Modeling of needle penetration force in denim fabric

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Abstract

Purpose – This paper aims to predict the needle penetration force (NPF) in denim fabrics using the artificial neural network (ANN) and multiple linear regression (MLR) models based on the effects of various sewing parameters.

Design/methodology/approach – In order to design the ANN and MLR models, four parameters including fabric weight, number of fabric layers, weave pattern, and sewing needle size are taken into account as the input parameters and NPF as the output parameter. According to these parameters, 140 samples of data were resulted. Each sample was tested five times. From these 140 data (input-output data pairs), 112 were used for training the ANN and MLR models and 28 samples were used to test the performance of ANN and MLR. Also, the NPF was measured on the Instron tensile tester to simulate sewing process.

Findings – The results indicated that the NPF in denim fabrics can be well predicted in terms of sewing parameters by using ANN and MLR models, in which the ANN model exhibits greater performance than MLR (RANN $= 0.989 >$ RMLR $= 0.901$).

Research limitations/implications – The NPF measurement method is limited at low speed.

Originality/value – Using the ANN model for forecasting NPF in denim fabrics can help the garment manufactures to produce high-quality denim products and improve the sewing process through reducing seam damage. The NPF could be also measured in the cycle loading conditions similar to sewing machine process by using a special designed tools mounted on the Instron tensile tester.

Keywords Denim fabric, Neural network, Sewing parameters, Needle penetration force

Paper type Research paper

1. Introduction

Nowadays, the role of garment industry in economic activities and human life is considerable (Guo *et al.*, 2011). Among woven fabrics which are used in garment industry, the denim fabrics are widely used as a main part of the garment fashion. Denim apparel is promoted by many consumers around the world; in particular, the success of these fabrics usage is because of its compatibility with every society and culture (Card *et al.*, 2006). The high quality of garments not only does depend on fabric quality, sewing threads and sewing machine parameters, but also depends on fabric sewability (Behera and Chand, 1997). The sewability of fabrics and its importance has been considered in the process of garment manufacturing. The sewability is defined as the ability of the material to be sewn efficiently and to provide a suitable performance for its end use (Stylios *et al.*, 1994). The study of sewability can help better

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comprehending of the interactions between one or more plies of fabric which are sewn with sewing thread (Zeto *et al.*, 1996).

Needle penetration force (NPF) is an important factor influencing on the quality of seams and fabric sewability. The NPF is created by the friction between the martial and sewing needle (Ujević *et al.*, 2008).

The researchers measured NPF to investigate the sewing damage in fabrics during sewing process.

A high penetration force is one of the key reasons causing the sewing damage; on the other hand, a fabric with high penetration force is more susceptible to damage. Sewing damage has directly negative effects on quality of garment. Therefore, the quantitative value of NPF could be used to determine the damage of sewn fabrics during sewing process (Stylios and Zhu, 1998; Zeto *et al.*, 1996; Gurarda and Meric, 2005).

The types of material, number of fabric layers, weave pattern, sewing needle size, and shape of needle point have a profound effect on the sewing NPF (Stylios and Xu, 1995; Ujević *et al.*, 2008).

The researches on NPF can be classified into three categories including the development of an instrument to measure the NPF (Carvalho *et al.*, 2009; Rocha *et al.*, 1996), the investigation of parameters that influence the NPF (Gurarda and Meric, 2007), and predicting the NPF based on theoretical and finite element methods (Lomov, 1998; Mallet and Du, 1999).

In particular, artificial neural network (ANN) and fuzzy logic models are other techniques of modeling, which are used in textile industry. In recent years, ANN has been successfully used in garment industry (Park *et al.*, 1997; Hui and Ng, 2005; Jaouadi *et al.*, 2006).

Stylios and Sotomi (1995) have applied neuro-fuzzy system to model the control of sewing machinery for complicated interactions with limp materials. At first, in order to predict fabric sewability from fabric properties a neural network was applied. Then for optimizing foot pressure and thread tension, the obtained sewability parameter was combined with machine speed in a fuzzy logic system. It was found it could be possible to optimize sewing machine settings under any sewing materials. Also, the foot and disc forces of sewing machines were optimized using the ANN model and neuro-fuzzy logic. The accuracy of the control system was verified by a good agreement between the target and obtained control surfaces for the foot and disc forces (Stylios and Sotomi, 1996).

Park and Kang (1999) objectively evaluated the seam pucker with five shape parameters by using three-dimensional image analysis and artificial intelligence. Barrett *et al.* (1996) developed an on-line fabric classification method to improve stitch formation and seam quality in sewing machine using a wavelet-based neural network approach. Needle penetration and presser foot forces were measured during sewing process and decomposed by using the wavelet transform. Prominent features were extracted by the wavelet transform of the NPF from the input to an ANN that classifies the type of fabric and number of sewn plies.

A new approach for forecasting seam pucker in garment manufacture was examined using ANNs (Stylios and Moore, 1993). The fabric bending stiffness, thickness, and weight were used as inputs to a neural network. The back-propagation (BP) technique was found especially successful to predict the seam pucker.

Hui *et al.* (2007) used ANN with the BP algorithm for the prediction of fabric sewing performance based on the fabric properties. The physical and mechanical properties of fabrics were considered as input units. The sewing performance was identified in terms of seam pucker, sewing needle damage, fabric distortion, and fabric overfeeding. Also, Hui and Ng (2009) designed the ANN to predict seam performance of commercial woven fabrics based on seam puckering, seam flotation, and seam efficiency.

