boundary (Jang 1993). It can contain elements with only a partial degree of membership. In fuzzy logic, the membership of a value becomes a matter of degree. A fuzzy set is an extension of a classical set. If $U$ is the universe of discourse and its elements are denoted by $x$, then a fuzzy set '$A$' in $U$ is defined as a set of ordered pairs.

$$A = \{x, \mu_A(x) | x\ X\} \qquad (2)$$

Where, $\mu_A(x)$ is the Membership Function (MF) of $x$ in $A$. The membership function maps each element of $U$ to a membership value between 0 and 1.

A Takagi-Sugeno FIS model was used to train the network. 2-4-3 generalized bell membership functions (gbellmf) were selected for the FIS as they yielded the least training error. Figure 1 shows a plot of the membership functions. The parameters associated with the membership functions change through the learning process until optimum ones are obtained. A gradient vector technique facilitates the computation of these parameters (or their adjustment) as in Artificial Neural Networks. A gradient vector provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. When the gradient vector is obtained, optimization routines can be applied in order to adjust the parameters to reduce error measure.

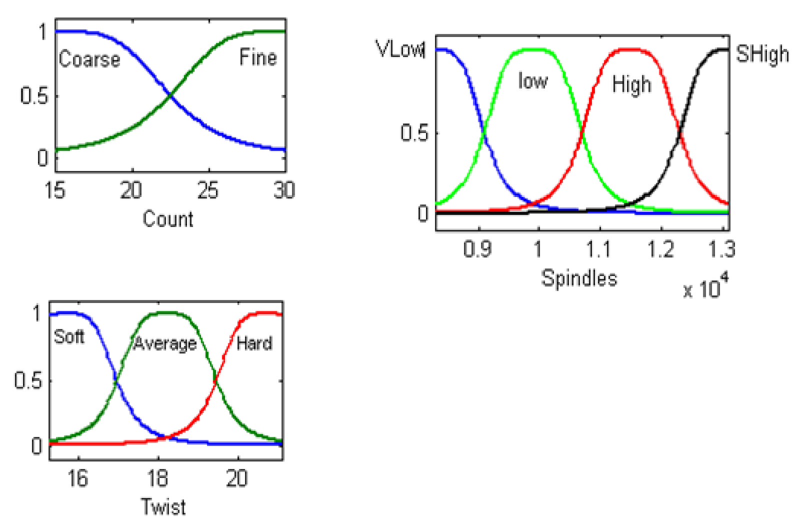


**Figure 1. Input Membership Functions a) Yarn count, b) Spindle speed c) Twist**

Figure 2 shows a plot of the system model. The system model a diagrammatical illustration of how an Adaptive Neural fuzzy inference system (Model1) is applied to the three inputs, count, spindle and twist to produce the predicted output C.

### 2.2 Fuzzylinguistic Rules

After determining the fuzzy set and the corresponding membership functions, linguistic terms are then used to create the corresponding fuzzy rules. For a 2-4-3 gbellmfs, the following linguistic terms where used.

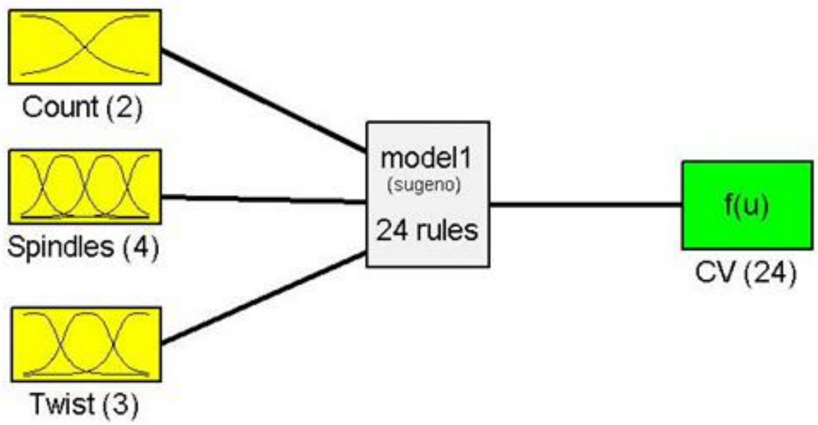


**Figure 2. System model: 3 inputs, 1 output, 24 rules**

**Table 3. Linguistic terms for each membership function**

| COUNT | SPINDLE SPEED | YARN TWIST |
|---|---|---|
| Coarse | Very Low | Soft |
| Fine | Very High | Hard |
| | Low | Average |
| | High | |



