Prediction of Weft Breaks in Air Jet Weaving Machine by Artificial Neural Network

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Abstract: The most important factors affecting the air jet weaving machine's efficiency are warp and weft breaks which are strongly connected to the yarn and machine parameters. The objective of this paper is to predict the number of weft breaks per million meters using back propagation algorithm in an artificial neural network system. Two models are used: first utilizing twelve parameters for the input layer and second applies only the five most correlated yarn parameters. The developed algorithm can predict the number of weft breaks per million meters. The results gave satisfactory coefficient of correlations (0.955) between the actual and predicted number of weft breaks.
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1. Introduction

In weaving, machine stoppages always lead to low production rates. Machine stoppages in weaving process usually occur as a result of warp breaks, weft breaks, mechanical breakdown, electrical faults, shortage of spare parts, power cuts, beam changing, cleaning, oiling and lubricating[1] . In the case of using 100% cotton yarn in air jet machines, warp and weft breaks cause machine stoppages during weaving. In addition, wrongly adjusted machine parameters and weaving conditions lead to yarn breaks during weaving [2].The tension of warp and weft yarns leads to high warp and weft breaks rate too. In many research works, low warp tension of 50cN had a significant effect on weft breaks due to the disturbance of the smooth passage of weft yarn across the shed**.** Increasing warp tension to 70 cN weft breaks were stabilized. Higher tensions (80 cN, 85 cN and 90 cN) in the warp did not have an effect on the weft break. This is in contrast with the warp breaks that occur more when the tension was over 70cN so at this tension the warp suffers longitudinal stresses while the weft, not as strained as the warp [2]. Low yarn tension creates a clinging effect, resulting in yarn breaks for both warp and weft [3]. The values of peak tension may reach about 30% of the tensile strength of yarn. Selection of high quality yarn to weave on high speed air jet machines needs to choose high quality yarn to weave on high speed air jet machines, it is to increase the efficiency and reduced yarn breaks [4].

Yarns spun from staple fibers are irregular. As very thin place occurs, it may fail under the balloon tension in spinning and a spinning break occurs. When such a very thin place survives spinning in a weavable singles yarn, it causes yarn breaks in weaving. The magnitude and frequency of very thin places depend on the number of fibers in the yarn crosses section, and the variability of fiber diameter [5]. It was observed during weaving with maximum weft densities that the machine stopped mainly due to weft stops. In the majority of machine stoppages, weft yarn got entangled with warp yarns especially at the selvage regions. The cloth-fell moved backwards with increasing weft density and decreased the front shed size. However, the cloth-fell position moved backwards more at the selvages due to the lower warp tension. This decreased shed openness at the selvages even more and warp yarns got into the profile of the reed before the completion of weft insertion, this was observed as the main reason causing weft stops very often and limited the maximum weavable weft density [6].On air-jet machines, weavability of elastane based stretch yarns was investigated where bobbins were divided in three categories according to the most important production processes for elastane yarn: core twist, core spun and air covered. The 'core twist' yarns didn't result in specific insertion problems. The 'core spun' yarns had problems due to being blown apart under influence of the airflow, causing weft stops. The 'air covered' yarns resulted in recurring fabric defects at the arrival side of the machine [7].The textile process involves the interaction of a large number of variables. The relations between these variables and the product properties could not be established conclusively. Artificial Neural Network (ANN) represents a promising step in this field where different techniques have been suggested to determine these relations but with limited success [8]. The predictability of the warp breakage rate from a sizing yarn quality index using a feed forward back-propagation network in an artificial neural network system was investigated. A good correlation between predicted and actual warp breakage rates indicated that the warp breakage rates can be predicted by neural networks. A model with a single sigmoid hidden layer with four neurons is able to produce better predictions than the other models of this particular data set in the study [9].An artificial neural network (ANN) model was developed to predict the drape coefficient . The results prove a significant relationship between the ANN inputs and the drape coefficient. The algorithm developed can easily predict the drape coefficient of fabrics at different diameters [10]. Seam puckering, seam flotation and seam efficiency were investigated by artificial neural networks and multiple logarithm regression methods for modeling seam performance of commercial woven fabrics. The results indicated that the artificial neural network (ANN) model has better performance in comparison with the multiple logarithm regression models [11].Applying ANN for the problem of the determination of the optimum value of LAP for specific materials and production conditions helps saving time and material in comparison with the traditional try and error methods. Five Artificial Neural Network Models were developed and showed quite promising results predicting the optimum value of LAP for given material and production parameters. A comparison between the performance of Neural Network and the conventional data analysis techniques (the multiple regression analysis) was conducted. It was concluded that the Artificial Neural Networks were much more efficient than conventional statistical techniques [12].An artificial neural network model was used in order to predict the bursting strength of the knitted fabrics including elastomeric yarns with nine neurons in single hidden layer and proved to be promising by the low prediction errors. Three parameters easily available from the manufacturers before the production were considered: basic yarn count, elastomeric yarn count and elastomeric yarn ratio used as input parameters [13].

