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Predicting Seam Performance of Commercial Woven Fabrics Using Multiple Logarithm Regression and Artificial Neural Networks

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Abstract In this study, the capability of artificial neural networks and multiple logarithm regression methods for modeling seam performance of commercial woven fabrics based on seam puckering, seam flotation and seam efficiency were investigated. The developed models were assessed by verifying Mean Square Error (MSE) and Correlation Coefficient (*R*-value) of test data prediction. The results indicated that the artificial neural network (ANN) model has better performance in comparison with the multiple logarithm regression model. The difference between the mean square error of predicting in these two models for predicting seam puckering, seam flotation, and seam efficiency was 0.0394, 0.0096, and 0.0049, respectively. Thus, the ANN model was found to be more accurate than MLR, and the prediction errors of ANNs was low despite the availability of only a small training data set. However, the difference in prediction errors made by both models was not significantly high. It was found that MLR models were quicker to construct, more transparent, and less likely to overfit the minimal amount of data available. Therefore, both models were effectively predicting the seam performance of woven fabrics.

Key words seam performance, commercial woven fabrics, multiple logarithm regression, artificial neural networks

In cut and sewn apparel products, seams are formed when two or more pieces of fabric are held together by stitches. As the seam is one of the basic requirements in the construction of apparel, seam quality has great significance in apparel products. Consumers evaluate the seam quality of a particular fabric mainly based on the seam performance of a particular fabric sewn by a particular sewing thread. Many previous studies [1–4] have shown that seam performance of a particular fabric depends on the interrelationship of fabrics, threads, stitch type, seam type, and sewing conditions. Sewing conditions include the needle size, stitch density, and the appropriate operation and maintenance of the sewing machines. The seam perform-

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ance of a particular fabric mainly depends on three aspects: seam puckering, seam flotation, and seam efficiency. Seam puckering is used to determine the seam appearance of fabrics sewn by sewing thread under a particular sewing condition [5,6]. Seam flotation is used to determine the degree of deformation along the seam line because of the interaction of the shear load (affecting the fabric through the sewing thread) and fabric extension in the area of the seam [5,7]. Seam efficiency is used to assess the durability of the seam, which is the ratio of seam strength to fabric strength of the fabrics sewn [8,9]. These three parameters are currently adapted by the apparel industry to assess the seam performance of commercial woven fabrics.

Generally, modeling and prediction of seam performance of fabric based on fabric properties and sewing parameters have been considered by many researchers. Over the years, one of the first approaches has been the use of mathematical models. In this category, studies such as the work of Germanova and Petrov [10], Fan et al. [11], Gersak [5] and Stylios [12] had to predict seam puckering and seam efficiency. In addition, statistical regression models for this purpose have been used by some researchers, namely Juciene and Dobilaite, Mariolis and Dermatas, and Koehl et al. [13–15].

The limitation of mathematical and statistical regression models was described in previous works [16,17]. Some branches of artificial intelligence (AI) called artificial neural networks (ANNs), genetic algorithm, machine learning and fuzzy set theory presented attractive alternatives for predictive modeling. In this category, studies such as Park and Kang [18] evaluating the shape parameters of seam puckering using a neurofuzzy approach, and Pavlinic et al. [19] predicting seam quality using machine learning were conducted. Other studies [20,21] gave good predictive performance using a hybrid approach in a particular area such as clothing comfort. However, ANN algorithms have been proved successful by many researchers for modeling in various textile and clothing areas [11,17,22–27]. This is a reason why ANN and multiple regression models were investigated in our study.

There is no previous work determining the suitable modeling tool for predicting seam performance based on various fabric properties. In this study, we aimed to compare the capability of two algorithms, statistical regression and ANN, for predicting the seam performance of commercial woven fabrics based on seam puckering, seam flotation and seam efficiency in order to identify a suitable modeling method of seam performance which is meaningful to textile and clothing industries.

