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Use of Artificial Neural Networks for Modelling of Seam Strength and Elongation at Break

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Abstract

The strength and elongation at break of a seam are very important characteristics of comfort clothing. Optimum seam strength must be durable enough to do our daily activities easily. Some parameters such as the type and count of the sewing yarn, the seam density, the size of the sewing needle, and type of stitch affecting the strength and elongation at break of the seam. In this study two kinds of fabrics (gabardine and poplin) were chosen for experiments. As sewing parameters, two different types of stitches (plain and chain stitch), five seam densities (3, 4, 5, 6 and 7 seams/cm), two kinds of sewing needles (SPI and SES), and three kinds of sewing yarns (cotton, core-spun, and PBT yarns) were used in experiments. With these materials 120 different seam variations were developed. Each sampless seam strength was tested according to the ISO 13935-1[1] standard using an Instron 4411 instrument. After the testing process, an artificial neural network model was developed to predict the seam strength and elongation at break values. The test results were applied to multi layer perceptron and radial basis function neural network modeling. These two neural network types were compared in terms of the accuracy of the modeling system. The results show that the artificial neural network model produces reliable estimates of seam strength and elongation at break (R=1, MSE=3.33E-05).

Key words: *textile fabrics, artificial neural networks, seam strength, modeling.*

Introduction

A seam is the assembly method that joins fabric pieces together to form parts or the whole of a garment. Seam assembly is the method most typically used on garments. In order to create a seam, a fabric is cut into pieces and sewn together with stitches. Various seams can be obtained by combining different fabric cutting, joining and stitching parameters, and these will lead to substantial variation in fabric drape performance [2]. The seam performance and parameters of a seam are highly related to its structural characteristics. Therefore investigating the performance-parameter relations will not only be beneficial to better understand the sewing process but also give the possible of achieving a computer-aided design of the seam. There are five factors that determine the strength of a seam: the fabric type and weight, thread fibre type, construction and size, stitch and seam construction, stitches per cm, and stitch balance [3].

Artificial neural networks (ANN) can be used in textile technology because most of the textile processes are non-linear. ANNs applications have been tried in many fields of textile technology. For instance, a soft computing system has been developed to model the relationship between yarn properties, fabric parameters, and shear stiffness using the ANN technique. It was found that an accurate and quite good ANN model can be achieved with just a few data points by integrating with the input variable selection method [4].

In literature an ANN model has been adopted to optimise wastewater treatment. Results indicated that ANN models can predict precisely the colour and chemical oxygen demand removal efficiencies for synthetic textile wastewaters [5]. ANN has also been used to predict the bulk density and tensile properties of needle punched nonwoven structures by relating them with the main process parameters [6]. Another example of ANN usage is that the production of a database with four acid dyes was firstly described, along with the large number of mixture dyeings carried out. Then these data were used to construct a network connecting reflectance values with concentrations in formulations. Results indicated that this approach is viable and accurate [7]. The other fields that ANN can be used in are as follows: determination of the structure-property relations of nonwoven fabrics, web density control in carding, prediction of yarn strength, ring and rotor yarn hairiness, total hand evaluation of knitted fabrics, classification of fabric and dyeing defects, tensile properties of needle punched nonwovens, quality assessment of carpets, dye concentrations in multiple dye mixtures, predicting the dyeing time, modeling of the H_2O_2/UV decoloration process, automated quality control of textile seams, fabric processability in garment making, and the evaluation of seam puckering in garments *etc* [4 - 22].

According to the literature review, ANN applications in the clothing industry have been used to predict the seam strength of notched webbings for parachute assemblies [23], the seam performance of commercial woven fabrics based on seam puckering, seam flotation and seam efficiency [24]. Additionally another aspect of these studies was to examine whether ANN could be used to predict the seam strength and elongation at break in poplin and gabardine woven fabrics, and if so, to suggest an appropriate sewing structure design (input variables, number of ANN neurons, training algorithms etc.) for a successful ANN model. For this purpose four sewing parameters (stitch type, seam density, sewing needle type, and sewing yarn type) were chosen for the sewing process. Then the sewed samples' seam strengths were tested by the Instron 4411 instrument. In order to find an average result, every test was repeated five times to model non-linear test results of the textile processes using two kinds of ANN types. With the help of the test results, the ANN models were trained and finally high performance predictions were made for different parameter values. Feed forward and generalised regression neural network types were used for the modeling of the sewing process. The efficiency of the models was evaluated using the mean square error (MSE) and correlation coefficient (R).