2. Material And Methods

Experimental measurements were done on air jet weaving machine in a mill environment using 9 different yarns as a weft with various properties shown in (Table 1).

Table 1.Yarns properties

Yarn code	Count [Ne]	Twist factor	Tenacity [cN/ tex]	Hairiness Index [H]	Thin places	Thick places	Neps	$[CV_m]$ %	Yarn Diameter [mm]	Diameter shape
1	60/1	3.93	16.4	4.02	8	53	89	13.89	0.137	0.88
2	60/1	3.93	25.5	3.04	23	33	62	13.28	0.132	0.85
3	40/1	4	16.2	5.4	7	53	182	13.64	0.177	0.86
4	20/1	3.4	17	9.32	2	161	138	14.89	0.319	0.80
5	80/1	4	12.7	3.98	32	269	354	16.33	0.123	0.86
6	20/1	4.2	19	6.76	11	173	116	15.07	0.275	0.84
7	20/1	4.2	20.4	5.46	0	120	117	13.66	0.255	0.87
8	30/1	4	20.2	5.71	1	106	23	14.09	0.249	0.75
9	36/1	4	20	4.95	2	144	77	14.67	0.218	0.79

It was used air jet weaving machine, its type (Picanol PAT-A-N1991- AIR JET), cams shedding mechanism, 635 picks per min, number of healdess equal 4 harness to weave plain fabric structure, 330 machine width and 160 fabric width.

Weft yarns were processed with different pressures of main and sub nozzles (3, 3.5, 4, 4.5, and5 bar) on the air jet machine with total number of samples 155. Coordination between main and sub nozzles' pressures was selected in order to give an acceptable degree of weavability, a straight and well tensioned weft yarns and a minimum number of defects in the fabric.

2.1 Measurement of weft breaks

The following (Equation. 1) is used to calculate the weft breaks per million meters.

$$Weft \quad breaks \quad /10^{6} m = \frac{Actual \quad weft \quad breaks \quad /hr \ * 10^{6}}{picks \quad /\min \ * \ Actual \quad time \quad /hr \ * \ Fabric \quad width} \tag{1}$$

3. Neural Network Design

Analysis of the causes of weft breakages on the air jet machine:

The weft breakages on the air jet machine are due to:

1-machine parameters: machine speed, machine width, main nozzle pressure, sub nozzle pressure, machine width, reed design, and weft insertion time.

2- Yarn physical properties: yarn structure, yarn morphology, yarn air drag coefficient, yarn diameter, yarn cross section shape, diameter variability along the weft length in the shed (thin places, thick places and neps).

3- Yarn mechanical properties: yarn strength, yarn elongation, yarn modulus of elasticity.

The above analysis shows the complexity of the relation between wefts breaks rate and yarn properties, in spite of the low value of the tension on the weft yarn during insertion but yarn breaks occurs. This may be due to the effect of air streams interaction with the yarn during insertion along the machine width. The interpretation of the weft breaking rate for each yarn before weaving will help the weaver to choose the machine settings. In this work the prediction of the weft breaking rate has been made using ANN system**.** Two models are used: the first one using twelve parameters for the input layer and the second model using only the five most correlated yarn parameters as elements for the input layer.

