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# Analytical Study of Factors Affecting Yarn Coefficient of Mass Variation Estimated by Artificial Neural Networks

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**Abstract**

Manufacturers aim to achieve the optimal quality, therefore, the evaluation of yarn parameters and the determination of factors that influence yarn quality is of great importance. The yarn coefficient of mass variation (CVm%) reflects the irregularity of the yarn which reflects the yarns' quality. This study investigates the parameters affecting the CVm% that was previously estimated using image processing and artificial neural networks. Yarn images and data were used as inputs into neural networks and CVm% was evaluated. In addition, two statistical methods were used which were: correlation and ANOVA to research the effect of yarn count, twist factor, blend ratio, and cotton type on CVm%. It was found that the yarn count and twist factor were the highest correlated parameters regarding CVm%.

*Keywords*: Yarn coefficient of mass variation; Image Processing; Artificial Neural Networks; ANOVA; Correlation

## 1 Introduction

The inspection and monitoring of the product throughout the production is considered a vital operation. Automation can help achieve the required quality standards and can be implemented by utilizing artificial intelligence methods. Classification and identification of textile materials, various quality parameters evaluation, and performance assessment are some of the applications of image processing and neural networks for fibers, fabrics, and yarns.

For Fibers, Kang et al. (2002) used image processing and a backpropagation neural network to identify trash in raw cotton and estimate its effect on the color of cotton, using a color difference equation [1]. Whitelock et al. (2016) employed Image processing to determine foreign materials in cotton, and to find the shape and the color of bark, grass, and leaf particles. Statistical analysis and response screening methods were carried out to separate bark, grass, and leaf particles and determine shape and color factors [2]. In addition, Feng Jia et al. (2016) identified ramie

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and cotton fibers, by analyzing the shape, texture, color, and surface stripes, and employing a backpropagation neural network to distinguish between both types of fibers [3].

Regarding fabrics, Uçar and Ertuğrul (2007) used regression and artificial neural networks to evaluate the fabric surface fuzz of plain knitted fabrics. The segmentation of the fuzz was done by image processing. Bi-variate correlation analysis was utilized to investigate the effect of yarn count, hairiness, and tightness factor on fabric surface fuzz [4]. Xuejuan Kang et al. (2015) combined a 2-D wavelet transform, a gray-level co-occurrence matrix, and Gabor wavelet with a probabilistic neural network to identify plain, twill, and satin fabrics [5]. Furthermore, Kuo et al. (2016) employed wavelet packets and a neural network for knitted fabric inspection. The system was used to classify seven categories; a non-defect and six types of defects, including holes, set marks (coarse fabric), dropped stitches, oil stains, streaks, and tight ends [6].

Shiau et al. (2000) employed a backpropagation neural network to study web images. The system was able to automatically recognize three categories; normal web, nep, and trash, and to determine neps and trash numbers [7]. Semnani et al. (2005) utilized image processing and linear functions to analyze the effect of yarn appearance on the quality of knitted fabrics. Yarn standards and samples were scanned and the images were processed and the yarn core was eliminated. Fabrics samples were processed and faults were detected. neural network linear classifiers were used to classify yarn faults and fabric defects. ANOVA test confirmed that yarn type affects fabric grade significantly [8]. Li et al. (2018) used a two-scale attention model and probabilistic neural networks for the grading of yarn surfaces. Fourier transform and the two-scale attention model were employed to identify yarn features. In addition, global and individual neural networks were used to grade yarns [9].

Gharehaghaji et al. used artificial neural networks and linear regression to estimate the breaking elongation % and strength of core-spun yarns. A backpropagation neural network with two hidden layers was utilized, moreover, two models of MLR used for each property. Correlation coefficient R-value and mean square error were determined [10]. El-Geiheini et al. employed image processing and artificial neural networks to assess yarn tenacity and elongation% for cotton and blend ring-spun yarns. Images of yarn samples were obtained by camera and processed and data vectors were determined and used as the network's inputs. Two backpropagation neural networks were developed in order to model tenacity and elongation% for each yarn type [11].

