# PREDICTION OF THE INCREASE IN YARN UNEVENNESS AFTER WINDING PROCESS USING STATISTICAL AND ARTIFICIAL NEURAL NETWORK MODELS

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### ABSTRACT

This paper investigated the prediction of the increase in unevenness of two types of yarn: Ne 30/1 CVCM (combed yarn Ne 30/1, 60% Cotton 40% Polyester) and Ne 30/1 COCM (combed yarn Ne 30/1 100% Cotton) after winding by artificial neural network (ANN) and by statistical models. Four technological winding parameters: the winding speed (Z1), the load on the friction discs of the yarn tensioner (Z2), the distance between the bobbin and the yarn guide (Z3) and the pressure of the package on the grooved drum (Z4) were used as the input parameters to investigate yarn unevenness after winding. The research results showed that by using statistical models, within the selected research range, four investigated technological parameters influenced the increase in unevenness of the two mentioned yarns. The regression coefficients represented the influence of each technological parameter on the increase in yarn unevenness: the winding speed parameter has the most influence on the increase in yarn unevenness with the biggest value coefficients b1 which was 1.2339 for the Ne 30/1 CVCM yarn and this value was 0.6996 for the Ne 30/1 COCM yarn. Moreover, the increase in yarn unevenness predicted by ANNs obtained a higher coefficient of determination (R2), while the mean square error (MSE) and the mean absolute error (MAE) were lower than the ones predicted by statistical models.

### KEYWORDS

Unevenness; Artificial neural network; Regression function; Predicting yarn unevenness; Winding.

## INTRODUCTION

Currently, Artificial Neural Network (ANN) is being widely applied in many fields, including textile and garment. Uster (Switzerland) has developed a fabric inspection system named Fabricscan. In this system, CCD (Change Coupled Device) cameras were used to scan the fabric surface. The scan signals were transmitted to ANN for analysis and evaluation [1, 2]. Samader Al. Malik et al. [3] have predicted yarn unevenness and tensile strength which were produced by ring spinning frame based on four different input parameters: the PES/CO blend ratio, twist multiplier, back roller cot hardness and break draft ratio by using ANN and Multiple Linear Regression (MLR). The built ANN has the following parameters: 4 - (3 - 3)2 - 1 (1 input layer with 4 neurons, 2 hidden layers (3 neurons each) and an output layer with 1 neuron). The number of learning samples in the research was 40 samples and the number of test samples was 8. The results showed that using ANN to predict yarn unevenness and tensile strength achieved higher accuracy than that predicted by MLR. Rocco Furfiri and Maurizio Gelli [4] predicted the tensile strength of yarn by ANN and MLR based on roving yarn. Input parameters included yarn count, yarn twist, mean length, average fineness and average strength of fibers in the roving yarn. The ANN was built with 3 layers: an input layer of 5 neurons (corresponding to 5 input parameters), a hidden layer of 10 neurons and an output layer of 1 neuron (corresponding to the strength of the yarn). The results showed that the yarn strength predicted by ANN was only 3% less different than this value measured by the real experimental strength while the prediction by MLR was 10% more different than in comparison to the experimental one. Ezzatollah Haghighat et al. [5] predicted the hairiness of PES/Viscose blended yarns by ANN and MLR based on the input parameters: the total draft, roving twist, yarn count, yarn twist, spindle speed, traveled weight, back zone setting, break draft, balloon control ring, front roller covering hardness and draft system angle. By comparing the parameters of coefficient of determination (R2), mean square error (MSE), and mean absolute error (MAE), the results showed that the prediction by ANN gave more accurate results

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**Table 1.** Central value and variation range of winding parameters.

| Parameters | Actual values | | | | Coded values | | | |
|---|---|---|---|---|---|---|---|---|
| | $Z_1$ [m/min] | $Z_2$ [cN] | $Z_3$ [cm] | $Z_4$ [N] | $x_1$ | $x_2$ | $x_3$ | $x_4$ |
| Top level | 1200 | 30 | 18 | 21 | +1 | +1 | +1 | +1 |
| Base level $Z_j^0$ | 900 | 20 | 14 | 14 | 0 | 0 | 0 | 0 |
| Bottom level | 600 | 10 | 10 | 7 | -1 | -1 | -1 | -1 |
| Variation range $\Delta Z_j$ | 300 | 10 | 4 | 7 | - | - | - | - |

than that predicted by MLR. Similar results have been obtained by the other researchers [6, 7].

ANN has been applied to predict yarn quality mainly at the spinning stage (before winding) and achieved high accuracy while using traditional techniques (MLR models) for prediction had many errors or predicted results with low accuracy. Up to now, the application of ANN to predict the yarn quality after winding based on technological parameters has not been mentioned.