3.1 Architecture

The number of hidden layers and the number of neurons in these layers determine the size of the network. Most practical applications use a network with three layers (an input layer, an output layer and a hidden layer). The number of input neurons normally corresponds to the number of input variables of the process to be modeled.A variety of training algorithms have been developed. The most widely used is the back propagation algorithm which is used to determine the weights. Back-propagation is given in (Equation . 2).

$$y_{k+1} = y_k - \phi_k g_k \qquad (2)$$

Where y_k - a vector of current weights and biases, g_k- the current gradient, and φ_k - the learning rate.

A fast training algorithm using standard numerical optimization techniques was adopted: the Levenberg–Marquardt algorithm shown in (Equation. 3).

$$S(\beta) = \sum_{i=1}^{m} [y_i - f(x_i, \beta)]^2 \qquad (3)$$

The primary application of the Levenberg–Marquardt algorithm is in the least squares curve fitting problem: given a set of m empirical datum pairs of independent and dependent variables, (x_i, y_i), optimize the parameters β of the model curve $f(x,\boldsymbol{\beta})$ so that the sum of the squares of the deviations would be minimized.

For this research, a total of 155 samples of different weft yarns were taken, of which 109 samples (70%) were used for training, 23 samples (30%) for validation, and 23 samples (30%) for testing of the neural network. There are 12 input parameters (yarn count, twist factor, yarn tenacity, hairiness index, thin places, thick places, neps, Cv_m%, yarn diameter, shape of yarn diameter, main nozzle pressure, and sub nozzle pressure) and one output (weft breaks/10^6m). The number of hidden neurons is a very significant factor in the neural networks system. In this research, it was found that the value of hidden neurons of 20 is the best value. It gives a minimum mean square error (MSE) and a maximum efficiency of the model, a high coefficient of correlation.

Two different architectures of artificial neural networks model were used: first ANN shown in (Fig. 1) using all possible affecting parameters into consideration, second one, using only the most correlated factors affecting on the weft breaks rate into consideration and is shown in (Fig. 2).

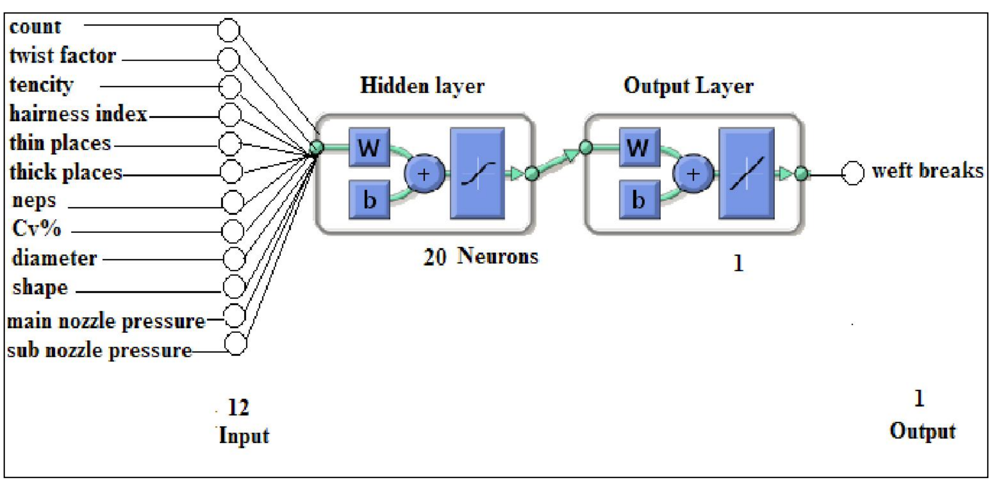

Fig. 1. First artificial neural network model (I).