Khan et al. (2009) evaluated the hairiness of wool worsted-spun yarns with a multilayer neural network. machine settings, yarn parameters, and fiber properties were introduced to the neural network to determine the Uster hairiness index. Multi-variate linear regression was employed, and the mean square error and the correlation coefficient were used to assess the network results [12]. Haghighat et al. (2012) employed multiple linear regression and neural networks to predict the hairiness of polyester/viscose blended yarns. Total draft, roving twist, yarn twist, yarn count, traveler weight, spindle speed, back zone setting, balloon control ring break draft, break draft, drafting system angle, and front roller covering hardness, were investigated and five different hairiness prediction models were developed using both multiple linear regression and artificial neural networks [13].

Jaouadi et al. (2009) investigated real yarn diameter determination for different yarns produced from various raw material, counts, and spinning processes. Images were obtained using a microscope and a camera with the yarn under tension and twist steps were applied. After applying image processing, edge detection was used to measure yarn diameter and an average yarn diameter was calculated [14]. Ünal et al. (2010) researched the retained spliced diameter

(RSD), splicing parameters, and fiber and yarn properties for several yarns. Yarn diameter was measured optically and then a feed-forward network and response surface method were employed. Mean fiber length, fiber diameter, short fiber content, yarn count, yarn twist, opening air pressure, splicing air pressure, and time of splicing air pressure were investigated [15]. Zhong et al. (2015) estimated yarn unevenness by utilizing histogram equalization with a median filtering algorithm. The system utilized image sequences of moving yarn and a projection curve, in order to assess the coefficient of variation of the fiber's diameter [16]. Maliket al. (2016) employed neural networks and linear regression models to predict the evenness and tensile properties of blended yarns. Blend ratios, break draft, twist multiplier, and back roller hardness were studied and three networks for evenness, tenacity, and elongation were developed. The mean absolute errors were derived and compared with the linear regression models [17].

This research was conducted to analyze the factors affecting predicted yarn CVm% for various yarn types, including carded cotton yarns, combed compact yarns, and carded blended yarns, by employing statistical methods which are: correlation and ANOVA analysis.

# 2 Experimental Work

## 2.1 Materials

Samples were collected from a ring spinning and compact spinning factories. Firstly, for the cotton ring-spun yarns, two samples of count Ne 24_100% Sudanese cotton with two twist factors 3.4 and 3.8, two samples of Ne 30 with 100% Sudanese cotton and 100% Benini cotton, and Ne 50_100% Benini cotton were manufactured. Secondly, For the blended ring-spun yarns, Ne 16 (50% Polyester −50% Benini cotton), Ne 20 (50% Polyester −50% Benini cotton), Ne 30 (50% Polyester −50% Benini cotton), and Ne 30 (65% Polyester −35% Benini cotton) were produced. The samples collected from the compact factory consisted of Ne 50 - Giza86, Ne 60 - Giza86, Ne 70 - Giza86, Ne 96 - Giza86, Ne 96 - Giza94, Ne 112 - Giza94.

## 2.2 Methods

In the previous research, three systems were developed to estimate the coefficient of mass variation of the different yarn types. The systems used the blackboard of the appearance tester, a digital camera, and MATLAB 2015 software to process images and data. Image enhancement by Gaussian filtering and scaling were employed and three backpropagation neural networks were developed.

The number of samples for the cotton ring-spun model, blend ring-spun model, and the compact model were 152, 108, 60 respectively. The network consisted of an input layer, two hidden layers with neurons of $(20 \sim -8)$, and an output layer for the coefficient of mass variation. The number of neurons in the hidden layers were set to be twenty and eight, for the first and second layers, respectively, while the output layer contained one output (CVm%) [18].

In this study, statistical measures were conducted in order to investigate the effect of the various parameters which are cotton type, blend ratio, twist factor, and count on the coefficient of mass variation. Correlation and ANOVA tests were carried out on the three systems results.

# 3 Results and Discussion

Three models were built to evaluate the yarn coefficient of mass variation (CVm%) for various yarn types. The following section presents the results achieved from the neural network and the statistical analysis of the outcome.