Due to the influence of winding technology, the quality of yarn including the yarn unevenness after winding has changed in comparison to before winding [8]. For woven fabrics, the yarn's unevenness will make the fabric look bad. Particularly for knitted fabrics, in addition to bad fabric appearance, the yarn unevenness also causes a lot of yarn breakages, even broken needles. The reasons for the yarn unevenness are very complicated: due to the raw materials, the spinning technology and the equipment, including the winding. Though it is impossible to eliminate yarn unevenness, reducing and limiting this phenomenon is important. To reduce the production cost, to yarn usage orientation, the increase in unevenness of the yarn after winding needs to be predicted. This paper presents the research results of predicting the increase in the unevenness of two types of yarn: the Ne 30/1 CVCM yarn and the Ne 30/1 COCM yarn based on four typical winding parameters that can be tested, controlled and often need to be adjusted during the winding process, which were the winding speed (*Z1*), the load on the friction discs of the yarn tensioner (*Z2*), the distance between the bobbin and the yarn guide (*Z3*) and the pressure of package on the grooved drum (*Z4*). The research results will contribute to reducing yarn production costs and orient the efficient use of yarn after winding.

## MATERIALS AND METHODS

### Materials

Yarn materials: The research used two types of ring combed yarns produced by Vinatex NamDinh (Vietnam) spinning mill: Ne 30/1 CVCM yarn (60% Cotton, 40% PES) and Ne 30/1 COCM yarn (100% Cotton).

### Methods

The winding process was performed on the winding model developed at Hanoi University of Science and Technology [9]. The Uster Tester 5 (Switzerland) was used to measure the yarn unevenness before and after winding by standard ASTM D1425M/1425M-14 [10]. Before testing, the yarns were conditioned for 24 hours in standard atmospheric conditions (65 ± 2% relative humidity and 20 ± 2°C temperature). The acquired results were obtained by using the built ANN and statistical models.

The orthogonal experimental planning level II [11] was applied to set up an experimental matrix with 4 technological winding parameters *Z1, Z2, Z3, Z4*. The range of values of the winding parameters was selected based on the actual survey of winding conventional yarns in the spinning mills and the allowable capacity of the winding model (Table 1).

Statistical models of the increase in yarn unevenness after winding in comparison to before winding have the general form:

$\Delta U$ [%] = $b_0 + b_1x_1 + b_2x_2 + b_3x_3 + b_4x_4 + b_{12}x_1x_2 + b_{13}x_1x_3 + b_{14}x_1x_4 + b_{23}x_2x_3 + b_{24}x_2x_4 + b_{34}x_3x_4 + b_{11}x_1^2 + b_{22}x_2^2 + b_{33}x_3^2 + b_{44}x_4^2$,

where: $b_0$, $b_1$, $b_2$, $b_3$, $b_4$, $b_{12}$, $b_{13}$, $b_{14}$, $b_{23}$, $b_{24}$, $b_{34}$, $b_{11}$, $b_{22}$, $b_{33}$, $b_{44}$ - the coefficients of the model, $x_1$, $x_2$, $x_3$, $x_4$ - coding variables of winding parameters.

The real variables $Z_j$ and the encoding variable $x_j$ were related by the formula:

$$Z_j = x_j \Delta Z_j + Z_j^0. \quad (1)$$

The increase in yarn unevenness $\Delta U$% was calculated by the formula:

$$\Delta U = \frac{U_s - U_t}{U_t} 100 \text{ [\%]}, \quad (2)$$

where: $U_t$ - unevenness of yarn before winding ($U_t$ = 9.44 % and 8.94 % for CVCM yarn and COCM yarn respectively), $U_s$ - unevenness of the yarn after winding determined according to each experiment.

The number of experiments $N$ with the number of variables $k$ = 4 was determined by the formula $N = 2^k + n_0 + 2k$, where, $n_0$ is the number of experiments in the center ($n_0$ = 1). Thus, $N$ = 25. Coefficient $\alpha = \sqrt{\sqrt{N.2^{k-2}} - 2^{k-1}} = \sqrt{\sqrt{25.2^2} - 2^3} = 1.414$ to set up the experimental matrix and conduct the experiment.

**Application of artificial neural network (ANN)**

By building an ANN with arbitrary concatenation or testing the learning process with many different networks and by examining the resulting errors, we can choose the network with the smallest error [12,13]. There are many types of neural networks, the most classic neural network application is the Multilayer Perceptron (MLP) network which is used commonly in many research fields.