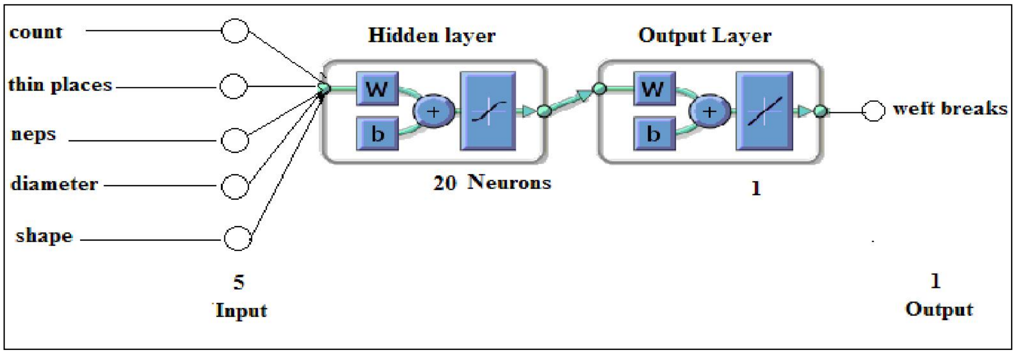

Fig. 2. Second artificial neural network model (II).

4. Results and Discussions

In order to evaluate the neural network models, a comparison between the actual and the predicted values of weft breaks was conducted. The error between the network output and the actual output was calculated by the mean square error (MSE). The mean square error (MSE) can be calculated as in (Equation 4).

$$mse = \frac{1}{N} \sum_{i=1}^{n} (y_i - x_i)^2 \quad (4)$$

Where N _ number of objects, y_i _ the neural network predicted values, and x_i _ the actual output values.

The performance of training algorithm for the first artificial neural network model (I) with a number of neurons in the hidden layer of 20 is illustrated in [Fig. 3]. Mean square error (MSE) decreased gradually and the training stopped at 14 epochs. The (MSE) were nearly the same for the training, validation, and test until the 4th epoch.

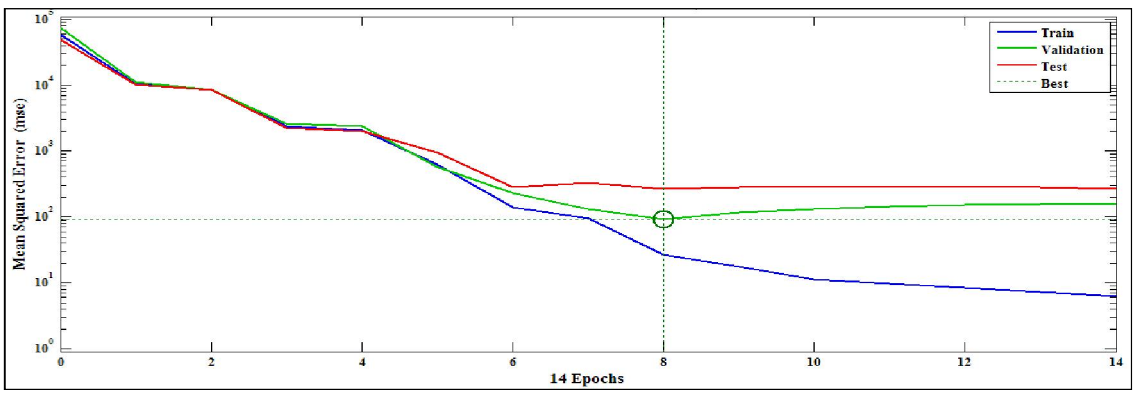

Fig. 3. Performance of the first ANN model (I).

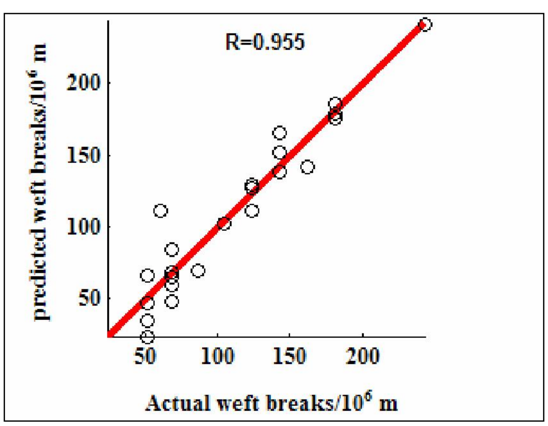

Fig. 4. Relation between actual and predicted weft breaks by ANN model (I).