Artificial Neural Networks (ANNs)

ANNs represent a set of very powerful mathematical techniques for modeling, control and optimization [28]. ANN is a powerful data modeling tool that is able to capture and represent each kind of input-out relationship [29]. A neural network is composed of simple elements called "neuron" or "processing element" operating parallel, which is inspired by biological neuronal systems. In nature, the network function is determined largely by weighted connection between the processing elements [30]. The weights of connections contain the "knowledge" of the network [28]. A neural network is usually adjusted or trained so that a particular input leads to a specific output [30]. The process of training is adjusting these weight values to slide down the prediction error [28]. Among the various kinds of algorithms for training neural networks, back propagation is the most widely used. This algorithm was detailed by Patterson [31] and Schalkoff [32].

Experimental

Preparation of Training and Testing Data Set

Fifty woven fabrics, commercially used for the manufacture of men's' and women's outerwear, were selected in the course of the garment manufacturing process. Particulars of fabric specimens are listed in Table 1. They differed in raw material content, mass, weave, and construction parameters.

A review of the past literature [5,19,33] indicates that the degree of seam puckering depends on the structure, construction and fineness of the fabric, its mechanical properties, sewing needle gauge and stitch length. The degree of seam efficiency depends on the thickness of sewing thread, extensibility of sewing thread and fabric strength [34]. The degree of seam flotation depends on the bending and shearing properties, the formability of fabric and extension of fabric [19]. Therefore, such fabric mechanical properties related to seam performance (as shown in Table 2) were determined in the area of low loads, using the KES-FB measuring system at standard measuring conditions [35,36]. In addition, fabric weight in g/m^2 and fabric strength in N were measured according to the ASTM D3776-96 standard and the ASTM D5034 test methods respectively.

All seam specimens were prepared by a 100% spun polyester (35 Tex) commercial sewing thread sewn on the fabric specimen under plain seam type (ISO 1.01.01) in single needle lockstitch (ISO 301). Stitch density (10 stitches per inch) commonly used for sewing of commercial woven fabrics were selected in this study. As our study is mainly concerned with the modeling of fabric properties on seam

Table 1 Particulars of Fabric Specimens.

Fabric Sample	Weave Construction	Material	Ends/cm	Picks/cm	Weight (gm/m^2)	Thickness (mm)
1	Plain	100% Cotton	32	18	884.5	1.31
2	Plain	100% Cotton	24	13	680.2	1.19
3	Plain	100% Cotton	39	26	544.3	0.86
4	Plain	100% Cotton	46	28	476.2	0.83
5	Plain	100% Cotton	72	40	342	0.57
6	Plain	100% Cotton	94	48	273.6	0.52
7	Plain	100% Cotton	104	53	214.4	0.59
8	Plain	100% Cotton	90	50	153.2	0.42
9	Plain	100% Cotton	128	70	254	0.33
10	Plain	100% Cotton	60	44	308	0.27
11	Plain	100% Cotton	136	62	151	0.39
12	Plain	100% Cotton	60	60	167	0.50
13	Plain	100% Cotton	130	70	150	0.35
14	Plain	100% Cotton	104	53	181	0.52
15	Plain	100% Cotton	160	78	136	0.36
16	Plain	100% Cotton	136	62	151	0.45
17	Plain	100% Cotton	164	62	184	0.55
18	Plain	100% Cotton	130	80	131	0.38
19	Plain	100% Cotton	72	72	102	0.25
20	Plain	100% Cotton	60	60	167	0.44
21	Plain	100% Cotton	172	70	250	0.55
22	Plain	100% Cotton	170	120	130	0.39
23	Plain	100% Cotton	110	53	183	0.54
24	Plain	100% Cotton	56	54	150	0.45
25	Plain	100% Cotton	150	80	206	0.51
26	Satin	98% Cotton 2% Spandex	190	60	255	0.56
27	Plain	98% Cotton 2% Spandex	96	56	185	0.34
28	Plain	55% Linen 45% Cotton	51	47	199	0.4
29	Twill	98% Cotton 2% Spandex	156	60	278	0.56
30	Satin	59% Cotton 38% Nylon 3% Spandex	196	92	216	0.48
31	Plain	97% Cotton 3% Spandex	164	78	198	0.32
32	Twill	98% Cotton 2% Spandex	124	44	260	0.5
33	Twill	78%Cotton 20%Polyester 2%Spandex	126	58	193	0.39
34	Twill	98% Cotton 2% Spandex	156	50	288	0.56
35	Plain	98% Cotton 2% Spandex	66	40	311	0.6
36	Twill	97% Cotton 3% Spandex	132	58	241	0.49
37	Plain	100% Cotton	94	46	270	0.41