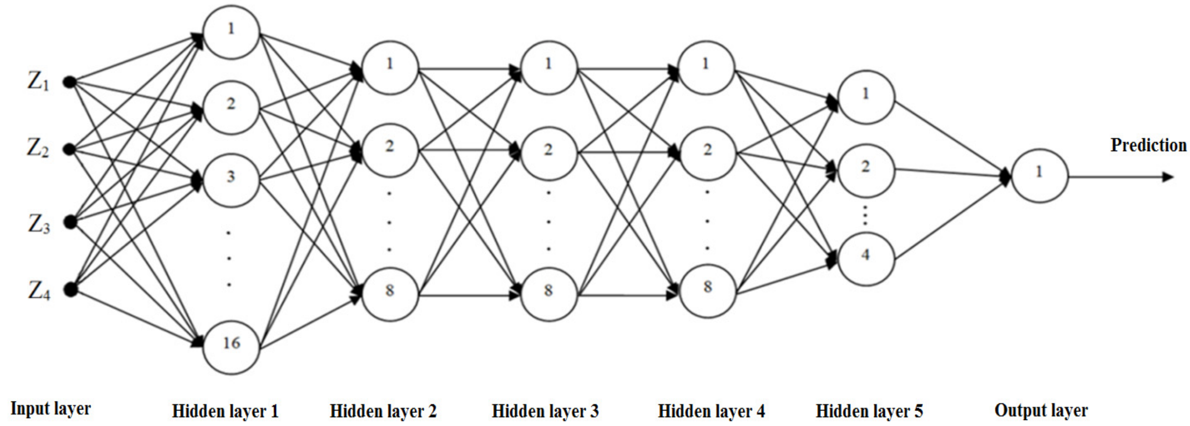



**Figure 1.** Structure of ANN model for predicting increase in unevenness of yarn.

In addition to the basic units, the ANN also has some general requirements on the network structure such as the neurons are arranged into layers, including a layer of input signal channels, a layer of output signal channels and may include several intermediate layers known as hidden layers. There are no connections between neurons on the same layer, only connections between neurons of two consecutive layers. The connections are oriented from the input to the output (linear network). Neurons on the same layer will have the same activation function.

The ANN networks (Figure 1) predict the increase in unevenness of yarn after winding based on 4 winding parameters (winding speed $Z_1$, the load on the friction discs of the yarn tensioner $Z_2$, the distance between the bobbin and the yarn guide $Z_3$ and the pressure of package on the grooved drum $Z_4$) which was a form of MLP network. For the feedforward network, learning by the error backpropagation algorithm using the Sigmoid activation function is suitable because of its continuity and its values do not suddenly decrease. Furthermore, the derivative of a Sigmoid function can be easily calculated and expressed as terms of a function of the form Sigmoid. Since there is no certain rule to select the number of layers and neurons in each layer, the network structure is selected by the trial-and-error method for several networks with different numbers of layers and different number units in layer(s). The training algorithm, training parameters and activation function have been trained with the objective of minimizing the training error and better generalization on unseen data. For example, the number of hidden neurons in every layer is selected with the trial-and-error method. A network with only 1 hidden neuron and one layer was started, and then the number of neurons and layer increased progressively and generated randomly in different networks. All the networks were trained with the data sets, and the network with the lowest error was selected. If the best error is still high, the number of hidden neurons is increased by 1. To avoid the overfitting effect, we chose the network with the lowest possible number of hidden neurons and acceptable error (i.e., the simplest possible network), which can still approximate the data. The ANN network structure in this study was selected by testing with 3 different networks (3, 4, 5 hidden layers) and evaluated by 3 performance parameters of the models: $R^2$ (Determining the number of systems), MSE (mean squared error), MAE (means absolute error).

The network has 3 hidden layers:

$4 - (8 - 4 - 4)_3 - 1$

$R_3^2 = 0.9681$, $MSE_3 = 0.0415$, $MAE_3 = 0.1210$

The network has 4 hidden layers:

$4 - (8 - 6 - 4 - 4)_4 - 1$

$R_4^2 = 0.9125$, $MSE_4 = 0.1137$, $MAE_4 = 0.1342$

The network has 5 hidden layers:

$4 - (16 - 8 - 8 - 8 - 4)_5 - 1$

$R_5^2 = 0.9997$, $MSE_5 = 0.0009$, $MAE_5 = 0.0187$

In comparison: $R_5^2 > R_3^2 > R_4^2$; $MSE_5 < MSE_3 < MSE_4$; $MAE_5 < MAE_3 < MAE_4$

So the network with 1 input layer of four neurons (4 winding parameters), 5 hidden layers (the number of neurons of the hidden layers is 16, 8, 8, 8, 4, respectively) and 1 output layer with the number of neurons is 1 (increase in yarn unevenness) has the highest $R_5^2$, and the smallest $MSE_5$, $MAE_5$ among the 3 tested networks and this network was chosen to predict the increase in the unevenness of yarn in our research.