Midha *et al.* (2010) designed an ANN model to predict the strength loss in threads during high speed industrial sewing. The different types of threads, thread linear density, fabric area density, number of fabric layers, stitch density, and needle size were used as input parameters. It was observed that the neural network system is able to predict the tenacity loss of threads after sewing. The seam strength of notched webbings for parachute assemblies was investigated using ANN and the Taguchi's design of experiments (Onal *et al.*, 2009). The results showed that the preciseness of ANN model is higher than Taguchi's design.

Few researchers theoretically predicted NPF and considered fabric and sewing parameters. However, there is no research work available predicting the NPF in denim fabrics using ANN and multiple linear regression (MLR) models. Therefore, this paper presents two models, ANN and MLR, in order to predict NPF and consequently sewing damage in denim fabrics.

2. Descriptions of the models

2.1 Artificial neural networks

ANN (neural networks) is a powerful modeling technique enabling to present any kinds of input-output relationship, and also to solve problems which are difficult for conventional computers or human beings (Majumdar, 2011).

When an ANN is trained, a particular input leads to a specific target output. A network can have several layers, each of which has a weight matrix W, a bias vector b, and an output vector. The layers of a multi-layer network have different performances. The network output is presented in an output layer. The rest of layers are hidden layers. Among the various kinds of networks, feed-forward BP network is widely used. BP trains multi-layer feed-forward networks with differentiable transfer functions. There are various training algorithms for feed-forward networks including *Trainlm, Traingdm* and so on. All these algorithms apply the gradient of the performance function (PF) to identify how to set the weights to minimize performance. *Trainlm* is often the fastest BP algorithm (MATLAB software, 2008).

PF allows a network's behavior to be graded. The typical PF used for training feed-forward networks is the mean squared errors of network (*mse*), mean squared error regularization (*msereg*), and sum of squared error (*sse*) are the other PF. In ANN, learning functions such as *Learngd* or *Learngdm* are used. Transfer functions calculate a layer's output from its net input. There are many forms of transfer functions from a simple linear scaling to nonlinear functions (Figure 1) including *Purelin*, *Logsig*, and *Tansig*, etc. Neural network training can be made more efficient if the preprocessing steps perform on the network inputs and targets (MATLAB software, 2008).

2.2 Multiple linear regression

MLR models are built from a potentially large number of predictive terms. The number of interaction terms augments exponentially with the number of predictor variables. The purpose is to develop a model of the relationship between one dependent variable Y and one or more independent variables X. The model gives the part of the variability of Y

taken in account or explained by the variation of X (MATLAB software, 2008). The MLR model has been used as predictive model in textile problems (Haghighat *et al.*, 2012).

3. Materials and methods

3.1 Fabric sample and needle size

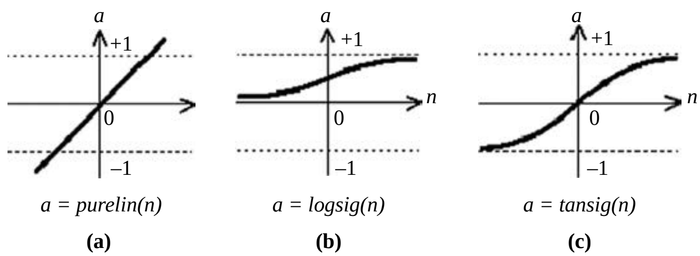
In order to predict the needle NPF, seven commercial samples of denim fabrics with different weights and weave patterns, commonly used for clothing, were prepared (Table I). It is known the needle size is one of the main factors influencing the NPF. Thus, five needles with different sizes (80, 90 100, 110, 120 Nm) were selected.

3.2 Measurement of NPF

Measuring of NPF has been performed on an Instron 5566 tensile tester (Figure 2(b)). In order to hold the fabric samples on the Instron tensile tester, a ring (Figure 2(a)) which previously was designed and constructed used (Doustar *et al.*, 2010). To prevent vertical movement of fabric during needle piercing, the ring was modified in such a way that two emery papers were stuck to its surfaces. The ring is mounted on the bottom jaw of Instron tensile tester. The needle was attached to the upper jaw of Instron by using a special designed needle bar (Figure 2(c)), so that the position of needle penetration relative to the center of ring to be eccentric. It is noted that with eccentric position of needle, it is possible to have different places on the fabric sample during needle penetration by rotating the ring.

To simulate the motion of needle in sewing machine, the cyclic penetration was performed five times for each fabric sample. The needle insertion speed and depth of needle insertion into the fabric structure were 460 mm/min and 12 mm, respectively.

Besides to fabric type and needle size effects, the fabric layer effect is also considered. As a consequence, according to the different fabric types, fabric layers and



$a = n$ $\qquad a = \frac{1}{1 + \exp(-n)}$ $\qquad a = \frac{2}{(1 + \exp(-2n))} - 1$