Table 1 (continued)

Fabric Sample	Weave Construction	Material	Ends/cm	Picks/cm	Weight (gm/m^2)	Thickness (mm)
38	Plain	100% Cotton	100	60	76	0.2
39	Plain	100% Cotton	92	52	213	0.38
40	Twill	97% Cotton 3% Spandex	132	58	247	0.44
41	Plain	55% Linen 45% Cotton	66	52	147	0.38
42	Plain	55% Linen 45% Cotton	64	48	168	0.34
43	Plain	98% Cotton 2% Spandex	190	60	251.5	0.5
44	Plain	65% Cotton 35% Polyester	110	76	99	0.21
45	Plain	55% Cotton 45% Viscose	101	50	123	0.32
46	Plain	55% Cotton 45% Ramie	60	60	124.5	0.31
47	Plain	55% Cotton 45% Polyester	110	76	94	0.20
48	Plain	55% Cotton 45% Linen	47	58	164.3	0.35
49	Plain	55% Cotton 45% Viscose	40	38	208.9	0.48
50	Plain	98% Cotton 2% Spandex	170	50	189.2	0.36

Table 2 Influence of fabric properties measured on the KES-FB in seam performance.

Fabric property	Unit
LT – linearity of extension curve	–
WT – tensile energy	cN cm/cm^2
EMT – fabric extension at 5N/cm	%
RT – tensile resilience	%
α – ratio of weft extension to warp extension (EMT_2/EMT_1)	–
G – shear rigidity	cN/cm deg
2HG – shear hysteresis at 0.5° shear angle	cN/cm
2HG5 – shear hysteresis at 5° shear angle	cN/cm
B – bending rigidity	cN cm^2/cm
2HB – bending hysteresis	cN cm/cm
T_0 – thickness under 0.5g/cm^2 pressure	mm
T_m – thickness under 50g/cm^2 pressure	mm

performance of various fabrics, a sewing thread and all sewing conditions were kept the same for preparing all seam specimens in the experiment.

Each seam specimen was analyzed regarding its impact on seam performance i.e. smoothness of the seams (e.g. seam puckering and seam flotation) and durability of the seams (e.g. seam efficiency) [34]. The seam puckering and seam flotation were performed by the regulation of the AATCC standard. The grades were divided into five classes [5,37]: 5, high quality seam appearance; 4, good appearance, insignificant seam puckering or flotation; 3, acceptable appearance, noticeable puckering or flotation; 2, below average appearance, significant puckering or flotation; 1, poor appearance, unacceptable puckering or flotation of the seam. In measuring the durability of seam, it was subjectively rated in the five classes commonly adopted by the field: 5, highest durability of sewn seam; 4, higher durability of sewn seam; 3, modest durability of sewn seam; 2, lower durability of sewn seam; 1, lowest durability of sewn seam. All seam specimens were judged by experienced field experts.

In the model formulation of seam performance, there are three separate models for seam puckering, seam flotation and seam efficiency respectively. For each model, the input variables include all fabric properties affecting the corresponding seam performance as shown in Table 2 and the output variable is the rating of seam performance.

Neural Networks Parameters

In this study, due to the availability of only a small sample data set, the five-fold cross-validation technique was used for evaluating the prediction error rate of the neural network model. Therefore, the data set of fifty samples was divided randomly into five subsets, each containing ten samples, in accordance with other works [17,38]. The subsets were combined together and five sets of train and test data were designed. Each time, four subsets were used as training set and one subset as testing set. Consequently, we trained and tested each designed network five times.

