Journal of Fiber Bioengineering and Informatics 14:1 (2021) 13–20
Cite as: M. Abdel-Hamied et al.
doi:10.3993/jfbim00345

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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Mar. 2021

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