Experimental

Materials and method

Gabardine fabric (weight: 275 g/m^2, thickness: 1.55 mm) and poplin fabric (weight: 245 g/m^2, thickness: 1.25 mm) were purchased from Tavsanli Textile Co. All sewing yarns were 30 tex and purchased from Coats. The fabric samples were cut according to the ISO 13935-1 [1] standard and then sewed with the parameters that are given in ***Table 1***. In order to make the needle point compatible with the fabric type, the SPI needle type was used just in gabardine fabric and the SUK type in poplin fabrics. The sewing needle properties can be seen below.

- SPI: Schmetz, 12.5 tex/12, very acute round point.
- SES: Schmetz, 12.5 tex/12, light ball point.
- SUK: Schmetz, 12.5 tex/12, medium ball point.

Pfaff 5488 and Pfaff 481 sewing machines were used in chain and plain stitches, respectively.

Sewing and testing process

By using two fabric types (poplin, gabardine), three kinds of sewing needles (SPI, SES, and SUK), five kinds of seam densities (3, 4, 5, 6, 7 stitches/cm), two kinds of stitch types (chain and plain) and three kinds of sewing yarns, 120 different sewing combinations were designed. In this paper, to fill the input variable space better for modelling of the seam strength and elongation at break by ANN, the experiments were repeated five times. The results of 120 experiments were divided for training (80%) and generalisation (20%). ANN is adjusted according to its error with 96 experimental results. The performance of the trained ANN was tested by feeding 24 experimental data, which was not previously used. After the sewing process, each sample was tested for the tensile strength and elongation at break of the seam according to the ISO 13935-1 [1] standard by the Instron 4411 instrument. Five tests were repeated for each variation in order to ensure the reliability of the test results.

Table 1. *Parameters of sewing.*

Fabric type	Stitch type	Seam density, seams/cm	Sewing needle type	Sewing yarn type
Gabardine Poplin	Plain Chain	3, 4, 5, 6, 7	SUK	Mercerized cotton
			SPI	PBT
			SES	PES/cotton core spun

ANN software

ANNs are parallel computational models which are able, at least in principle, to map any nonlinear functional relationship between an input and output hyperspace to the accuracy desired. From a mathematical point of view ANN is a complex non-linear structure with many parameters that are adjusted (calibrated, or trained) in such a way that the ANN output becomes similar to that of the output measured for a known data set. ANN typically consists of interconnected 'units' which serve as model neurons. The function of the synapse is modelled by an adjustable weight, which is associated with each connection. Each unit converts the pattern of incoming activities in such a way that it reacts with a single outgoing activity and then broadcasts it to the other units. It performs this conversion in two stages: first multiplying each incoming activity called 'total input', then transforming the total input to an outgoing activity [25, 26].

ANN is a typical non-mechanical model for modelling complex information and is known to have 2 intrinsic advantages. The first advantage is its flexible capacity for apprehending the data used for training. Being intrinsically nonlinear, a trained ANN can grasp certain subtle patterns that tend to be overlooked by common statistical methods. The second advantage is its high predictive accuracy, i.e., the predictive capability for "new" data (untrained data) [27, 28].

All ANN calculations were carried out using Matlab 7 software with an ANN toolbox on a PC with an Intel Core2 Duo E8300 3.0 GHz processor and 3 GB RAM. MATLAB provided a platform for numeric calculation, analysis, and visualisation. The ANN toolbox was used to model the system designed with the radial basis function (RBF) and multi layered perceptron (MLP) types of ANN architecture and then trained in the simulation phase.

Multi Layered Perception (MLP) neural network modelling

A typical MLP network is settled in layers of neurons, where every neuron in a layer computes the sum of its inputs $\boldsymbol{x}$ and passes this sum through an activation function (f). The output of the two layer MLP network ($\boldsymbol{o}$) is defined in a matrix form;

$$\mathbf{o} = f^2(\mathbf{W}^1 f^1(\mathbf{W}^1\mathbf{x} + \mathbf{b}^1) + \mathbf{b}^2) \qquad (1)$$

Where $\mathbf{W}_{(\mathbf{i,j})}$ is weight matrices

$$(\mathbf{W}^1 = \begin{bmatrix} w_{1,1} & w_{1,2} & \dots & w_{1,S0} \\ w_{2,1} & w_{2,2} & \dots & . \\ . & . & \dots & w_{2,S0} \\ w_{S1,1} & w_{S1,2} & \dots & w_{S1,S0} \end{bmatrix},$$

$\mathbf{W}^2 = [w_{1,1}\ w_{1,2} \dots w_{1,S1}]$), $\mathbf{b}_{(\mathbf{i})}$ is the bias vector ($b^1 = [b_1\ b_2 \dots b_{S1}]^T$, $b^2 = [b_1]$) and f is the activation functions (f^1logistic, f^2 linear).