Using the fuzzy sets and linguistic terms, a set of 'If-Then' Rules are created. Fuzzy rules provide a quantitative reasoning that maps input fuzzy sets with output fuzzy sets.A fuzzy rule base consists of a number of fuzzy rules. For example in case two inputs A and B with an out CInput Membership Functions, $A, x_i$ $B, y_i$, Output membership functions $c, z_i$

Where $x, y, z$ are variables representing $A, B, C$ linguistic terms. Fuzzy 'If-Then' can be created as:

$$If\ A\ is\ x\ and\ B\ is\ y\ then\ C\ is\ z$$

Twenty-four 'If-Then' rules were trained. Linguistic rules help in understanding the relationship between the various input parameters and the output. Table 4 shows the rules that were used to train the ANFIS model.

**Table 4. Linguistic ‘If-Then’ rules used for training ANFIS**

| RULE | COUNT | SPINDLE SPEED | YARN TWIST | CV-MF |
|---|---|---|---|---|
| 1 | Coarse | V.Low | Soft | 1 |
| 2 | Coarse | V.Low | Average | 2 |
| 3 | Coarse | V.Low | Hard | 3 |
| 4 | Coarse | Low | Soft | 4 |
| 5 | Coarse | Low | Average | 5 |
| 6 | Coarse | Low | Hard | 6 |
| 7 | Coarse | High | Soft | 7 |
| 8 | Coarse | High | Average | 8 |
| 9 | Coarse | High | Hard | 9 |
| 10 | Coarse | V.High | Soft | 10 |
| 11 | Coarse | V.High | Average | 11 |
| 12 | Coarse | V.High | Hard | 12 |
| 13 | Fine | V.Low | Soft | 13 |
| 14 | Fine | V.Low | Average | 14 |
| 15 | Fine | V.Low | Hard | 15 |
| 16 | Fine | Low | Soft | 16 |
| 17 | Fine | Low | Average | 17 |
| 18 | Fine | Low | Hard | 18 |
| 19 | Fine | High | Soft | 19 |
| 20 | Fine | High | Average | 20 |
| 21 | Fine | High | Hard | 21 |
| 22 | Fine | V.High | Soft | 22 |
| 23 | Fine | V.High | Average | 23 |
| 24 | Fine | V.High | Hard | 24 |

### 2.3 ANFIS Architecture

Data obtained from the experiments was divided into two sets: Checking and Training data. Twenty sets of data where used for checking the network while eight data sets where used to check the network. Training of the model was carried out for ten epochs. A hybrid-training algorithm was used to train the network. An average error of 0.403 and 1.702 where obtained for the training and checking data sets respectively.

Figure 3shows the resulting ANFIS structure for a model having three inputs, 2-4-3 input membership functions (*Inputmf*) and having twenty-four rules (rules). The lines show how each of the rules are applied to the membership functions to form an output membership function (*Outputmf*). An output is generated from the inference process as shown in the structure below.

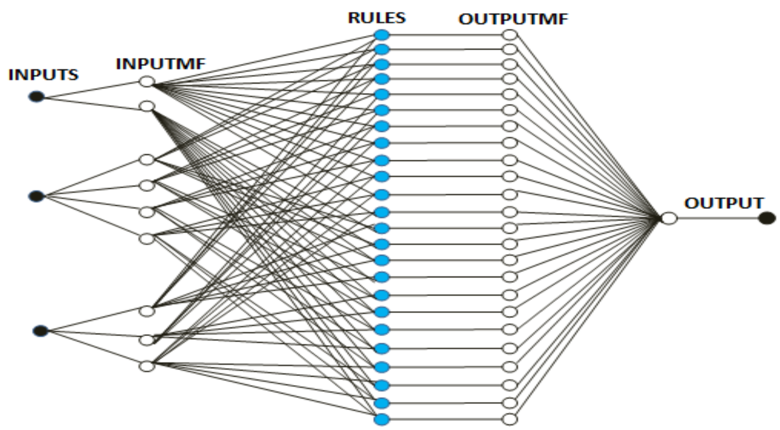


**Figure 3. ANFIS Structure; three inputs (Count, Twist and Spindle speed), one output (Yarn unevenness), Twenty-four rules**

Figure 3 shows the various layers of the ANFIS and how a fuzzy rule set is applied to give result a given output.