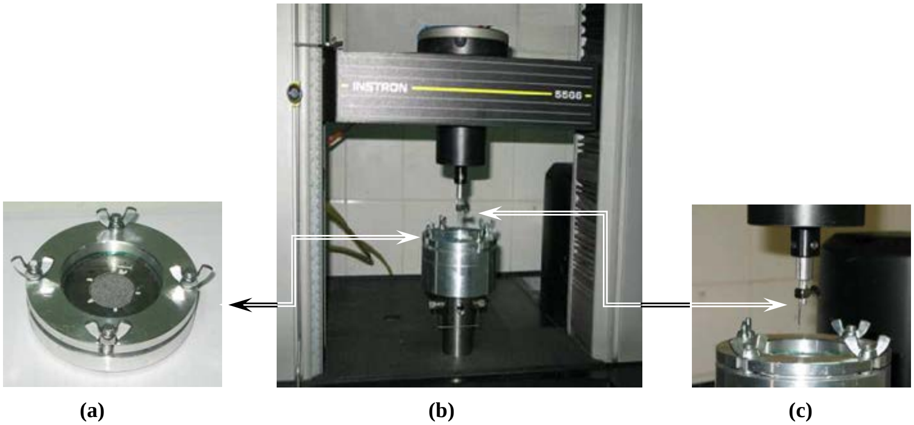
Notes: (a) *Purelin*; (b) *Logsig*; (c) *Tansig*

Figure 1.
Graph of transfer function

Table I.
Physical characteristics of denim fabrics

Fabric code	D1	D2	D3	D4	D5	D6	D7
Weight (g/m^2)	225 (6.63)[a]	300 (8.84)	370 (10.90)	375 (11.05)	402 (11.85)	421 (12.41)	441 (13.00)
Weave pattern	T2/1	T3/1	T2/1	T3/1	T3/1	T3/1	T3/1

Note: [a]The values in parentheses are the fabric weight in terms of (Oz/yd^2)



Notes: (a) Ring; (b) Instron tensile tester together with special attachments; (c) needle bar

Figure 2. Experimental set up to measure NPF on Instron tensile tester

needle size (seven different fabrics, four various layers and five needle size), the number of samples is 140. Each sample was tested five times; therefore, the total number of examined cases was 720. Figure 3 shows a typical result of NPF versus time obtained in this research on the Instron tensile tester.

The force that is considered as NPF is the maximum penetration force between five cycles for each sample. Thus, the average of NPF values for five tested cases of sample was calculated. Table II shows the experimental values of NPF in different conditions.

In order to observe the sewing damage as a result of needle penetration process, some pictures are captured from fabric surface by using a proper digital lens (Dino Capture) connecting to the PC.

3.3 ANN model

In order to normalize and scale the input and output values in neural network, before training, the mapminmax preprocessing is used. It causes the input and output

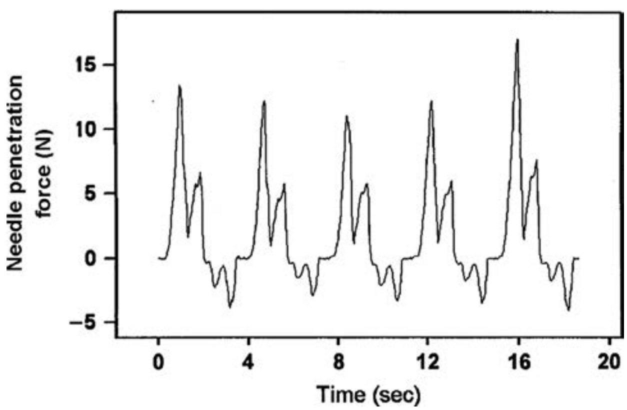


Figure 3. A typical NPF versus time at five cycles loading

No.	NFL	NS	FW	WP	NPF
1	1	80	225	T2/1	2.9
2		90			3.7
3		100			4.4
4		110			5.0
5		120			6.0
6		80	300	T3/1	2.2
7		90			2.5
8		100			2.6
9		110			4.5
10		120			4.7
11		80	370	T3/1	3.0
12		90			3.5
13		100			4.7
14		110			6.6
15		120			7.2
16		80	402	T3/1	3.5
17		90			4.7
18		100			5.3
19		110			6.9
20		120			9.0
21		80	421	T3/1	4.3
22		90			5.4
23		100			5.5
24		110			7.2
25		120			9.2
26		80	441	T3/1	5.7
27		90			8.0
28		100			9.0
29		110			11.1
30		120			12.0
31		80	375	T2/1	4.7
32		90			6.6
33		100			6.6
34		110			7.4
35		120			9.1
36	2	80	225	T2/1	5.4
37		90			6.6
38		100			7.5
39		110			10.4
40		120			12.0
41		80	300	T3/1	3.5
42		90			5.0
43		100			5.3
44		110			7.3
45		120			8.0
46		80	370	T3/1	6.0
47		90			6.5
48		100			8.4
49		110			12.0
50		120			12.9

(*continued*)

Table II.
The measured experimental values of NPF in different conditions

No.	NFL	NS	FW	WP	NPF
51		80	402	T3/1	7.1
52		90			9.2
53		100			10.3
54		110			14.9
55		120			15.1
56		80	421	T3/1	8.0
57		90			10.1
58		100			10.4
59		110			13.8
60		120			16.6
61		80	441	T3/1	11.6
62		90			15.3
63		100			15.6
64		110			20.3
65		120			21.8
66		80	375	T2/1	8.3
67		90			11.0
68		100			11.1
69		110			14.8
70		120			16.1
71	3	80	225	T2/1	7.6
72		90			10.1
73		100			12.2
74		110			15.2
75		120			17.5
76		80	300	T3/1	4.7
77		90			6.6
78		100			7.2
79		110			11.4
80		120			11.8
81		80	370	T3/1	7.6
82		90			10.3
83		100			12.4
84		110			17.0
85		120			18.8
86		80	402	T3/1	9.4
87		90			12.8
88		100			14.5
89		110			18.1
90		120			21.0
91		80	421	T3/1	11.6
92		90			15.1
93		100			15.2
94		110			21.0
95		120			21.7
96		80	441	T3/1	15.9
97		90			21.7
98		100			21.8
99		110			27.1
100		120			30.4

(*continued*)

Table II.