Where $\mathbf{W}_{(\mathbf{i,j})}$ is the weight between (i) the output and (j) input, and the superscript defines the layer number. MLP networks can learn to adjust the weight using the back propagation approach.

The back propagation algorithm for the MLP is the generalisation of the least mean square (LMS) algorithm, which should adjust the network parameters in order to minimise the mean square error;

$$e = \frac{1}{2}\sum_{\mu=1}^{p}(t^\mu - o^\mu)^2 \qquad (2)$$

Where, t is the target, o the MLP output, and μ is the sample instant of q size.

The steepest descent algorithm for the approximate mean square error at the k th iteration;

$$w^m{}_{i,j}(k+1) = w_{i,j}(k) - \eta\frac{\partial e}{\partial w_{i,j}}$$
$$b^m{}_i(k+1) = b_i(k) - \eta\frac{\partial e}{\partial b_i} \qquad (3)$$

Where η is the learning rate [29, 30].

The MLP architecture realized is shown in ***Figure 1***. Four inputs of the ANN were the stitch type, seam density per cm, sewing needle type, and sewing yarn type. The ANN had one hidden layer and one output. The value of the output indicated the seam strength and seam elongation at break, respectively. Four MLP models were developed: ANN1-ANN2 and ANN3-ANN4 indicate the seam strength and seam elongation model for gabardine and poplin fabrics, respectively.

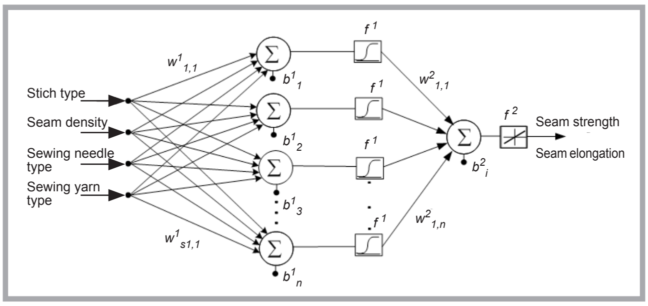

Figure 1. Schematic diagram of MLP network realized (n = number of the neurons).

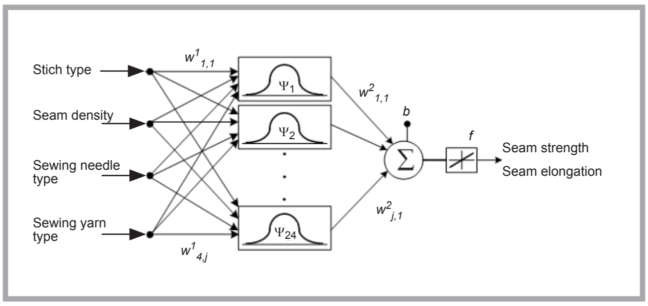

Figure 2. RBF type ANN structure designed for modelling the sewing process.

Radial Basis Function (RBF) neural network modeling

The RBF network is a three-layer feed-forward network that generally uses a linear transfer function for the output units and a nonlinear transfer function (Gaussian function) for the hidden units. Its input layer simply consists of the source nodes connected by weighted connections to the hidden layer and the net input to a hidden unit is the distance measured between the input presented at the input layer and the point represented by the hidden unit. The nonlinear transfer function is applied to the net input to produce a radial function of the distance. The output units implement a weighted sum of the hidden unit outputs [31]. Some parameters affect the performance of RBF: the number and location of the centers, the structure of the RBF functions at the hidden units, and the determination method of the network weights. RBFs can be used for classification, control, discrete pattern classification, function approximation, signal processing or any other application which requires the mapping of an input to an output [32].

The RBF architecture designed is presented in ***Figure 2***. The ANN model designed has four inputs (stitch type, seam density/cm, sewing needle type, and sewing yarn type), one hidden layer and one output (seam strength and elongation at break).

Results and discussion

Modelling of the sewing process using MLP

The performance of an MLP model depends on the number of neurons in the hidden layer. Determination of the optimal value of neuron numbers has no common rule, instead a trial and error approach can be used in this process, as we have already used. As can be seen in ***Tables 2*** and ***3***, the performance of MLP

Table 2. MSE and R values of different ANN models for gabardine fabric.