## 3.1 Artificial Neural Networks Performance

To develop the various models, photographs of the yarn samples were preprocessed and the input vectors for the neural network were defined. The neural network consisted of one input layer, two hidden layers, and an output layer, with one output, which is CVm%. The number of neurons in the first and second hidden layers was set to be twenty and eight, respectively.

The mean absolute errors for the training phase, calculated in order to estimate the overall performance of the CVm%, were concluded to be 0.194, 0.144, 0.046 for the blend yarn model, cotton ring-spun yarn model, and cotton compact yarn model. In addition, the error values of the validation phase were 0.256, 0.197, and 0.116. Fig. 1 displays the networks performance in both phases.

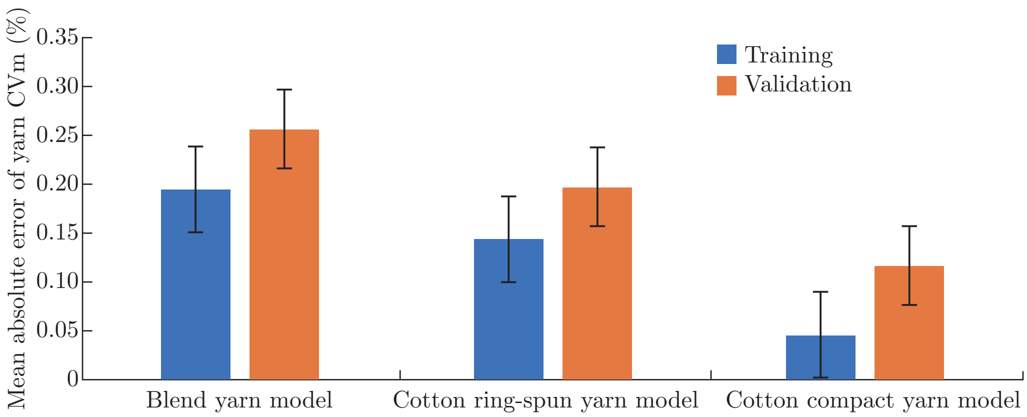


Fig. 1: Training and validation performance of the neural networks for blend yarn model, cotton ring-spun yarn model, and cotton compact yarn model.

## 3.2 Statistical Analysis

In order to determine the effect of yarn count, twist factor, blend ratio, and cotton type on the coefficient of mass variation, first a correlation test was conducted and the ANOVA was carried out. Sections 3.2.1 and 3.2.2 demonstrates the results achieved from the two tests.

### 3.2.1 Correlation

To understand the relationship between the various input parameters and the CVm%, correlation analysis was employed for the three systems.

According to the output data shown in Table 1, yarn count is the highest correlated factor to the yarn coefficient of mass variation followed by the twist factor, but the cotton type has the least effect on it.

Table 1: Correlation outcome for cotton ring-spun yarn

| | CVm% |
|---|---|
| Yarn count | 0.789 |
| Twist factor | 0.635 |
| Cotton type | 0.552 |

Table 2 presents the correlation values for the blend ring-spun yarn, where it is evident that both of yarn count and twist factor are the highest correlated factor to yarn coefficient of mass variation. On the other hand, blend ratio has no significant effect on it.

Table 2: Correlation outcome for blend ring-spun yarn

| | CVm% |
|---|---|
| Yarn count | 0.891 |
| Twist factor | −0.851 |
| Blend Ratio | 0.332 |

According to the output data shown in Table 3, both the twist factor and yarn count are the highest correlated factor to yarn coefficient of mass variation. In addition, cotton type has a significant effect on it.

Table 3: Correlation outcome for cotton compact yarn

| | CVm% |
|---|---|
| Twist factor | 0.909 |
| Yarn count | 0.834 |
| Cotton type | 0.708 |

### 3.2.2 ANOVA

For each yarn type, the effect of yarn count and the effect of cotton type or blend ratio was analyzed. Results are demonstrated in the following sections.

#### 3.2.1.1 Cotton Ring-Spun Yarn

To assess the effect of yarn count, ANOVA was conducted at the same twist factor and cotton type. Table 4 demonstrates the outcome of the analysis where the P-value was determined to be to 1.86E-10.

Regarding the effect of cotton type and as presented in Table 5, the cotton type has an insignificant effect on the coefficient of mass variation where the P-values equals 0.067649.