No.	NFL	NS	FW	WP	NPF
101		80	375	T2/1	11.1
102		90			15.2
103		100			17.8
104		110			21.0
105		120			25.6
106	4	80	225	T2/1	9.8
107		90			13.4
108		100			15.8
109		110			20.0
110		120			22.6
111		80	300	T3/1	7.4
112		90			6.3
113		100			8.5
114		110			12.2
115		120			15.3
116		80	370	T3/1	10.4
117		90			12.4
118		100			13.4
119		110			20.0
120		120			21.0
121		80	402	T3/1	10.9
122		90			13.8
123		100			17.3
124		110			24.0
125		120			25.0
126		80	421	T3/1	13.0
127		90			17.5
128		100			18.0
129		110			24.0
130		120			26.9
131		80	441	T3/1	20.2
132		90			24.4
133		100			28.2
134		110			35.7
135		120			39.2
136		80	375	T2/1	14.9
137		90			19.2
138		100			20.6
139		110			26.0
140		120			29.8

Notes: NPF – needle penetration force (N); NS – needle size (Nm); FW – fabric weight (g/m^2); WP – weave pattern

Table II.

values fall within a specified range eliminate the influence of different units of their parameters, and remove any influence of quantitative effects on the training process (MATLAB software, 2008). According to equation (1), the input and output values (v_i) are scaled in the range [-1, 1] by using the function mapminmax (Chattopadhyay and Guha, 2004):

$$x_i = 2\left(\frac{v_i - v_{\min}}{v_{\max} - v_{\min}}\right) - 1 \quad \mathrm{i} = 1, 2 \ldots \mathrm{n} \tag{1}$$

where *xi* is the scaled value, $v_{\max}$ and $v_{\min}$ are respective maximum and minimum values of input and output.

For predicting the NPF, several neural network models with two and three layers were planned. The designed networks have four input units and one unit output (Figure 4).

Moreover, 12 ANNs (*N1*…*N12*) with different data sets, different transfer and PFs, number of hidden layers, and number of neurons in hidden layers, were designed (Table III). In all networks, *Trainlm* was used as learning function.

To model the ANN, first, the five-fold cross-validation technique was used. Hence, the data set of 140 samples was randomly divided into five subsets. The subsets were combined together and five sets of training and testing data were formed. Each time, four subsets were used for training set and one subset for testing set (training set and test set contain 112 and 28 samples, respectively), accordingly, each planned network was trained and tested five times.

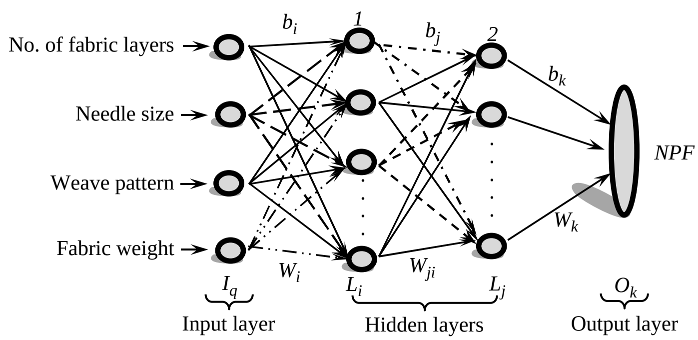


Figure 4. Architecture of a multilayer feed forward network

Code	Network structure	Learning function	Performance function	No. of hidden layers	Transfer function Hidden layer 1	Hidden layer 2	Output layer
N1	4-8-6-1	*LearnGDM*	*mse*	2	*Tansig*	*Tansig*	*Tansig*
N2	4-8-6-1	*LearnGDM*	*msereg*	2	*Tansig*	*Tansig*	*Purelin*
N3	4-8-6-1	*LearnGDM*	*sse*	2	*Tansig*	*Tansig*	*Tansig*
N4	4-10-8-1	*LearnGDM*	*mse*	2	*Tansig*	*Tansig*	*Purelin*
N5	4-8-1	*LearnGDM*	*mse*	1	*Tansig*	–	*Tansig*
N6	4-8-1	*LearnGD*	*mse*	1	*Tansig*	–	*Purelin*
N7	4-6-1	*LearnGD*	*mse*	1	*Tansig*	–	*Purelin*
N8	4-8-6-1	*LearnGDM*	*mse*	2	*Tansig*	*Purelin*	*Purelin*
N9	4-8-1	*LearnGD*	*mse*	1	*Tansig*	–	*Tansig*
N10	4-8-6-1	*LearnGD*	*mse*	2	*Tansig*	*Logsig*	*Purelin*
N11	4-8-6-1	*LearnGD*	*mse*	2	*Tansig*	*Tansig*	*Logsig*
N12	4-6-1	*LearnGD*	*mse*	1	*Tansig*	–	*Logsig*

Table III. Different network architectures

Then, the training sets (112 samples) were used for training the designed neural networks. Finally, after training the networks, it is essential to evaluate the stability and the performance of achieved networks; thus the testing sets (28 samples) were applied for testing the networks. In this study, the MATLAB (R2008b) software was used to perform neural network and MLR modeling.

3.4 MLR model

In the present work, MLR model was presented to predict the NPF based on independent variables of sewing parameters including fabric weight, number of fabric layers, needle size and weave pattern.