	Model	Hidden Layer Neuron Number	Mean Square Error (MSE)			Correlation Coefficient (R)		
			Learning	Generalization	All	Learning	Generalization	All
Seam strength, kgF	ANN1-5	5	4.0415E-01	4.7679	1.2769	0.9946	0.9641	0.9845
	ANN1-10	10	3.4519E-16	11.1315	2.2263		0.9087	0.9731
	ANN1-15	15	5.4711E-23	4.2109	0.8422		0.9580	0.9895
	ANN1-20	20	3.8970E-19	1.2214	0.2443		0.9863	0.9969
	ANN1-25	25	1.0929E-18	7.6199	1.5240		0.9507	0.9822
	ANN1-30	30	1.4188E-25	27.8748	5.5750	1.0000	0.9104	0.9448
	ANN1-35	35	2.7635E-19	9.8476	1.9695		0.9354	0.9770
	ANN1-40	40	1.3034E-15	11.0615	2.2123		0.9609	0.9765
	ANN1-45	45	1.6980E-25	37.4820	7.4964		0.8369	0.9206
	ANN1-50	50	4.4019E-24	14.0592	2.8118		0.9028	0.9686
Seam elongation at break, %	ANN2-5	5	1.6106E-01	0.8306	0.2950	0.9225	0.7281	0.8695
	ANN2-10	10	1.2098E-18	0.0545	0.0109		0.9887	0.9958
	ANN2-15	15	4.3189E-13	0.3012	0.0602		0.9417	0.9761
	ANN2-20	20	2.6296E-15	0.6223	0.1245		0.8468	0.9501
	ANN2-25	25	6.8741E-17	0.3777	0.0755		0.8871	0.9683
	ANN2-30	30	1.1089E-12	0.3364	0.0673	1.0000	0.9201	0.9733
	ANN2-35	35	1.5848E-18	0.3468	0.0694		0.9232	0.9725
	ANN2-40	40	1.8928E-20	0.3773	0.0755		0.8888	0.9685
	ANN2-45	45	1.1394E-14	0.2897	0.0579		0.9074	0.9755
	ANN2-50	50	1.8864E-25	1.1894	0.2379		0.5679	0.8965

Table 3. MSE and R values of different ANN models for poplin fabric.

	Model	Hidden Layer Neuron Number	Mean Square Error (MSE)			Correlation Coefficient (R)		
			Learning	Generalization	All	Learning	Generalization	All
Seam strength, kgF	ANN1-5	5	1.0464E-01	2.2099	0.5257	0.9987	0.9768	0.9934
	ANN1-10	10	1.3699E-13	0.2032	0.0406		0.9977	0.9995
	ANN1-15	15	4.6835E-19	0.8931	0.1786		0.9852	0.9977
	ANN1-20	20	1.1668E-19	2.0654	0.4131		0.9808	0.9950
	ANN1-25	25	2.8711E-24	2.4961	0.4992		0.9835	0.9941
	ANN1-30	30	8.3985E-20	2.3910	0.4782	1.0000	0.9728	0.9940
	ANN1-35	35	2.2304E-18	0.7218	0.1444		0.9898	0.9982
	ANN1-40	40	5.5516E-28	3.2998	0.6600		0.9377	0.9913
	ANN1-45	45	1.9562E-17	6.1497	1.2299		0.8860	0.9837
	ANN1-50	50	9.9108E-24	19.3807	3.8761		0.9006	0.9573
Seam elongation at break, %	ANN2-5	5	3.3305E-05	0.0062	0.0013		0.9985	0.9996
	ANN2-10	10	2.2586E-09	0.0148	0.0030		0.9959	0.9990
	ANN2-15	15	4.2601E-13	0.0495	0.0099		0.9885	0.9969
	ANN2-20	20	2.0684E-18	0.1598	0.0320		0.9684	0.9900
	ANN2-25	25	7.6856E-22	0.1841	0.0368	1.0000	0.9597	0.9883
	ANN2-30	30	2.7244E-18	0.2700	0.0540		0.9624	0.9846
	ANN2-35	35	4.4000E-12	0.3576	0.0715		0.9489	0.9787
	ANN2-40	40	2.8376E-16	0.6183	0.1237		0.9247	0.9670
	ANN2-45	45	4.7435E-22	1.2801	0.2560		0.7986	0.9250
	ANN2-50	50	4.9560E-12	0.9014	0.1803		0.8443	0.9472