Since the objective of training is to obtain an effective generalization of the relationship between inputs and the outputs, memorization or over-fitting of networks was prevented by using the weight decay technique [39]. This involved modifying the performance function. On the basis of MATLAB software, the mean square error regularization (MSEREG) performance function was used instead of common mean square error function. This function is as follows:

$$MSEREG = \gamma(MSE) + (1-\gamma)MSW \tag{1}$$

where γ is the performance ratio and

$$MSW = \frac{1}{n}\sum_{j=1}^{n} w_j^2 \tag{2}$$

In equation (2), n is the number of weighted connections and w_j is the connection weights of neural networks. This performance function causes the network to have smaller weights and biases. This will force the network response to be smoother and less likely to over-fit [40].

Based on the neural network toolbox of MATLAB software, weight decay generally provides better generalization performance network. This is due to the fact that weight decay does not require a validation data set to be separated from the training data set. It uses all of the data, and this advantage is especially noticeable when the size of the data set is small [40].

Before training, it is often useful to scale the inputs and outputs so that they always fall within a specified range, and to eliminate the effect of different units of input and output parameters. Therefore, data normalizing was carried out in such a way that there was zero mean and unit standard deviation [41].

One of the important parameters in the back propagation learning algorithm is the learning rate. Choosing a large learning rate value accelerates the training but causes big errors at the output or destabilizes the training cycles, but a small value provides convergence with smaller errors and prolongs training time [42]. In this study, we used the adaptive learning rate with momentum training algorithm to enhance the training performance. Momentum rate was generally optimized at 0.9 [41].

The number of hidden neurons and number of hidden layers are usually adjusted by trial and error. Studies by various researchers have shown that neural networks with one hidden layer are suitable for the majority of applications, and the second hidden layer can improve the performance of the network if there is a complex relationship between input and output parameters [41]. In this study, we adopted one hidden layer for constructing ANNs. Meanwhile, we adopted Hyperbolic Tangent activation function for neurons of hidden layers and linear activation function for neurons of output layer because it was proved to provide the best performance in ANNs [41].

Statistical Regression Method

Statistical regression is a model for analyzing and modeling of dependent variables as a function of one or more independent variables. The simplest form of regression is multiple linear regression. Statistical regression, especially multiple linear regression, has been one of the most popular methods for making predictive models in a wide range of textile-related problems [27,29,42,43], and is accepted as a conventional method [42].

However, in past works [6,10,11,13] it has been reported that the relationship between fabric properties and seam performance of fabric are close to curvilinear in nature. This means that logarithm exercise could be used as a predictor in the multiple regression model. Therefore, in this study, we applied the common logarithm method to transform all values of independent variables in the multiple regression model for predicting seam puckering, seam flotation and seam efficiency respectively. Each regression model is expressed in the equation (3).

$$\log(y) = \beta_0 + \sum_{i=1}^{n} \beta_i \log(x_i) \tag{3}$$

where x_i = dependent variable, i; y = independent variable; β_i = beta coefficient associated with dependent variable, i; β = intercept calculated in logarithmic space; and n = number of independent variables.

The stepwise regression procedure was used in this study as it automatically selected the variables to be entered into the model. Variables with p-values less than 0.05 were entered into the regression model and removed from the model if their p-value increased above 0.10. In addition, variables were also removed if they were considered to have counterintuitive beta coefficients. As a result, excessive numbers of these variables were prevented from entering the model.

Here, the same five sets of data used for evaluating ANN model were used in such multiple regression. Then, the resulting three predictive multiple logarithm regression models were applied to the testing data sets.

Results and Discussion

To measure the performance of multiple regression model and the ANNs, we used correlation coefficient (R-value) and mean square error (MSE). The results of two models for predicting training and testing data are shown in Tables 3 to 6.

Table 3 Performance of ANN on training data sets.

Data set	MSE (Seam puckering)	MSE (Seam flotation)	MSE (Seam efficiency)	*R*-value (Seam puckering)	*R*-value (Seam flotation)	*R*-value (Seam efficiency)
1	0.0633	0.0552	0.0441	0.913	0.923	0.982
2	0.0582	0.0457	0.0364	0.938	0.930	0.990
3	0.0742	0.0612	0.0468	0.928	0.939	0.987
4	0.0655	0.0431	0.0387	0.942	0.941	0.986
5	0.0617	0.0455	0.0355	0.937	0.950	0.981
Average	0.0646	0.0501	0.0403	0.932	0.937	0.985

Table 4 Performance of ANN on testing data sets.