For this purpose, the same five sets of data (training and testing sets) in ANN model were used for the MLR algorithm. At first, the MLR models were developed by samples of training sets. Then, the created algorithms were assessed by the testing data sets.

For instance, by using the first set of data, the equation (2) was derived with a MLR algorithm:

$$\text{Needle penetration force} = -26.17 + 3.981{*}NFL + 0.224{*}NS + 0.055{*}FW - 0.475^{*}WP \quad (2)$$

where NFL: no. of number of fabric layers, *NS*: needle size, *FW*: fabric weight, and *WP*: weave pattern.

4. Result and discussion

4.1 The performance of ANN and MLR models in predicting NPF

In this study, two different models of were developed to predict the NPF. The capability of ANN model for forecasting the NPF was examined by designing several architectures of ANN.

For each model, ANN and MLR models, the values *R* and *MSE* (equation (3)) between the experimental and predicted values of NPF were calculated. Moreover, to verify the network model, *PF/3* value was used. Since this factor is more sensitive to the difference between experimental and predicted values; it shows more precise results than correlation coefficient:

$$MSE = \frac{\sum_{i=0}^{n}(p_i - e_i)^2}{n} \quad (3)$$

where *MSE* is mean square error between experimental and predicted values, pi: predicting value, ei: experimental value, and *n:* is the number of patterns.

In order to investigate the performance of ANN and MLR models for forecasting NPF, the designed ANN and MLR models were evaluated using the testing data sets. The achieved results of models are given in Tables IV-VI.

In Table IV, the values of *R*, *PF/3*, and *MSE* obtained by testing networks with five testing data sets are separately depicted. Table V presents the average of these values, which were obtained by training networks with five training data sets.

These results show that the efficiency of ANN for prediction NPF is high (*N1*…*N10*), however some networks do not have great efficiency (*N11*, *N12*). Among the trained networks, network *N9* has partly the greatest performance on the training and testing data sets.

Code	Data set	R-value	Testing PF/3	MSE
N1	1	0.963	18.196	6.182
	2	0.983	11.195	5.016
	3	0.993	6.929	0.562
	4	0.995	6.211	0.428
	5	0.988	12.233	0.669
	Average	0.984	10.953	2.571
N2	1	0.922	21.287	13.417
	2	0.986	9.790	6.179
	3	0.988	9.661	1.011
	4	0.992	8.145	0.480
	5	0.993	7.523	0.932
	Average	0.976	11.281	4.404
N3	1	0.938	21.003	8.975
	2	0.986	9.784	5.158
	3	0.973	14.971	2.706
	4	0.990	9.767	0.813
	5	0.992	9.452	1.809
	Average	0.976	12.995	3.892
N4	1	0.933	21.372	14.287
	2	0.969	14.588	5.234
	3	0.993	7.622	0.975
	4	0.989	10.951	0.923
	5	0.989	9.093	1.237
	Average	0.975	12.725	4.531
N5	1	0.975	13.969	3.452
	2	0.992	7.969	1.004
	3	0.991	7.200	0.942
	4	0.988	9.600	4.583
	5	0.985	9.946	0.877
	Average	0.986	9.737	2.171
N6	1	0.972	17.927	8.478
	2	0.992	7.134	0.933
	3	0.993	8.497	2.389
	4	0.994	6.741	0.445
	5	0.982	15.034	0.869
	Average	0.986	11.066	2.623
N7	1	0.981	17.238	6.659
	2	0.993	8.440	1.606
	3	0.987	11.331	2.658
	4	0.987	10.080	0.849
	5	0.985	13.709	0.743
	Average	0.986	12.160	2.503
N8	1	0.988	11.258	2.039
	2	0.994	7.152	0.851
	3	0.984	14.385	4.102
	4	0.990	9.252	0.852
	5	0.988	8.697	0.769
	Average	0.989	10.149	1.722
N9	1	0.982	12.304	2.941

(*continued*)

Table IV.
Performance of ANN model on testing data sets

Code	Data set	R-value	Testing PF/3	MSE
	2	0.992	8.001	1.116
	3	0.993	8.198	2.985
	4	0.986	11.366	0.902
	5	0.991	10.210	0.658
	Average	0.989	10.016	1.720
N10	1	0.923	22.846	10.996
	2	0.993	8.485	0.881
	3	0.976	13.614	2.104
	4	0.994	6.624	0.362
	5	0.969	14.433	1.410
	Average	0.971	13.201	3.150
N11	1	0.512	55.046	69.947
	2	0.703	50.105	74.092
	3	0.371	63.518	117.252
	4	0.267	63.777	133.170
	5	0.597	63.439	176.873
	Average	0.490	59.177	114.267
N12	1	0.786	43.972	45.978
	2	0.660	51.669	75.312
	3	0.599	57.770	116.157
	4	0.381	64.368	133.170
	5	0.685	58.531	126.873
	Average	0.622	55.262	99.498

Table IV.

Code	R-value	Training PF/3	MSE
N1	0.981	13.039	2.176
N2	0.978	12.998	2.494
N3	0.974	14.319	2.918
N4	0.977	13.429	2.687
N5	0.986	11.241	1.437
N6	0.988	12.725	1.513
N7	0.986	13.347	1.508
N8	0.983	13.269	2.382
N9	0.987	11.567	1.601
N10	0.971	16.745	3.999
N11	0.475	66.036	127.002
N12	0.659	60.610	107.679

Table V.
Performance of ANN model on training data sets

Generally, according to the results, it is clear that the performance of the ANN model is better than MLR model. For example, the network *N9* is compared with MLR model; it is observed that the performance of *N9* to predict the NPF is higher than the performance of MLR model. The average of *R*-value in *N9* is higher than the average of *R*-value in MLR on testing data sets ($0.989 > 0.901$), and *MSE* value for *N9* is less than corresponding value for MLR model ($1.720 < 10.594$).