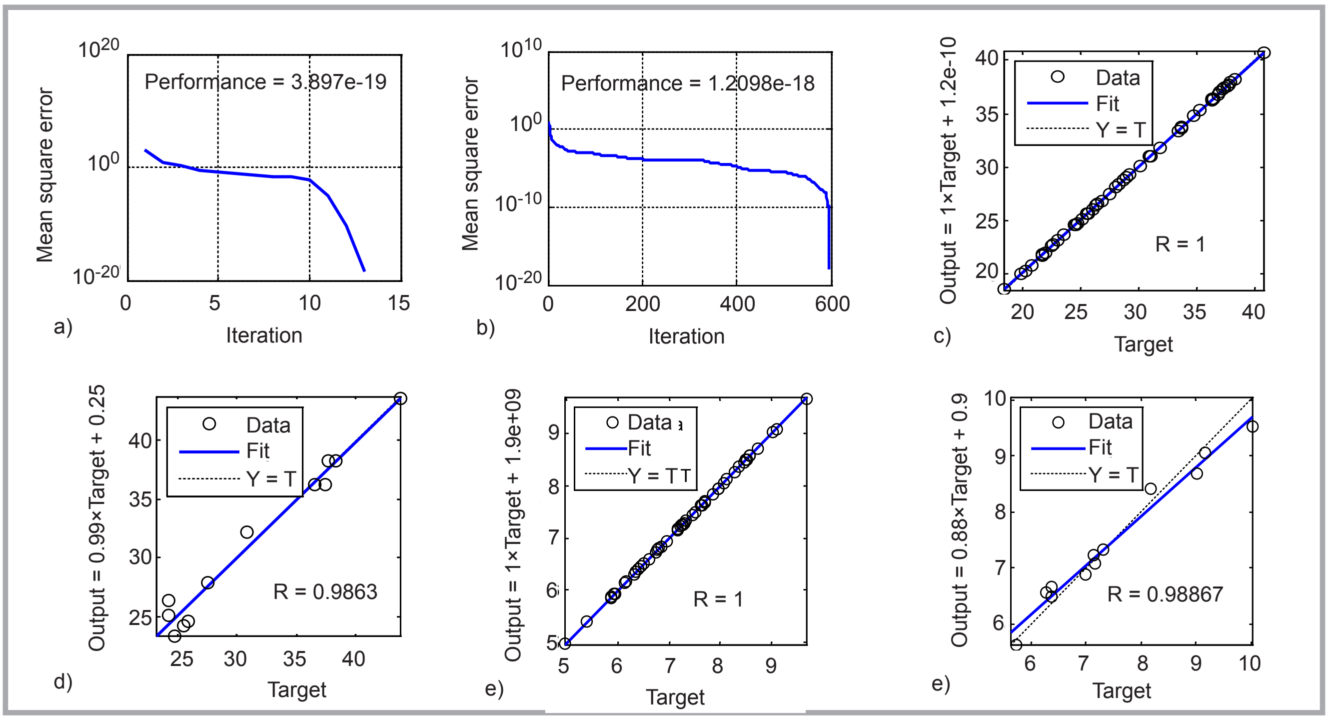

Figure 3. Training performances and R values of gabardine fabric;a) Seam strength training performance, b) Elongation at break training performance, c) R of training of seam strength, d) R of training of elongation at break, e) R of testing of seam strength, f) R of testing of elongation at break.