For example a rule may be given by:

If count (A) is fine ($x_1$) and Speed (B) is low ($y_1$) and twist (C) soft ($z_1$) then:

$$f_1 = px_1 + qy_1 + rz_1 + s \qquad (3)$$

The rules can be created for each of the inputs, A, B and C.

**Layer 1 (*Inputmf*)**
Every node in this layer is adaptive node with a node function as given below:

$$O_{1i} = \mu_{xi}(A)\ (i = 1,2)\ or\ O_{1i} = \mu_{yi}(B)\ (i = 1,2,3,4)\ or\ O_{1i} = \mu_{zi}(C)\ (i = 1,2,3) \qquad (4)$$

$x_i$, $y_i$, $z_i$, are linguistic terms like (coarse, fine) associated with each of the nodes. The output of this layer is the membership grade of a fuzzy set

**Layer 2**
It consists of a fixed node (not shown in Figure 4) the output of the node is a product of all incoming signals before rules are applied as shown in the following function:

$$O_{2i} = \mu_{xi}(A)\, \mu_{yi}(B)\, \mu_{zi}(C) = w_i \qquad (5)$$

Each output of this layer represents the firing strength of each rule. In general any T-norm operator that can perform fuzzy AND can be used as a node function in this layer

**Layer 3, (Rules)**
Every node in this layer is a fixed node. The *i* th node in this layer calculates the ratio of the *i* th rules firing strength to the sum of all firing strength. The output of this layer is called the normalized firing strength.

$$O_{3i} = \frac{w_i}{w_1+w_2+w_3} = \overline{w_i} \qquad (6)$$

**Layer 4 (*Outputmf*)**
Every node in this layer is an adaptive node with a node function

$$O_{4i} = \overline{w_i} f_i = \overline{w_i}(p_i(A) + q_i(B) + r_i(C) + S_i) \qquad (7)$$

$\overline{w_i}$ , is the normalized firing strength from layer 3, P,q,r,s are set parameters and are referred to as the consequent parameters.

**Layer 5**
The layer after the rules is a fixed node and computes the overall output as a summation of all incoming signals:

$$O_{5i} = \sum \overline{w_i} f_i = \frac{\sum w_i f_i}{\sum w_i} \qquad (8)$$

## 3.0 Results and Discussion

### 3.1 Prediction performance and model validation

Most of textile processes are inexact, computationally hard with no known algorithm to predict them, therefore this warrants for application a higher order prediction model such as ANFIS to study the processes compared to other soft computing techniques. Figure 5 and 6 show plots of actual and predicted values for the ANFIS and linear regression for polyester cotton yarns. Figure 7 and 8 show model validation using $R^2$which provides a measure of how well observed outcomes are replicated by the model, as the proportion of total variation of outcomes explained by the model. ANFIS model had a $R^2$ of 0.86 and RMSE of 0.65 compared to linear regression which had an $R^2$ of 0.41 and RMSE 1.33.