Network training

To train the network, the supervised learning rule was used. Error backpropagation is a learning algorithm applied to adjust synaptic weight, which is a form of supervised learning. Currently, there is no general rule for selecting learning data sets, a simple way is to choose the learning data set which covers the entire possible input space. Here, the input of the algorithm is a set of learning data $\{(Z_s, D_s)\}$ where, $Z_s = [Z_1, Z_2, Z_3... Z_N]$ is the input vector (technological parameters) and $D_s = [d_1, d_2, d_3... d_N]$ is the desired output vector (increase in unevenness) of the yarn determined according to each experiment. The learning process includes the following steps:

1. Calculate output:

When a sample $Z_s$ = *[$Z_1$, $Z_2$, $Z_3$....$Z_N$]* is put on the network, it propagates from the input Z through the hidden layers Y to the output layer M. In the case of an ANN with one hidden layer:

a. Sum of input connections of the hidden neuron *j* was calculated by formula 3 [3; 15]:

$$a_j = \sum\nolimits_{i=1} u_{ji} Z_i + b_j, \tag{3}$$

where: $Z_i$ - input signal *i*, $u_{ji}$ - synaptic weight, $b_j$ - bias term connected to the *j* unit.

Calculate the output of the j hidden neuron:

$$Y_j = f(a_j). \tag{4}$$

In case the network is designed with many hidden layers, the calculation method is similar, the output of one hidden layer will be the input of the next hidden layer.

b. Output layer *M*

Input of the k output neuron:

$$b_k = \sum_{j=1} Y_j W_{kj}, \tag{5}$$

in where: $W_{kj}$ is the corresponding weight.

The output value of neuron k in the output layer M is:

$$M_k = f(b_k). \tag{6}$$

2. Evaluate output error:

Calculate the error of the network *E* according to the formula:

$$E = \frac{1}{2}\sum_k (d_k - M_k)^2, \tag{7}$$

in where: $d_k$ - the increase in unevenness determined by experiment, $M_k$ - the increase in unevenness predicted by ANN at the k neuron in the output layer for the sample $Z_s$.

The ANN was trained by feeding the output layer with samples and gradually adjusting the weight coefficients so that the output class response would match the desired values. In fact, after each learning cycle, if $E \leq E_{max}$, the learning process is ended, and the result weights are given. If $E > E_{max}$, a new learning epoch is restarted by returning to the first step in adjusting the weights $W_{kj}$ and $u_{ji}$ based on the principle of backpropagation error. The values of the synaptic weight are gradually adjusted. In our research, the learning process using the error backpropagation algorithm can be ended with two specified conditions: the chosen value $E_{max}$ = 0.01 or the number of learning epochs is 300. The network will stop according to the first coming condition.

**Evaluation of the predictive performance of the models**

The prediction results of the ANN were compared to those predicted by statistical models by 3 performance parameters [3]:

The coefficient of determination represents the relationship between the predicted value and the experimental value ($R^2$).

Mean square error (MSE):

$$MSE = \frac{1}{N}\sum_{k=1}^{N}(M_k - d_k)^2 = \frac{1}{N}\sum_{i=1}^{N}(\Delta)^2, \tag{8}$$

Mean absolute error (MAE):

$$MAE = \frac{1}{N}\sum_{k=1}^{N}|M_k - d_k| = \frac{1}{N}\sum_{i=1}^{N}|\Delta|, \tag{9}$$

In where: $M_k$ - the increase in yarn unevenness predicted by ANN or statistical models, $d_k$ - the increase in yarn unevenness determined by experiment (desired value), *N* - number of experiments.

## RESULTS AND DISCUSSION

### Predicting increase in yarn unevenness by statistical model

To determine the mathematical relationship between the increase in yarn unevenness after winding and four selected technological parameters, it was necessary to establish an experimental matrix and conduct experiments to determine yarn unevenness. The experimental matrix and the determined results of the increase in yarn unevenness ΔU % (according to formula 2) were presented in Table 2.

Using the Design Expert software, we have calculated the regression coefficients, checked the coefficients according to Student's standards and checked the conformity of the regression equations according to Fisher's standards. The statistical models on the increase in yarn unevenness with the coding variables have the following forms:

For the Ne 30/1 CVCM yarn:

$\Delta U_1$ =3.9952 + 1.2339$x_1$ + 0.7221$x_2$ + 0.5688$x_3$ + 0.6318$x_4$ + 0.2994$x_2$ $x_4$ + 1.4831$x_3$ $x_4$

$R^2$ = 0.8733

For the Ne 30/1COCM yarn:

$\Delta U_2$ = 2.2396 + 0.6996$x_1$ + 0.3927$x_2$ + 0.31$x_3$ + 0.2966$x_4$ - 0.1394$x_2$ $x_3$ + 0.2869$x_2x_4$ + 0.7994$x_3$ $x_4$

$R^2$ = 0.8986

Within the selected research range, four technological parameters (winding speed ($x_1$), the load on the friction discs of the yarn tensioner ($x_2$), the distance between the bobbin and the yarn guide ($x_3$) and the pressure of the package on the grooved drum ($x_4$) influence the increase in the unevenness of the two mentioned yarns. The regression coefficients represented the influence of the technological parameters on the increase in yarn unevenness. The winding speed parameter has the most influence on the increase in yarn unevenness (the coefficients $b_1$ = 1.2339 (in the $\Delta U_1$ model), $b_1$ = 0.6996 (in the $U_2$ model) mean the biggest values), followed by the influence of load $x_2$ (coefficient $b_2 < b_1$ in models $\Delta U_1$, $\Delta U_2$).