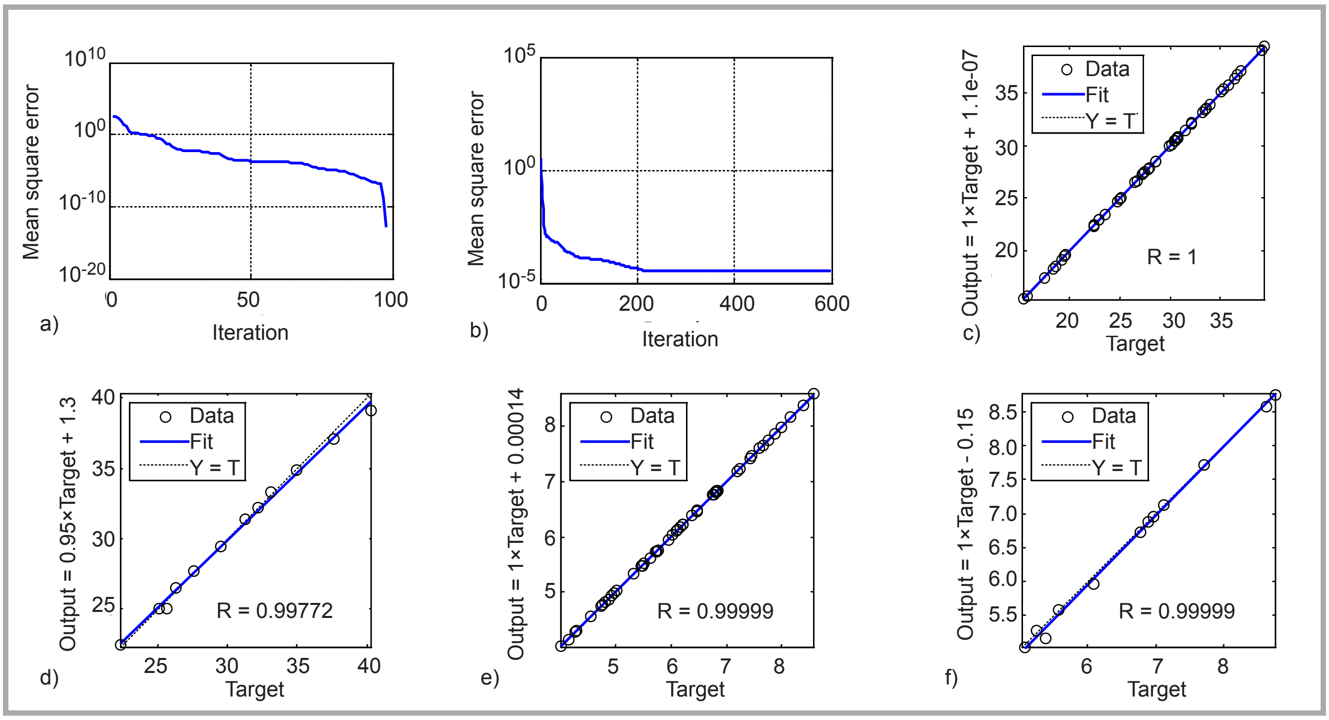

Figure 4. Training performances of MLP and R values of poplin fabric; a) Seam strength training performance, b) Elongation at break training performance, c) R of training of seam strength, d) R of training of elongation at break, e) R of testing of seam strength, f) R of testing of elongation at break.

with 5, 10, 15, 20, 25, 30, 35, 40, 45 and 50 neurons in the one hidden layer was evaluated according the mean square error (MSE) and correlation coefficient (R). In order to show the ANN performance clearly, the MLP type for gabardine ANN1-20 and ANN2-10, ANN1-10 for poplin and ANN2-5 were chosen for the seam strength and seam elongation at break, respectively.

The ANN model was trained by the steepest descent algorithm. The momentum constant and learning rate were 0.842 and 0.485, respectively. The results of 96 experiments were used for training the ANN. The training performances of the ANN1-20 and ANN2-10 for seam strength and elongation are presented in ***Figures 3.a*** & ***3.b***. The trained ANNs models were tested with 24 new experimental results. The correlation coefficient values of learning and generalisation ANN1-20 and ANN2-10 for gabardine fabric are shown in ***Figures 3.c, 3.d, 3.e** & **3.f***.

The training performances of the ANN1-10 and ANN2-5 for seam strength and seam elongation are shown in ***Figures 4.a** & **4.b***. The correlation coefficient values of learning and generalsation ANN1-40 and ANN2-25 for poplin fabric are presented in ***Figures 4.c, 4.d, 4.e*** and ***4.f***.

Modeling of the sewing process using RBF

We developed a seam performance estimation model based on two independent variables: seam strength and elongation at break. The results of 96 experiments were used for training with a 0.5 spread, and 24 experiments were used for generalisation. The correlation coefficient values of learning and generalisation for gabardine and poplin fabrics are shown in ***Figures 5*** and ***6***, respectively.

Comparison of MLP and RBF output performances

In this section, we compare the performance of the MLP and RBF models in terms of the estimation accuracy of the sewing process. A comparison of MLP and RBF performances for gabardine and poplin fabric can be seen in ***Figures 7*** and ***8*** (see page 122), respectively. Additionally MSE and R values of the MLP and RBF models for both poplin and gabardine fabrics are shown in ***Table 4*** (see page 123).

According to ***Figures 7** & **8*** and ***Table 4***. the RBF model's output performances (MSE and R) are better than the MLP model's for both the training and testing processes. Except for poplin fabric, the MLP is better than the RBF regarding the elongation at break output in the testing process.

Conclusion

In this paper, the performance of the MLP and RBF ANN models developed were evaluated in order to the modeling sewing process. A procedure is presented for modelling using two ANN types (MLP and RBF) from the seam strength and elongation at break test results in order to determine the relationship between the results and sewing parameters. The success of neuron numbers in the hidden layer of the modelling structure was studied. Higher values of correlation coefficients (R=1) and lower MSE (3.33E-05) values show that the model and its values predicted are close for both MLP and RBF. By comparing the two ANN types, it is concluded that the best modelling results were obtained using MLP in the training process and RBF in the testing process; however, in general there is a consistent similarity between the ANN models and test results. With the help of the ANN models sewing parameters can be chosen in order to form an optimum