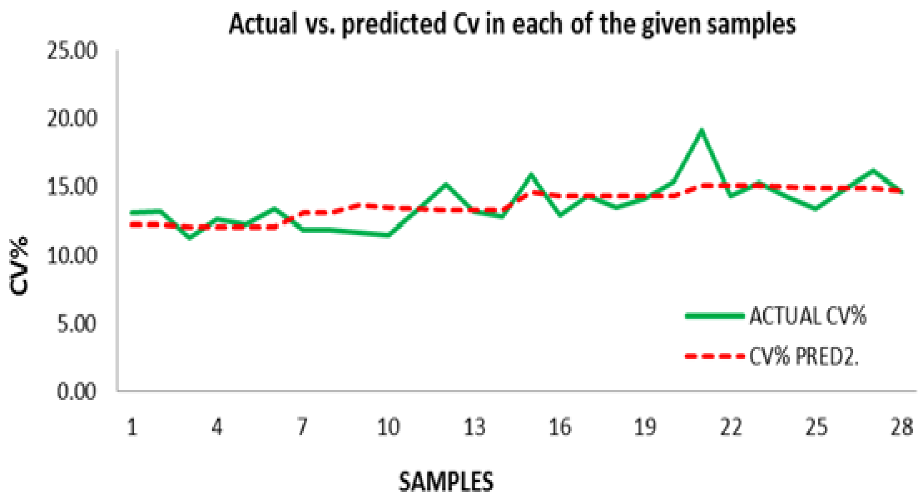


**Figure 5. Prediction performance for each sample-linear regression model**

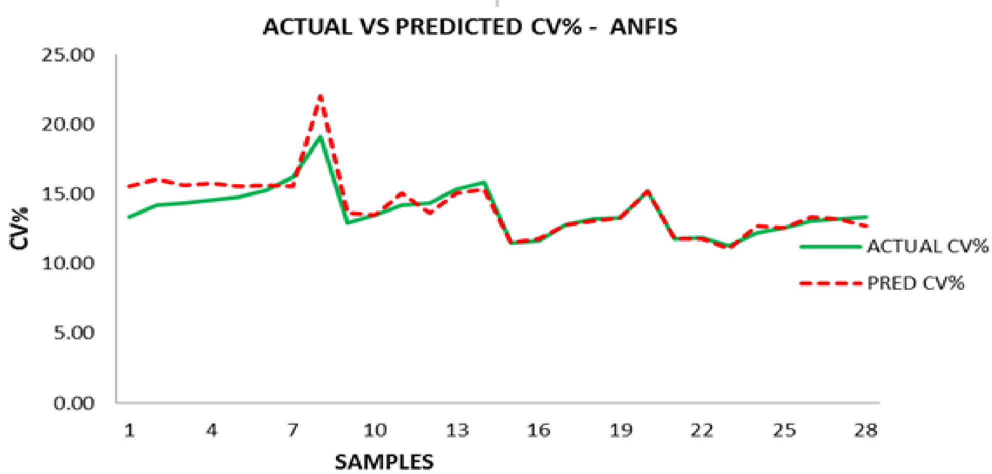


**Figure 6. Prediction performance for each sample - ANFIS model**

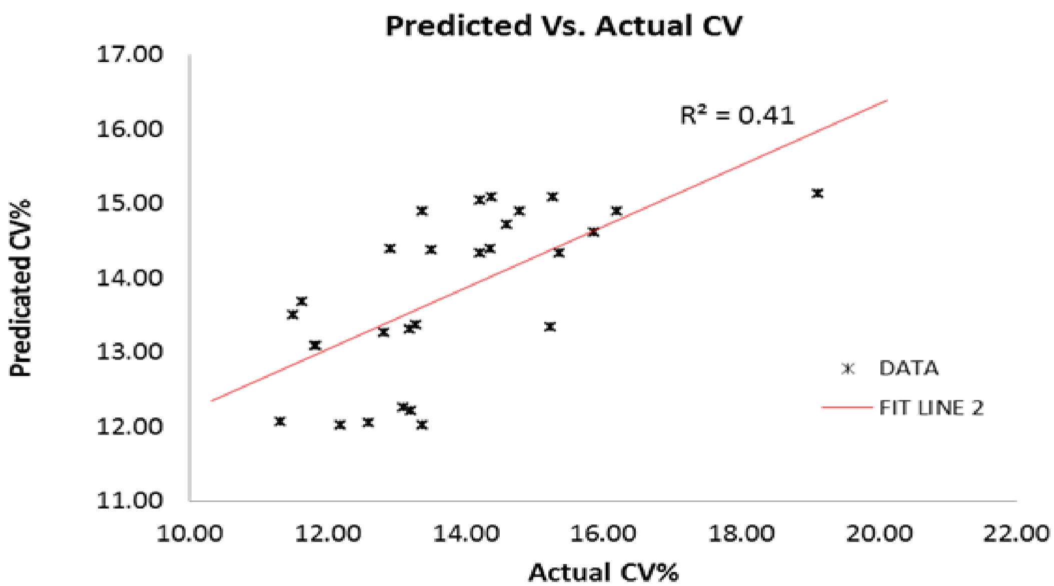


**Figure 7. Predicted Vs. Actual CV%-linear regression**

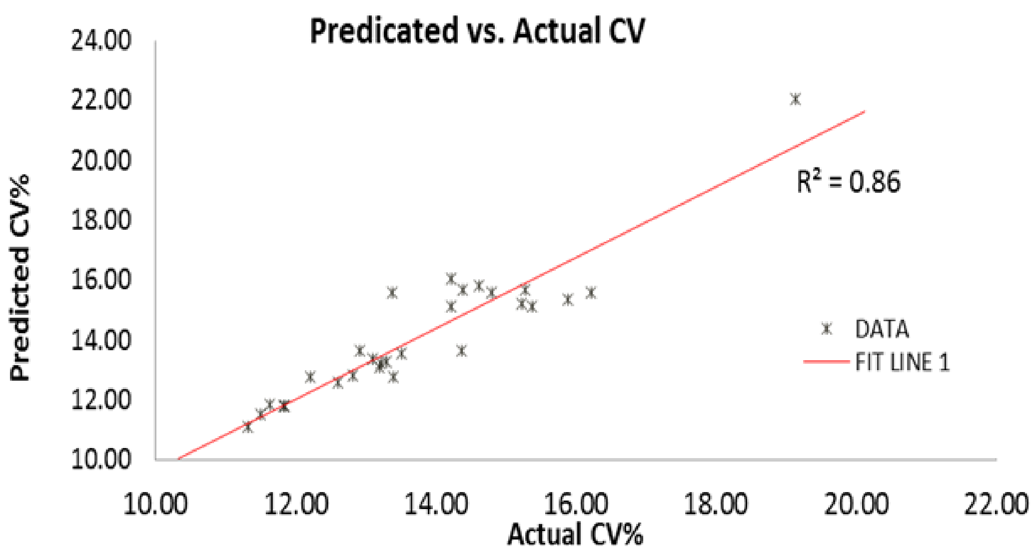


**Figure 8. Predicted Vs. Actual CV%-ANFIS**

### 3.2 Data fit comparisons of models

Prediction performance of the model was compared against that of linear regression as shown in Table 5. The ANFIS model had an $R^2$ of 0.86 compared to 0.41. Table 5 shows a summary of the goodness fit for both the ANFIS and obtained linear regression model. Figures5 and 6 show plots of the actual and predicted coefficient of variation for linear regression and ANFIS model. Plots of the ANFIS results show better performance as can be observed. A value of R2 closer to one meant a better fit for ANFIS.

The R2 from the ANFIS showed that the model could account for 86% of the variations in the data about the average, which is good fit. While regression could only account for 41%

For ANFIS the 0.14 (14%) remaining can be ascribed to both assignable causes like processing parameters and conditions of both spinning and speed-frame and random causes like inherent fiber diameter variations.

**Table 5. Descriptive statistics of all models for the prediction of yarn unevenness**

| | **LINEAR REGRESSION** | | | | **ANFIS** |
|---|---|---|---|---|---|
| Regression Coefficients | $X_1$<br>7.31 | $X_2$<br>0.61 | $X_3$<br>0 | C<br>0.11 | |
| RMSE | 1.33 | | | | 0.65 |
| SSE | 46.47 | | | | 10.86 |
| $R^2$ | 0.41 | | | | 0.86 |
| Adjusted $R^2$ | 0.39 | | | | 0.86 |