**Table 2.** Experimental matrix and the results of determining the increase in yarn unevenness ΔU %.

| $N^0$ | $x_0$ | $x_1$ | $x_2$ | $x_3$ | $x_4$ | $Z_1$ | $Z_2$ | $Z_3$ | $Z_4$ | Ne 30/1 CVCM | Ne 30/1 COCM |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | $\Delta U_1$ [%] | $\Delta U_2$ [%] |
| 1 | + | - | - | - | - | 600 | 10 | 10 | 7 | 1.8 | 1.23 |
| 2 | + | + | - | - | - | 1200 | 10 | 10 | 7 | 5.72 | 3.58 |
| 3 | + | - | + | - | - | 600 | 30 | 10 | 7 | 3.6 | 2.01 |
| 4 | + | + | + | - | - | 1200 | 30 | 10 | 7 | 6.07 | 3.42 |
| 5 | + | - | - | + | - | 600 | 10 | 18 | 7 | 1.17 | 0.78 |
| 6 | + | + | - | + | - | 1200 | 10 | 18 | 7 | 2.85 | 2.07 |
| 7 | + | - | + | + | - | 600 | 30 | 18 | 7 | 2.75 | 1.28 |
| 8 | + | + | + | + | - | 1200 | 30 | 18 | 7 | 2.97 | 1.79 |
| 9 | + | - | - | - | + | 600 | 10 | 10 | 21 | 1.06 | 0.11 |
| 10 | + | + | - | - | + | 1200 | 10 | 10 | 21 | 2.54 | 0.89 |
| 11 | + | - | + | - | + | 600 | 30 | 10 | 21 | 3.71 | 2.28 |
| 12 | + | + | + | - | + | 1200 | 30 | 10 | 21 | 3.81 | 2.35 |
| 13 | + | - | - | + | + | 600 | 10 | 18 | 21 | 4.03 | 2.46 |
| 14 | + | + | - | + | + | 1200 | 10 | 18 | 21 | 7.31 | 3.69 |
| 15 | + | - | + | + | + | 600 | 30 | 18 | 21 | 5.03 | 2.8 |
| 16 | + | + | + | + | + | 1200 | 30 | 18 | 21 | 11.03 | 5.15 |
| 17 | + | 0 | 0 | 0 | 0 | 900 | 20 | 14 | 14 | 3.92 | 2.27 |
| 18 | + | α | 0 | 0 | 0 | 1324 | 20 | 14 | 14 | 5.08 | 3.28 |
| 19 | + | -α | 0 | 0 | 0 | 475 | 20 | 14 | 14 | 1.17 | 0.45 |
| 20 | + | 0 | α | 0 | 0 | 900 | 34.14 | 14 | 14 | 4.77 | 3.02 |
| 21 | + | 0 | -α | 0 | 0 | 900 | 5.86 | 14 | 14 | 3.39 | 1.9 |
| 22 | + | 0 | 0 | α | 0 | 900 | 20 | 19.65 | 14 | 4.87 | 3.24 |
| 23 | + | 0 | 0 | -α | 0 | 900 | 20 | 8.34 | 14 | 3.07 | 1.79 |
| 24 | + | 0 | 0 | 0 | α | 900 | 20 | 14 | 23.9 | 4.45 | 2.91 |
| 25 | + | 0 | 0 | 0 | -α | 900 | 20 | 14 | 4.1 | 3.71 | 1.24 |

**Table 3.** The actual and predicted results of the increase in unevenness of Ne 30/1 CVCM yarn by ANN.

| $N_0$ | $\Delta U_1$ [%] Experiments | ANN |
|---|---|---|
| 1 | 1.8 | 1.8027 |
| 2 | 5.72 | 5.7445 |
| 3 | 3.6 | 3.5868 |
| 4 | 6.07 | 6.0761 |
| 5 | 1.17 | 1.1325 |
| 6 | 2.85 | 2.8493 |
| 7 | 2.75 | 2.7335 |
| 8 | 2.97 | 2.9695 |
| 9 | 1.06 | 1.0510 |
| 10 | 2.54 | 2.5266 |
| 11 | 3.71 | 3.6915 |
| 12 | 3.81 | 3.8355 |
| 13 | 4.03 | 4.0110 |
| 14 | 7.31 | 7.325 |
| 15 | 5.03 | 5.0354 |
| 16 | 11.03 | 10.904 |
| 17 | 3.92 | 3.9111 |
| 18 | 5.08 | 5.0986 |
| 19 | 1.17 | 1.1458 |
| 20 | 4.77 | 4.7583 |
| 21 | 3.39 | 3.4130 |
| 22 | 4.87 | 4.8942 |
| 23 | 3.07 | 3.0788 |
| 24 | 4.45 | 4.438 |
| 25 | 3.71 | 3.7061 |