#### 3.2.1.2 Blend Ring-Spun Yarn

Similar to the cotton ring-spun yarn analysis, the effect of the yarn count and blend ratio were investigated. Table 6 shows the P-value for the analysis of the blend ratio effect where the P-value

Table 4: Cotton ring-spun yarn: ANOVA at the same twist factor and cotton type

| Source of Variation | SS | df | MS | F | P-value | F crit |
|---|---|---|---|---|---|---|
| Between Groups | 35.68693 | 1 | 35.68693 | 61.29971 | 1.86E-10 | 4.019541 |
| Within Groups | 31.43725 | 54 | 0.582171 | | | |
| Total | 67.12418 | 55 | | | | |

Table 5: Cotton ring-spun yarn: ANOVA at the same twist factor and yarn count

| Source of Variation | SS | df | MS | F | P-value | F crit |
|---|---|---|---|---|---|---|
| Between Groups | 1.0201 | 1 | 1.0201 | 3.459125 | 0.067649 | 3.995887 |
| Within Groups | 18.28388 | 62 | 0.294901 | | | |
| Total | 19.30398 | 63 | | | | |

Table 6: Blend ring-spun yarn: ANOVA at the same twist factor and yarn count

| Source of Variation | SS | df | MS | F | P-value | F crit |
|---|---|---|---|---|---|---|
| Between Groups | 5.510756 | 1 | 5.510756 | 10.57469 | 0.001856 | 3.995887 |
| Within Groups | 32.30989 | 62 | 0.521127 | | | |
| Total | 37.82064 | 63 | | | | |

Table 7: Blend ring-spun yarn: ANOVA at the same twist factor and blend ratio

| Source of Variation | SS | df | MS | F | P-value | F crit |
|---|---|---|---|---|---|---|
| Between Groups | 23.16971 | 1 | 23.16971 | 123.7732 | 4.23E-14 | 4.072654 |
| Within Groups | 7.862188 | 42 | 0.187195 | | | |
| Total | 31.0319 | 43 | | | | |

was 0.001856 indicating a significant effect on CVm%. Table 7 presents the P-value (4.23E-14) of the analysis of the effect of yarn count on the coefficient of mass variation.

#### 3.2.1.3 Cotton Compact Yarn

Table 8 and Table 9 demonstrate count effect and cotton type effect for the cotton compact yarn, where the P-values were 5.02E-13 and 1.27E-08 respectively.

Table 8: Cotton compact yarn: ANOVA at the same twist factor and cotton type

| Source of Variation | SS | df | MS | F | P-value | F crit |
|---|---|---|---|---|---|---|
| Between Groups | 9.45606061 | 1 | 9.456061 | 266.4179 | 5.02E-13 | 4.351243 |
| Within Groups | 0.70986667 | 20 | 0.035493 | | | |
| Total | 10.1659273 | 21 | | | | |

Table 9: Cotton compact yarn: ANOVA at the same twist factor and yarn count

| Source of Variation | SS | df | MS | F | P-value | F crit |
|---|---|---|---|---|---|---|
| Between Groups | 3.34651429 | 1 | 3.346514 | 89.57143 | 1.27E-08 | 4.38075 |
| Within Groups | 0.70986667 | 19 | 0.037361 | | | |
| Total | 4.05638095 | 20 | | | | |

# 4 Conclusion

In this research, yarns' coefficient of mass variation (CVm %) was estimated by using machine vision and learning, after which, statistical analysis was employed to determine the significant factors for the CVm %.

For the ring-spun yarn model, the training error was concluded to be 0.144 for yarn's CVm%. For the blended yarn model, the mean absolute error for CVm% was found to be 0.194. The compact yarn model had the best behavior out of the three models, where the mean error of the training was deduced to be 0.046.

It was deduced that for cotton and blend ring-spun yarn, yarn count followed by twist factor had the highest correlation to CVm%. As for the cotton compact yarn, it was found that the twist factor had the highest correlation.

ANOVA outcomes show that only for the cotton ring-spun yarn, cotton type does not influence CVm%. Furthermore, the yarn count was found to have a significant effect on CVm% for all yarn types.

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