Data set	MSE (Seam puckering)	MSE (Seam flotation)	MSE (Seam efficiency)	*R*-value (Seam puckering)	*R*-value (Seam flotation)	*R*-value (Seam efficiency)
1	0.0617	0.0487	0.0388	0.821	0.853	0.901
2	0.1011	0.0986	0.0283	0.772	0.801	0.863
3	0.0581	0.0488	0.0356	0.897	0.926	0.928
4	0.2108	0.1111	0.0787	0.638	0.778	0.813
5	0.1105	0.0785	0.0436	0.821	0.887	0.902
Average	0.1084	0.0771	0.0450	0.790	0.849	0.881

Table 5 Performance of multiple logarithm regression on training data sets.

Data set	MSE (Seam puckering)	MSE (Seam flotation)	MSE (Seam efficiency)	*R*-value (Seam puckering)	*R*-value (Seam flotation)	*R*-value (Seam efficiency)
1	0.0877	0.0637	0.0582	0.891	0.893	0.921
2	0.0601	0.0551	0.0465	0.907	0.899	0.943
3	0.0711	0.0781	0.0536	0.882	0.921	0.937
4	0.0781	0.0687	0.0488	0.895	0.918	0.946
5	0.0723	0.0693	0.0521	0.910	0.928	0.934
Average	0.0739	0.0670	0.0518	0.897	0.912	0.936

Table 6 Performance of multiple logarithm regression on testing data sets.

Data set	MSE (Seam puckering)	MSE (Seam flotation)	MSE (Seam efficiency)	*R*-value (Seam puckering)	*R*-value (Seam flotation)	*R*-value (Seam efficiency)
1	0.0811	0.0783	0.0402	0.858	0.882	0.867
2	0.1211	0.1003	0.0367	0.750	0.789	0.823
3	0.0738	0.0683	0.0374	0.847	0.882	0.877
4	0.3144	0.1366	0.0863	0.589	0.801	0.803
5	0.1488	0.0899	0.0489	0.786	0.898	0.886
Average	0.1478	0.0947	0.0499	0.766	0.850	0.851