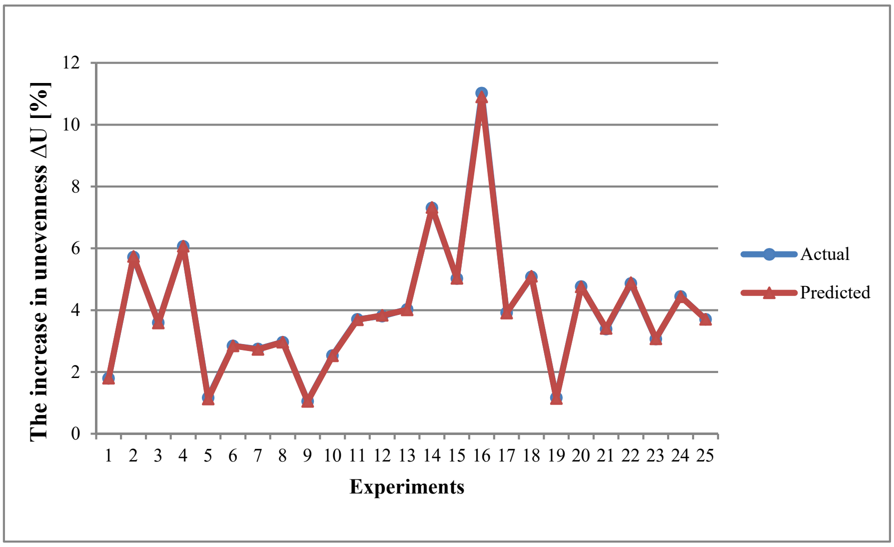



**Figure 2**. Performance of ANN model for the increase in yarn unevenness of Ne 30/1 CVCM yarn.

## Predicting increase in yarn unevenness by ANN

The software "Prediction of yarn product quality after winding" was established. The software was written in Python language. Its capacity was 656 MB and it runs on a Windows environment. The prediction results of the increase in yarn unevenness provided by this software based on the set of learning data (ΔU1, ΔU2 with 25 experiments which were used in the above statistical models) were presented in Table 3 and Table 4 and the graphs on Figures 2 and 3.

It can be seen in Figure 2 and Figure 3 above, that MLP models could approximate accurately the increase in yarn unevenness with very small differences between the actual values (the blue line) and the estimated values (the red line). Thus, the outputs of the network have almost coincided with the experimental values.

The performance was further assessed with the following measures: coefficient of determination ($R^2$), MSE (Mean Square Error), MAE (Mean Absolute Error). The numerical errors were collected in Table 5.

**Table 4.** The actual and predicted results of the increase in unevenness of Ne 30/1 COCM yarn by ANN.

| $N_0$ | $\Delta U_2$ [%] | |
|---|---|---|
| | **Experiments** | **ANN** |
| 1 | 1.23 | 1.3648 |
| 2 | 3.58 | 3.6340 |
| 3 | 2.01 | 2.2282 |
| 4 | 3.42 | 3.4864 |
| 5 | 0.78 | 0.7809 |
| 6 | 2.07 | 2.1865 |
| 7 | 1.28 | 1.3162 |
| 8 | 1.79 | 1.8497 |
| 9 | 0.11 | 0.1645 |
| 10 | 0.89 | 0.8961 |
| 11 | 2.28 | 2.5374 |
| 12 | 2.35 | 2.4137 |
| 13 | 2.46 | 2.6677 |
| 14 | 3.69 | 3.7911 |
| 15 | 2.8 | 2.8797 |
| 16 | 5.15 | 5.0074 |
| 17 | 2.27 | 2.3645 |
| 18 | 3.28 | 3.3000 |
| 19 | 0.45 | 0.5441 |
| 20 | 3.02 | 3.1038 |
| 21 | 1.9 | 2.0280 |
| 22 | 3.24 | 3.2621 |
| 23 | 1.79 | 2.0198 |
| 24 | 2.91 | 2.9480 |
| 25 | 1.24 | 1.3032 |