For example, the performance of network *N9* to predict the NPF is high. The average of *R*-values on training and testing data sets in *N9* are 0.987 and 0.989, respectively. In addition, the *MSE* values on training and testing data sets are 1.720 and 1.601, respectively. However, the performance of MLR model to predict the NPF with average values of *R* and *MSE* (0.901 and 10.594) on testing data sets is not acceptable.

In addition, the value of *PF/3* shows that the preciseness of ANN in network *N9* to predict the NPF is 90 percent.

	Training		Testing	
Data set	*R*-value	*MSE*	*R*-value	*MSE*
1	0.903	7.090	0.902	15.578
2	0.908	8.738	0.916	12.017
3	0.913	9.561	0.905	8.407
4	0.911	9.798	0.892	7.342
5	0.910	9.358	0.890	9.629
Average	0.909	8.909	0.901	10.594

Table VI. Performance of MLR model on training and testing data sets

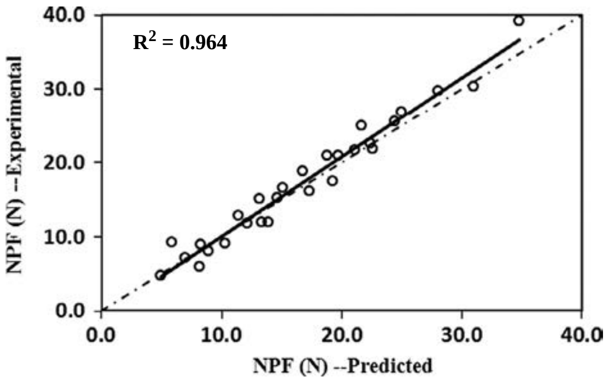


Figure 5. The relationship between experimental and predicted (ANN model; *N9*) values of NPF on testing data set 1

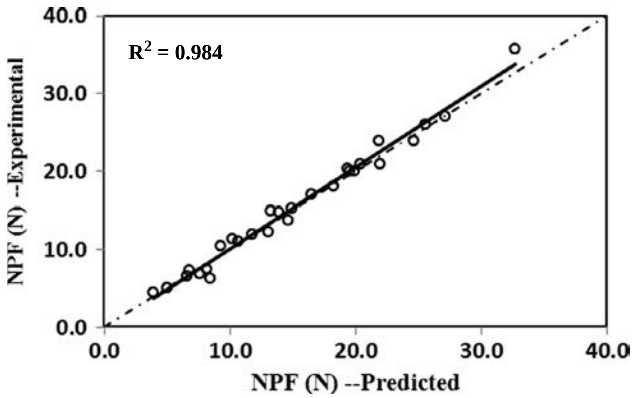


Figure 6. The relationship between experimental and predicted (ANN model; *N9*) values of NPF on testing data set 2

Totally, the performance of ANN is better than MLR model. Figures 5-10 show the relationship between experimental and predicted values on testing data sets in the network *N9*, and on testing data set 2 in MLR, which confirm the neural networks are suitable method for forecasting NPF.

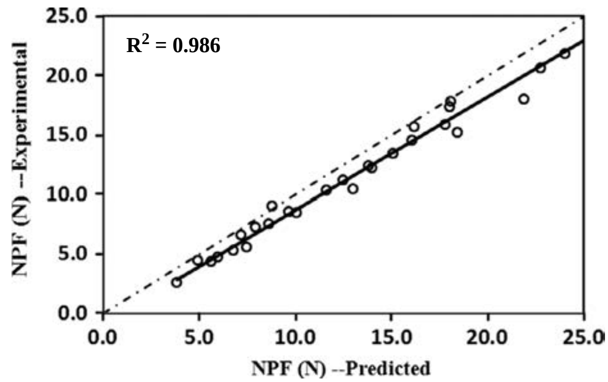


Figure 7.
The relationship between experimental and predicted (ANN model; *N9*) values of NPF on testing data set 3

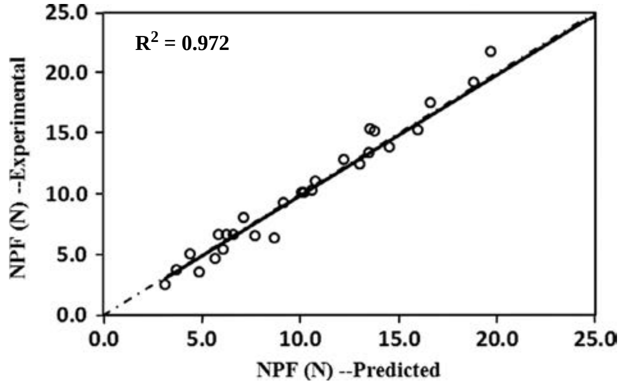


Figure 8.
The relationship between experimental and predicted (ANN model; *N9*) values of NPF on testing data set 4