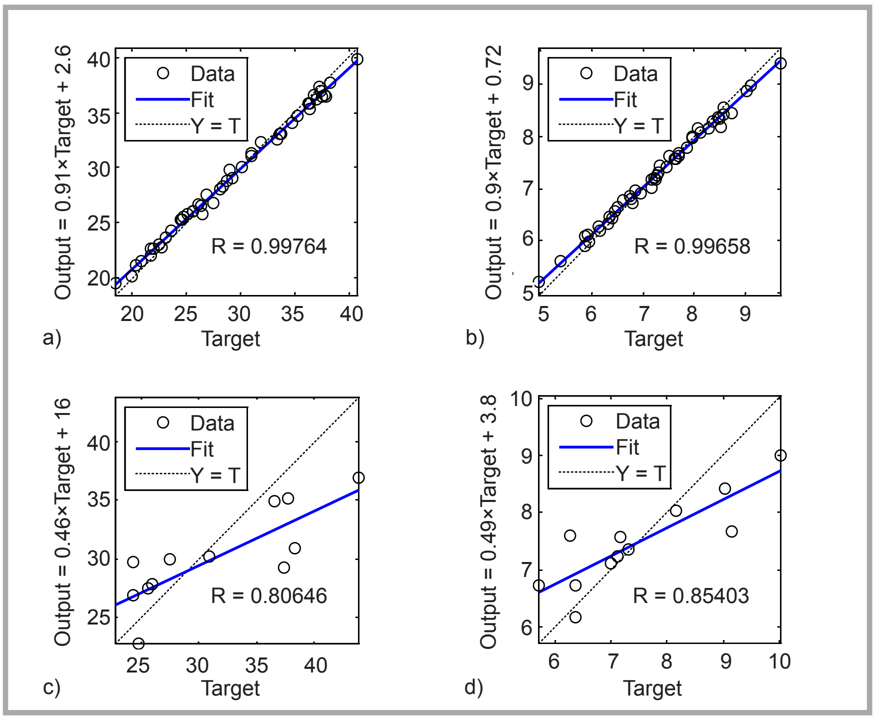

Figure 5. *R values of RBF training and testing of gabardine fabric; a) R of training of seam strength, b) R of training of elongation at break, c) R of testing of seam strength, d) R of testing of elongation at break.*

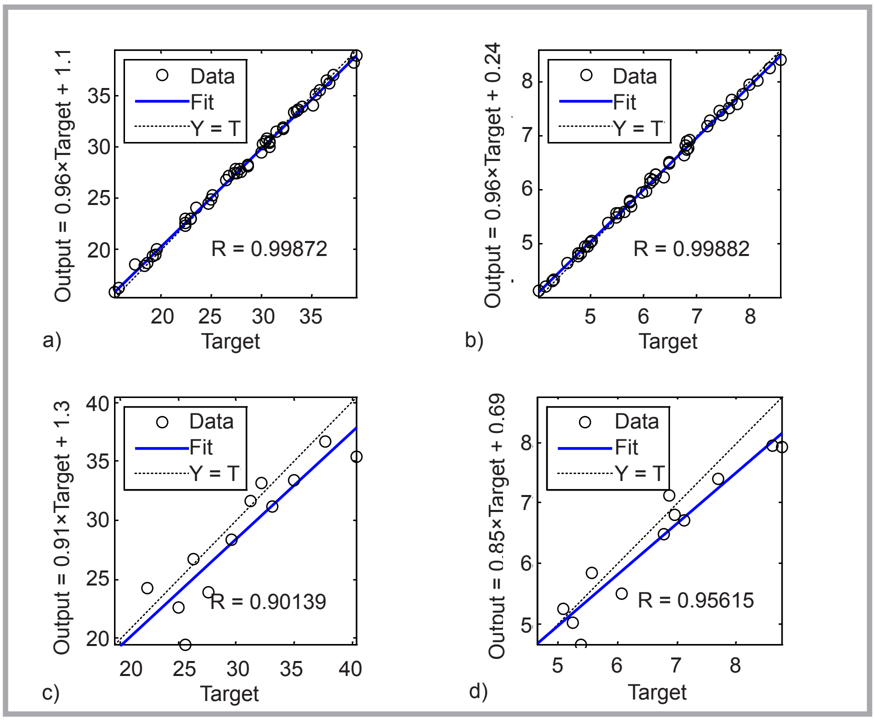

Figure 6. *R values of RBF training and testing of poplin fabric; a) R of training of seam strength, b) R of training of elongation at break, c) R of testing of seam strength, d) R of testing of elongation at break.*