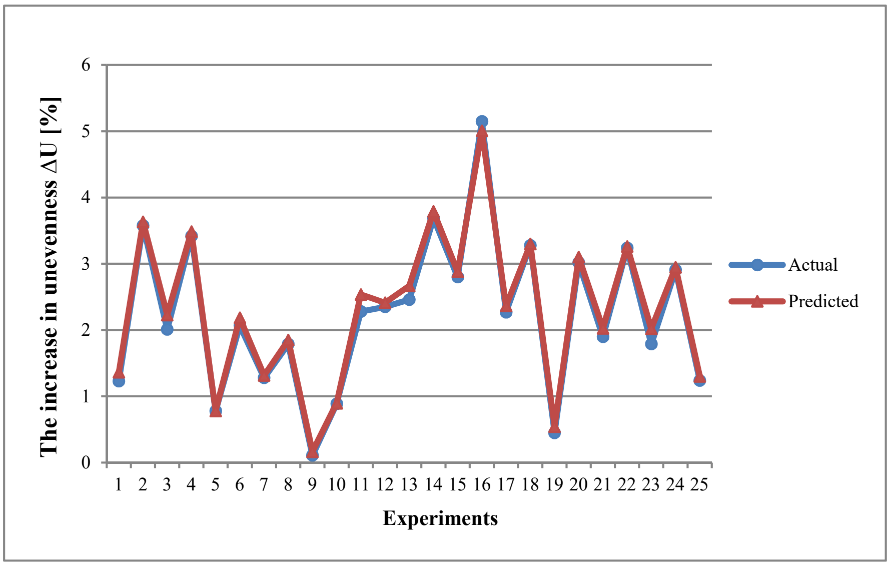


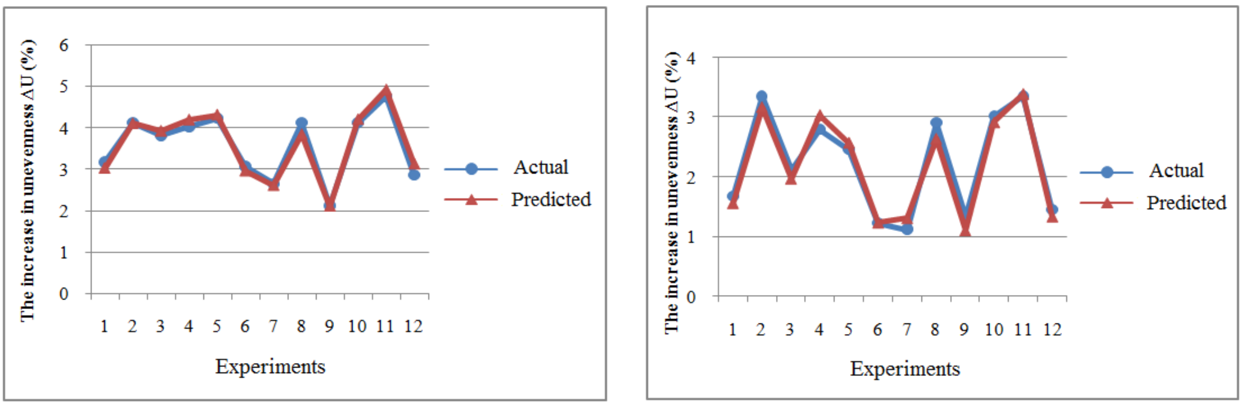

**Figure 3.** Performance of ANN model for the increase in unevenness of Ne 30/1 COCM yarn.

**Table 5.** The performance of predicting the increase in yarn unevenness of the models compared to the statistical model.

| Parameters | Ne 30/1 CVCM | | Ne 30/1 COCM | |
|---|---|---|---|---|
| | **Statistical Model** | **ANN** | **Statistical Model** | **ANN** |
| **$R^2$** | 0.8733 | 0.9997 | 0.8986 | 0.9893 |
| **MSE** | 0.6649 | 0.0009 | 0.3134 | 0.0138 |
| **MAE** | 0.6469 | 0.0187 | 0.1643 | 0.095 |