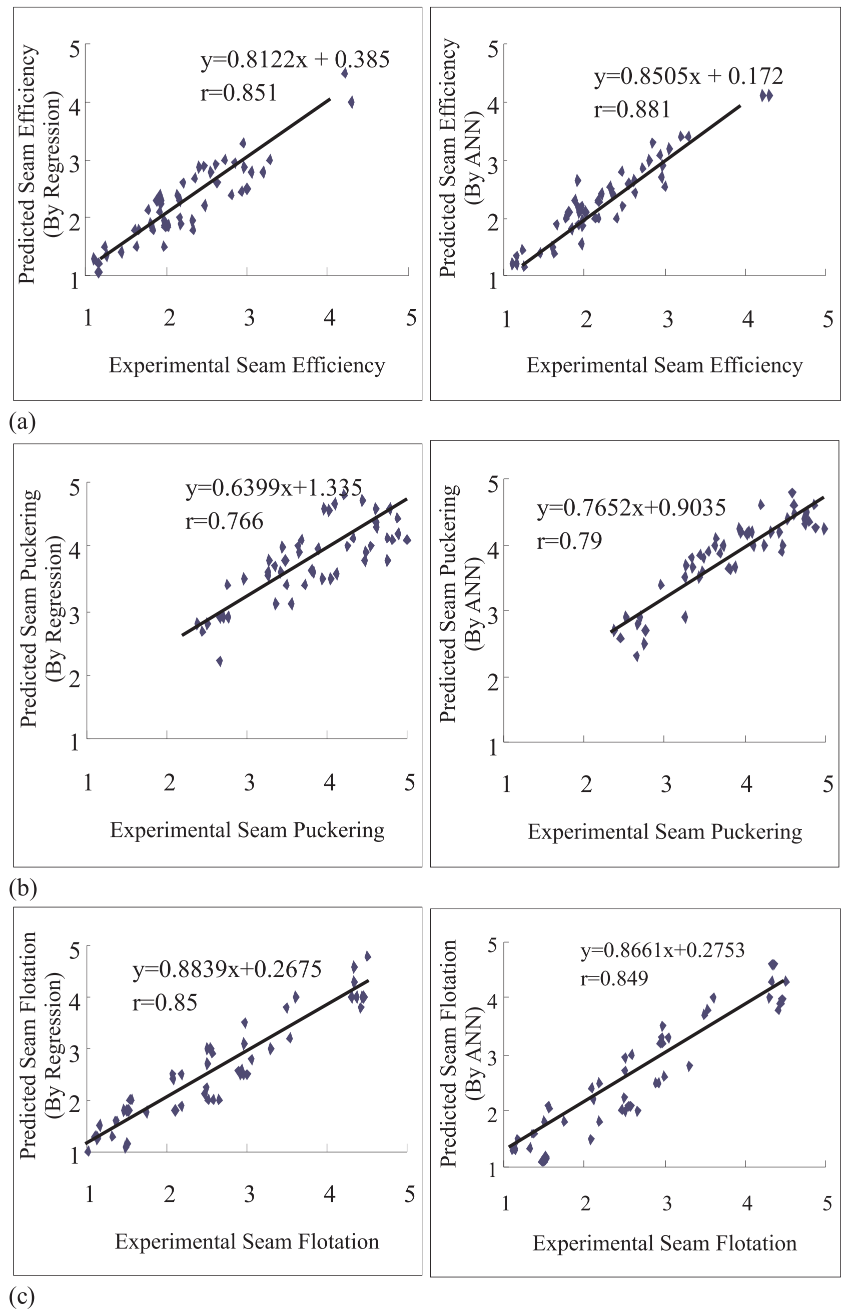

Figure 1 Comparison between regression and ANN model predictions of (a) seam efficiency, (b) seam puckering, and (c) seam flotation.

In order to test the performances and validate the predictions of the regression models and ANN models, we used a testing data set to compare with the predictions from the models on the basis of the measured fabric properties. Figures 1(a) to 1(c) compare the predicted and experimental ratings in seam efficiency, seam puckering, and seam flotation respectively.

The obtained results of average MSE and correlation coefficient of five sets of testing data indicated that the performance of the ANN model was better than the multiple regression model. The differences between the MSE value of the two models for predicting seam puckering, seam flotation and seam efficiency were 0.0394, 0.0096, and 0.0049, respectively. In relation to seam puckering, the maximum MSE in the neural network model for predicting testing data was lower than the maximum MSE in the multiple regression model for similar prediction (0.2108<0.3144). Similarly, the maximum MSE for predicting the seam flota-

Table 7 Comparison of *R*-value between artificial neural network and multiple logarithm regression.

	ANN	Logarithm Regression	ANN vs. Logarithm Regression (%)
For training data			
• Seam Puckering	0.932	0.897	3.90
• Seam Floatation	0.937	0.912	2.74
• Seam Efficiency	0.985	0.936	5.24
For testing data			
• Seam Puckering	0.790	0.766	3.13
• Seam Flotation	0.849	0.850	0
• Seam Efficiency	0.881	0.851	3.53

tion and seam efficiency in the neural network model was lower than the prediction in multiple regression model. Therefore, it is important to consider the lowest MSE in the prediction of testing data occurring in the neural network model. Table 7 shows the difference between correlation coefficient of the two models.

The performance of the multiple regression model with a common logarithm method in explaining seam performance is quite close to the performance of ANN model (within five percent) because both of them are dealing with the non-linear relationship. It indicates that these two modeling methods could effectively capture the non-linear relationship, especially in prediction of seam performance.

Conclusions

In this study, we used an ANN technique based on a back propagation algorithm with weight decay technique and multiple regression with common logarithm method to predict the seam performance of woven fabrics based on seam puckering, seam flotation and seam efficiency respectively.

The ANN model was found to be more accurate than multiple regression and the prediction errors of ANN were low despite the availability of only a small training data set. However, the difference of prediction errors made by both models was not significantly high. It was found that regression models were quicker to construct, more transparent, and less likely to overfit the minimal amount of data available. Therefore, both models were effectively predicting the seam performance of woven fabrics.

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