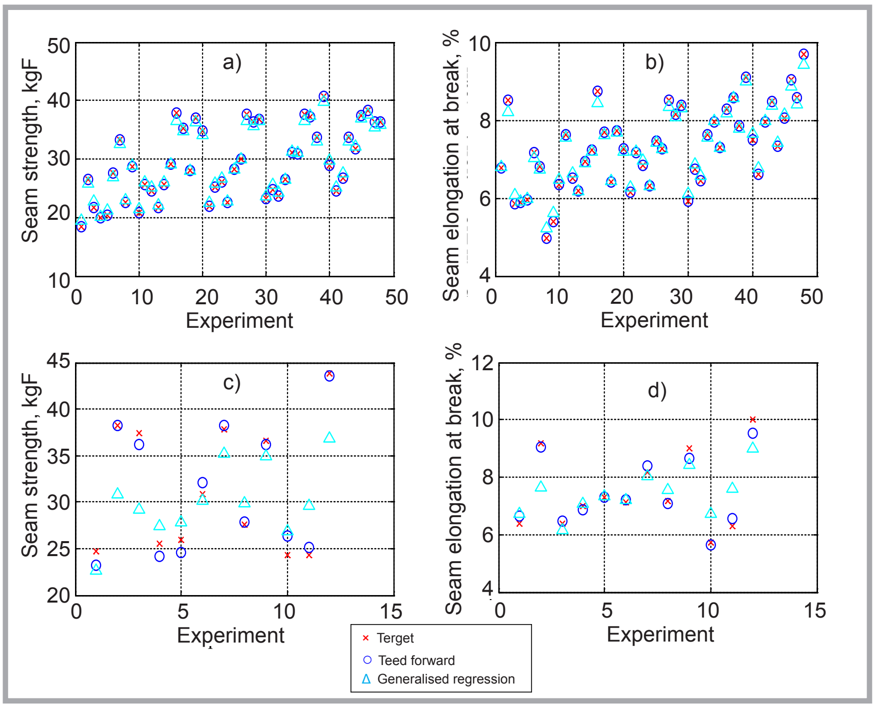

Figure 7. *Comparison of neural networks (MLP and RBF) for gabardine fabric; a) Training data of seam strength, b) Training data of elongation at break, c) Testing data of seam strength, d) Testing data of elongation at break.*

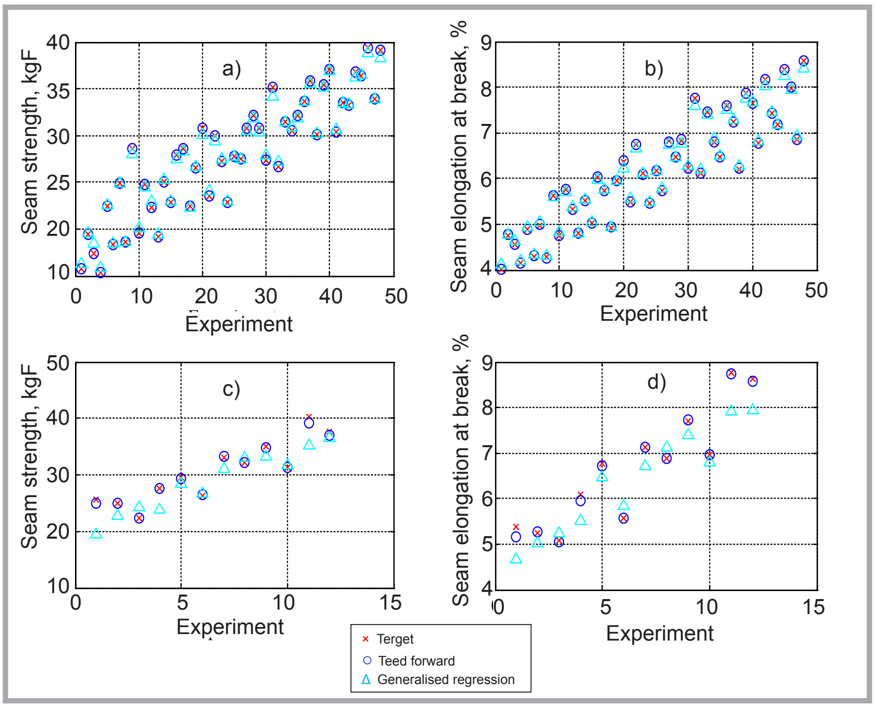

Figure 8. *Comparison of neural networks (MLP and RBF) for poplin fabric; a) training data of seam strength, b) training data of elongation at break, c) testing data of seam strength, d) testing data of elongation at break.*

sewing process. Thus time and costs can be reduced.

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Table 4. Comparison of MSE and R values of MLP and RBF models.

Fabric type		MLP				RBF			
		Seam strength		Elongation at break		Seam strength		Elongation at break	
		MSE	R	MSE	R	MSE	R	MSE	R
Gabardine	Train	3.90E-19	1.0000	1.21E-18	1.0000	4.41E-01	0.9976	0.0164	0.9966
	Test	1.22E+00	0.9863	0.0545	0.9887	1.94E+01	0.8065	0.5672	0.8540
Poplin	Train	1.37E-13	1.0000	0.2032	0.9977	1.57E-01	0.9987	0.0053	0.9988
	Test	3.33E-05	1.0000	0.0062	0.9985	7.93E+00	0.9014	0.2153	0.9562

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