To test the neural network model (I) 23 samples were used and the relation between actual weft breaks and predicted weft breaks is illustrated in [Fig. 4]. It was noticed that there was an acceptable correlation between actual weft breaks and predicted weft breaks calculated by the neural networks trained. The correlation coefficient obtained (R= 0.955) gives a consistent quality of the forecast given by the training algorithm.

The correlation coefficient "R" between different yarns properties and the values of actual weft breaks was calculated and it was found that the most significant parameters affecting the weft breaks are yarn count, thin places, Neps, diameter, and yarn diameter shape with R values = 0.857, 0.75, 0.56, -0.77, and 0.63 respectively. Therefore, a new ANN model (II), shown in [Fig. 2], was prepared with the most significant parameters as input parameters for the ANN to predict the weft breaks.

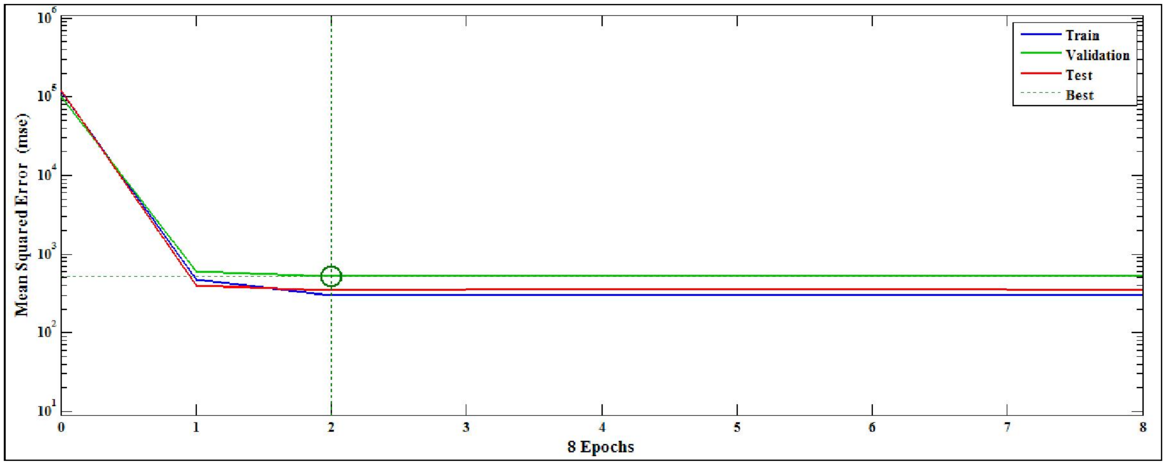

Fig. 5. Performance of the second ANN model (II).

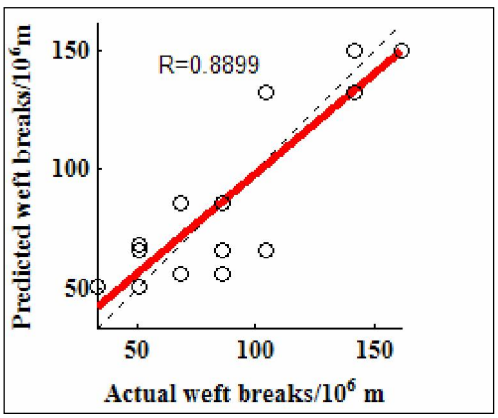

Fig. 6. Relation between actual and predicted weft breaks by ANN model (II).

The performance of the second artificial neural network model (II) is shown in [Fig. 5] with hidden neurons 20 in the hidden layer. The mean square errors were found constant from the first epoch to the 8^{th} epoch. In the neural network model (II), the predicted weft breaks is compared with the actual weft breaks in [Fig. 6]. It can be observed that significant effects ensued with neural network model (II) with coefficient of correlation R= 0.8899.

4. Conclusion

In this paper, an artificial neural network based on a back propagation algorithm was developed and optimized to predict weft breaks' rates for different yarns properties. The results obtained from ANN can be used to predict weft breaks. The coefficient of correlation between the actual and predicted values was found to be 0.955. It was proven that the yarn properties, which mostly affect the rates of weft breaks, are yarn count, thin places, neps, yarn diameter, and yarn diameter shape. Thus, it can be presumed that the neural network can predict weft breaks' rate efficiently.

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