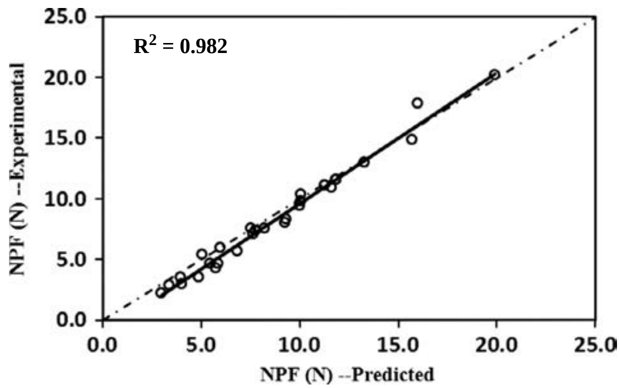


Figure 9.
The relationship between experimental and predicted (ANN model; *N9*) values of NPF on testing data set 5

The architect of networks is important factor to have the best predicting values. By comparing the planned networks (*N1…N12*), it is observed that the transfer function is one of the important parameters in network architect. The results show that using *Logsig* in output layer is not reasonable, because the performance of networks dramatically reduces (*N11*, *N12*). The statistical analysis (One Way ANOVA) clears that the PFs have no significant influence on the performance of neural networks (*N1*, *N2* and *N3*).

According to Tables IV and V, it is generally concluded that by increasing the accuracy of network, the performance of network to predict NPF increases. For instance, in networks which have an appropriate architect, the average values of R and MSE on training data sets are satisfactory. As a result, the performance and stability of model to predict NPF on testing data sets increases (i.e. the value of R increases and MSE decreases).
Moreover, if the methodology of networks is not properly selected, as it could be found in networks *N11* and *N12,* the stability of model for predicting NPF will not be acceptable.

The poor performance of MLR model in prediction NPF infers that the correlation between sewing parameters and the NPF is partially nonlinear, because the MLR is based on the first order equations. Thus, the results of this work showed that ANN model with one or two hidden layers is proper for nonlinear relationships.

4.2 The effect of needle size on the NPF and predicting the sewing damage
As is well known and mentioned before, the NPF is an indication of sewing damage in fabric and hence the sewing damage increases with NPF. Moreover, it was confirmed that the sewing needle size and shape of needle point have a main influence on the NPF and sewing damage (Stylios, 1986; Stylios and Xu, 1995).

The statistical analysis of data shows that at a specified number of fabric layers, fabric weight and weave pattern, with increase of needle size the values of NPF increases. For instance, the effect of needle size on NPF for fabrics with T3/1 weave pattern was presented in Figure 11.

Generally, NPF increases when the diameter of needle becomes greater, especially, in the heaviest fabric (D7: 441 g/m^2). The same trend was obtained for fabrics with T2/1 weave pattern (Table II).

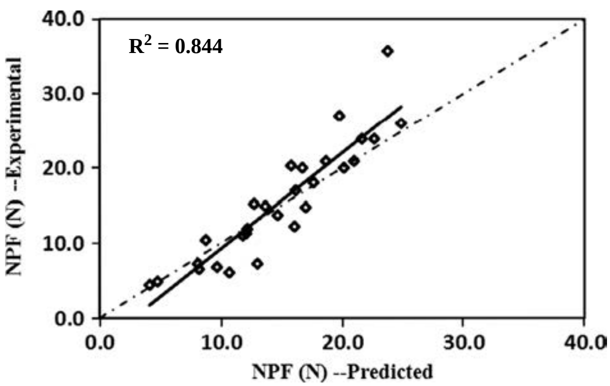
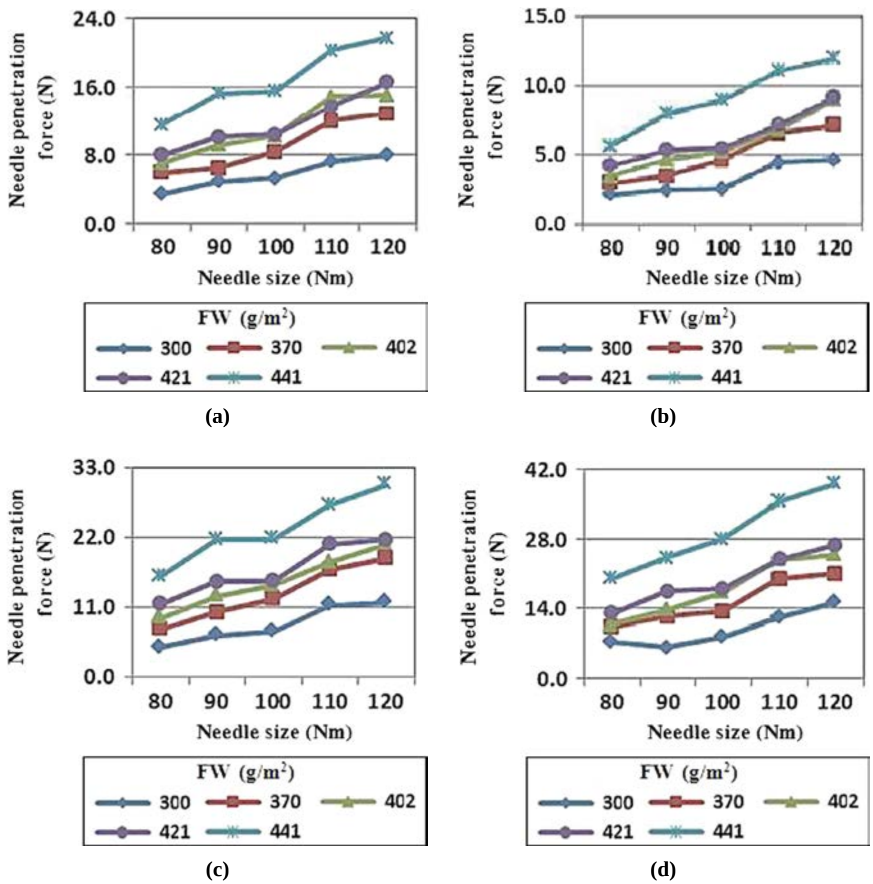