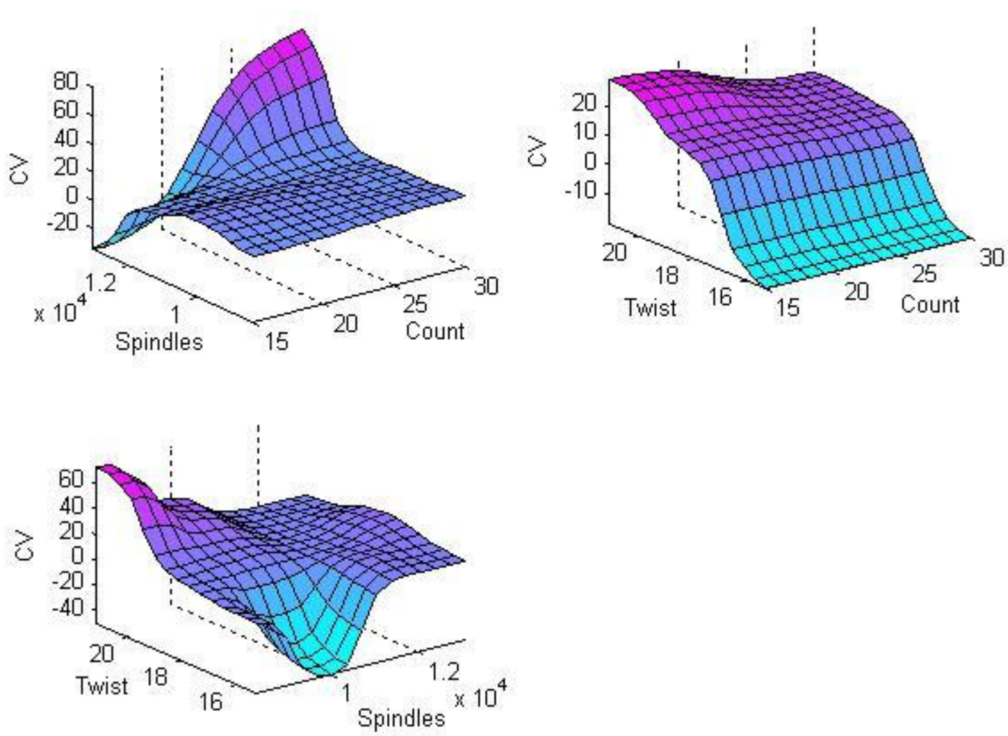


**Figure 4. Surface plots; a) Spindle speed, Count vs. CV b) Twist, Count vs. CV c)Twist, Spindle speed vs. CV**

### 3.3 Influence of inputs on yarn unevenness

From the rules generated by the FIS (4), influence of each of the inputs can be shown. From rule one, if count is coarse, spindle speed is very low and yarn twist is soft, then yarn unevenness will be given by output membership function one. If count is coarse, spindle speed is Very low and count is average then spindle speed is given by membership function 2. If spindle speed is very low, count is coarse, and yarn twist is hard, then yarn unevenness will be given by membership function 3. If count is coarse and spindle speed is low but yarn twist is soft then yarn unevenness will be given by the membership function 4 Similar relationships can be drawn from each of the rules presented in the Table 4**.** The relationship created by each of the rules between membership functions can be converted into surface plots to best visualize the interaction of each of the inputs on the output. Figure 4 shows surface plots that relate inputs to the outputs

## 4. Conclusion

This research studied the influence of spindle speed, yarn twist, and yarn count on polyester/cotton (65:35) yarn unevenness. Findings showed that an increase in yarn twist increased yarn unevenness while increase in yarn count led to a reduction in yarn unevenness. This was consistent with findings of other publications elsewhere (Majumdar, 2010; Admuthe et al., 2010; Chattopadhyay, 2007; Cyniak et al., 2006).

From the summary table 5, it can be concluded that ANFIS performed better than its linear regression counterpart did as it had a better $R^2$= 0.86 and RMSE=0.65 and SSE=10.86. A higher $R^2$ for ANFIS also signified a stronger relationship between predicted values and the actual value and so a better predictor of yarn unevenness. It can be concluded that the ANFIS model for predicting yarn unevenness was successfully modeled.

The inferior prediction of the linear model is due to the fact that it has assumptions which can't govern some real life environments in the textile industry. The ANFIS model proved to be superior because it's able to model inexact computational problems with various formations. Secondly, the utilization of the matlab code is beneficial because it can be easily integrated into other machine computer control programs.

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