**Table 6.** Experimental results and prediction of ANN with testing dataset.

| Experiments | $Z_1$ [m/min] | $Z_2$ [cN] | $Z_3$ [cm] | $Z_4$ [N] | The increase in yarn unevenness | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | **Ne 30/1 CVCM yarn** | | | **Ne 30/1 COCM yarn** | | |
| | | | | | **Experiments** | **Statistics Model** | **ANN** | **Experiments** | **Statistics Model** | **ANN** |
| 1 | 700 | 20 | 12 | 7 | 3.18 | 2.99 | 3.02 | 1.68 | 1.72 | 1.56 |
| 2 | 900 | 10 | 10 | 7 | 4.13 | 3.86 | 4.10 | 3.36 | 2.19 | 3.17 |
| 3 | 600 | 30 | 10 | 4,1 | 3.81 | 3.69 | 3.92 | 2.13 | 2.08 | 1.97 |
| 4 | 1200 | 10 | 15 | 7 | 4.03 | 3.95 | 4.19 | 2.80 | 2.45 | 3.04 |
| 5 | 1000 | 10 | 15 | 14 | 4.24 | 3.83 | 4.31 | 2.46 | 2.19 | 2.57 |
| 6 | 800 | 15 | 14 | 14 | 3.07 | 3.22 | 2.95 | 1.23 | 1.81 | 1.23 |
| 7 | 800 | 14 | 10 | 14 | 2.65 | 2.58 | 2.60 | 1.12 | 1.38 | 1.31 |
| 8 | 900 | 10 | 12 | 4,1 | 4.13 | 3.57 | 3.84 | 2.91 | 2.17 | 2.64 |
| 9 | 700 | 12 | 14 | 7 | 2.12 | 2.20 | 2.10 | 1.34 | 1.39 | 1.10 |
| 10 | 1000 | 10 | 12 | 4,1 | 4.13 | 3.98 | 4.20 | 3.02 | 2.41 | 2.91 |
| 11 | 1000 | 12 | 10 | 7 | 4.77 | 4.35 | 4.92 | 3.36 | 2.47 | 3.39 |
| 12 | 800 | 20 | 10 | 14 | 2.86 | 3.02 | 3.12 | 1.45 | 1.70 | 1.34 |
| **MAE** | | | | | | **0.222** | **0.124** | | **0.439** | **0.148** |
| **MSE** | | | | | | **0.073** | **0.022** | | **0.313** | **0.028** |




(a) (b)

**Figure 4.** Testing graph of ANN model for $\Delta U$ [%] of: (a) Ne 30/1 CVCM yarn, (b) Ne 30/1 COCM yarn.

Table 4 shows that predicted results by ANN have an $R^2$ value higher than that one given by the statistical model: 0.9997 > 0.8733 for Ne 30/1 CVCM yarn and 0.9893 > 0.8986 for the Ne 30/1 COCM yarn. Moreover, the MAE and MSE values determined by ANN were lower than those predicted by statistical models, with MAE values 0.0187 < 0.6469 for Ne 30/1 CVCM yarn and 0.095 < 0.1643 for Ne 30/1 COCM yarn and with MSE values: 0.0009 < 0.6649 for Ne 30/1 CVCM yarn and 0.0138 < 0.3134 for Ne 30/1 COCM yarn. The results show that the increase in yarn unevenness predicted by ANNs was more accurate than that predicted by statistical models. However, predictions by ANNs do not point out the influence of the factors on the results.

The performance of the built ANN model was further assessed by testing a data set of 12 experiments which were used for model testing and did not match with the learning data set, in which the technological parameters were selected in the defined research range. The test results are presented in Table 6. The graphs show the test results and the predicted values by the built ANN model are shown in Figure 4.

The test results of the ANN were accepted as good because the MAE and MSE errors were small which were 0.124; 0.022 for Ne 30/1 CVCM yarn and 0.148; 0.028 for Ne 30/1 COCM yarn. These results demonstrated that the built ANN model including 1 input layer, 5 hidden layers and 1 output layer obtained a good performance, and it was appropriate for determination of the increase in yarn unevenness. With the test set, the results confirmed that the predicting by using ANN has smaller MAE, and MSE values (achieving higher accuracy) than these of statistical models.

## CONCLUSIONS

1. In this study, the increase in unevenness of two types of yarn (Ne 30/1 CVCM, Ne 30/1 COCM) after winding was successfully predicted by statistical models and by artificial neural network (ANN) based on four winding technological parameters: Winding speed, the load on the friction discs of the yarn tensioner, the distance between the bobbin and the yarn guide and the pressure of package on the grooved drum. The ANN structure to predict the increase in yarn unevenness after winding has been built with 1 input layer, 5 hidden layers and 1 output layer. Among them, there were 4 neurons in the input layer which corresponded to 4 technological winding parameters, the number of neurons in the five hidden layers was 16, 8, 8, 8, and 4 respectively and the number neurons of in the output layer were 1, which was the increase in yarn unevenness value.

2. The coefficient of determination ($R^2$) of ANN models reached 0.9893; 0.9997 for Ne 30/1 CVCM yarn and Ne 30/1 COCM yarn, respectively which were higher than this parameter predicted by statistical models which were only 0.8733; 0.8986 for Ne 30/1 CVCM yarn and Ne 30/1 COCM yarn, respectively. Meanwhile, the parameters MAE and MSE predicted by ANN were smaller than those predicted by statistical models. That proves, predicting by ANN achieved higher accuracy than predicting by statistical models. However, predicting by statistical models can see the degree of influence of each factor on the predicted results.

3. In actual production, if it is found difficult to apply statistical models to predict the increase in yarn unevenness after winding, because the accuracy is low, and the results may be influenced by many factors, we should use ANN. However, predicted by ANN will not provide the influential degree of each factor on the results.

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