Figure 10.
The relationship between experimental and predicted (MLR model) values of NPF on testing data set 2



Notes: (a) One layer; (b) two layers; (c) three layers; (d) four layers

Figure 11.
The effect of needle size on the NPF under sewing with different fabric weights (300-441 g/m^2), and various number of fabric layers

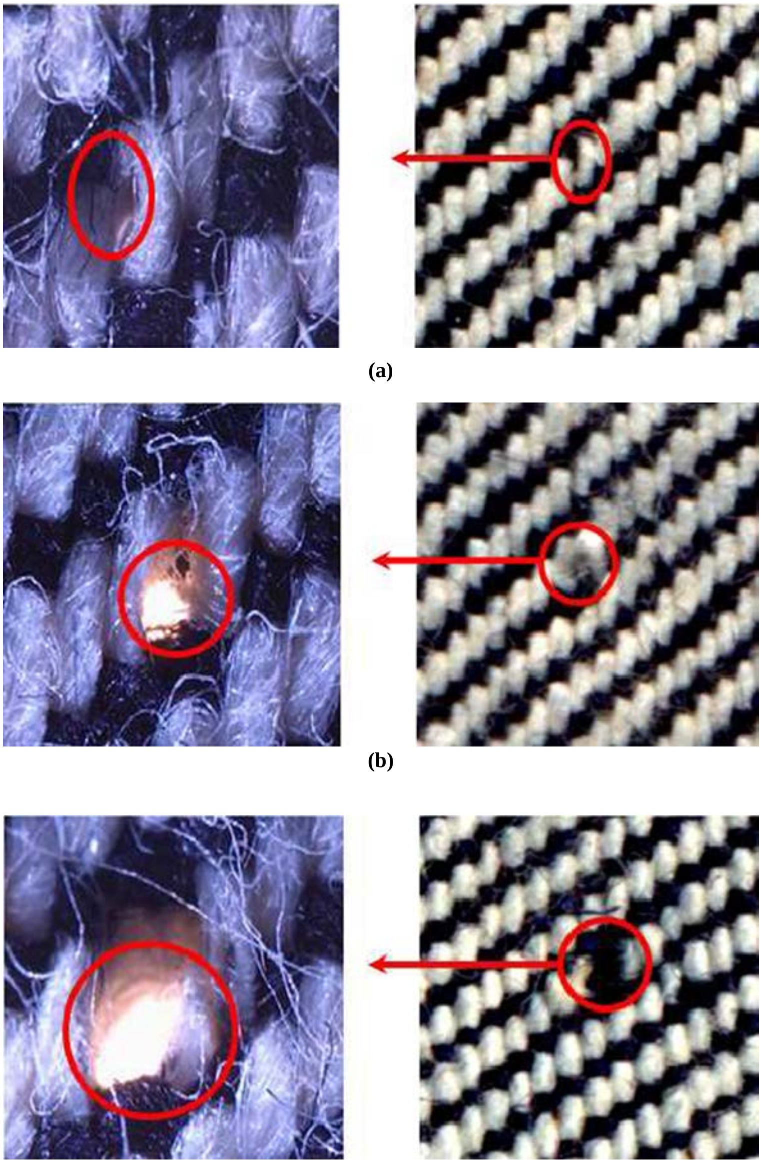
The sewing damage was affected by needle size and it increases when the needle becomes coarser.

This phenomenon is well demonstrated in Figure 12. It is clear that with a coarser needle, the sewing damage over the fabric surface is increased. Therefore, by predicting NPF using ANN and MLR models, it is possible to forecast the sewing damage.

Nevertheless, in order to minimize the sewing damage caused by needle, according to type and characteristics of fabric and sewing threads, the correct needle type and size can be selected (Stylios and Zhu, 1998).

5. Conclusion

In this paper, two models including ANN and MLR were developed to predict the NPF in denim fabrics. In ANN model, several architectures of feed-forward BP networks were planned. In these models the fabric weight, number of fabric layers, weave pattern and needle size are used as inputs and NPF as output values.



(a) (b) (c)

Notes: (a) Needle 80 Nm; (b) needle 100 Nm; (c) needle 120 Nm

Figure 12. Pictures of needle penetration through the fabric surface

According to results, both of models could predict the NPF in denim fabrics. However, it is found that the performance of ANN model was more precise than that of MLR model, since the values *R* and *MSE* in ANN model in compared with MLR model were higher and much lower, respectively. The result suggests that ANN has a greater great efficiency in prediction of penetration force. The calculated value of *PF/3* exhibited that the prediction accuracy of the developed ANN model was 90 percent. The results also showed that the relationship between input parameters (fabric weight, number of fabric layers, weave pattern, and sewing needle) and NPF is nonlinearly correlated. This study also indicated that the NPF could be predicted with high accuracy based on fabric properties and sewing parameters in denim fabrics. The use of ANN model for forecasting NPF in denim fabrics can help the garment manufactories to produce high quality denim products and improve the sewing process through reducing sewing damage. Further research works are needed to extend this study for other fabric types particularly elastic woven structures.

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