Prediction and analysis of fabric-evoked prickle properties of different textile woven fabrics using Artificial Neural Networks method

Rabie A. M. Asad1, 2, Fengxin Sun2, Yassir A. Eltahir1, Mahmoud H. M. A. Shibraen1, Weidong Yu2

[1]*Faculty of Industries Engineering and Technology, University of Gezira, Wad-Medani, P.o. Box 20, Sudan.*

[2]*Key Laboratory of Textile Science & Technology, Ministry of Education, Donghua University, Shanghai, P. R. China.*

@gmail.com*1976***Corresponding Author**： Dr. Rabie A. M. Asad, rabieasad

ABSTRACT

This paper aims to discuss the design and development of an Artificial Neural Networks (ANNs) model to understand a human perception of the tactile prickliness properties of textile wear fabric materials, and create an objective system to express those prickle perceptions in terms of measurable mechanical properties. The objective and also subjective hand measurement of the textile materials used for wear fabric has been check up on with consideration given the aspects of both dermatitis and comfort. In this study, attempt to predict the prickliness (itchiness) of wear fabric by their physical properties using a back-propagation network and a stepwise regression. Handle properties of fabrics were measured by universal test equipment (KES-F) and total prickle-score (TPS) values of the wear fabrics were determined by a group of panelists consisting of some textile experts. The optimum construction of neural network was investigated through the change of layer and neuron number. The results showed that the back-propagation network could predict the (TPS) values of wear fabric with a meaningful difference. These wear fabrics were used to show that the results of neural network were in good agreement with subjective test results.

KEYWORDS: Wear Fabrics, Prickliness, Anns, Tactile Comfort, Human Sensory, KES-F

INTRODUCTION

There are mainly four types of mechanical sensory perceptions of wear fabrics. Namely: wear sensations during activity; prickle, itch and rashes; touch and pressure sensations; and roughness and scratchiness sensation (Y. Li, 2001). We know that in wear fabrics, skin comfort is a key feature in garment manufacturing, especially for the "next to" skin fabric materials (Apurba Das et al., 2010). When a fabric is worn next to the skin, occasionally an unpleasant sensation known as fabric-evoked prickle originates, this sensation results from the mechanical stimulation of specific nerve endings in the human skin rather than an allergic reaction (Garnsworthy et al., 1988; Garnsworthy R. K. et al. 1988; Matsudaira et al., 1990). Therefore, fabric-evoked prickle is defined as the discomfort feeling when worn garment next to human skin. It is the combination of physical, biological and psychological processes (Garnsworthy R.K. et al., 1988; Naylor G.R.S., 1992; Li Y., 2006). According to this definition, the nociceptors are the sensory receptors which are responsible for sensing the prickle pain when a garment is worn (Goldstein, 2010; Sleivert, 2002). These receptors have relatively high thresholds to act as warning devices that enable the organism to take protective action in time (Dargahi et al., 2004). Thus, the degree of discomfort caused by fabric prickle varies from person to person, skin type, humidity and temperature of the atmosphere as well as in the microclimate, type of fiber used in garment, etc. (Westerman et al., 1984). A number of studies (Garnsworthy R. K., 1988; Garnsworthy R. K. et al., 1988; M atsudaira et al., 1990; Naylor G.R.S., 1992; Ramsay, et al., 2012; Naylor G. R. S., 1992; Vlattas et al., 1991) have been carried out to understand the prickle characteristics of fabrics. They conclude from their results that, stiff fiber ends protruding from a fabric surface and contacting the skin during wear, act mechanically as simple Euler's rods and if they are able to sustain a sufficient force before the buckling, they trigger the nerve endings resulting in the "prickle" sensation.

Gransworthy et al. carried out extensive study to understand the causes of prickle and itch from the skin contact of fabrics. They concluded that, fabric-evoked prickle is the result of low-grade activity in nociceptors, and that the stimuli are protruding fiber ends exerting loads of approximately 75 mN or more against the skin (Garnsworthy et al., 1988; Matsudaira et al., 1990).

Measuring and assessment of the tactile prickle propensity of a fabric is a difficult task with the primary assessment being subjective to sensory responses from wearers and handle feeling. From a research perspective, collection of this data is both time consuming and relatively expensive.

Therefore, a number of scientists have tried to measure and evaluate fabric prickliness. Matsudaira et al. they developed laser hairiness meter, where the fibers protruding from the fabric surface are counted by laser beam. This study gives a fairly good indication of prickliness of fabric (Matsudaira et al., 1990; Matsudairaet al., 1990). In addition, Matsudaira et al. they used a modified audio pick-up technique for measuring the mean force per contact with the protruding fiber (Matsudaira et al., 1990). They observed that this technique is the most effective measure of fabric prickle and the result obtained from this instrument correlate well with the subjective perception of fabric prickle. Ramsay et al. were developed a new technique and prototype instrument for rapidly assessing the propensity of fabric-evoked prickle on single jersey acrylic and wool fabrics. The instrument gave results consistent with the known coarse fiber content of the fabric. In both cases, the instrument results were highly correlated with human assessment of the fabrics, ranking them in the same order as an expert panel of judges (Ramsay et al., 2012).

Many studies have been conducted to analyze the relationship between various fabric parameters and tactile prickle comfort properties by using statistical methods (Ti Li, et al. 2012; Naebe, et al. 2013; Maryam et al., 2014; Naylor et al.2014; Stanton et al., 2014). However, the statistical methods used have some limitations. One of the most common problems faced in statistical modeling is the non-linear relationship of different fabric parameters with tactile prickle comfort properties. Furthermore, most of the fabric parameters which directly influence the prickliness properties such as thickness, fabric weight, bending, etc., are related to each other and are derived from basic fabric specifications such as fiber length and diameter, yarn linear density, etc. Hence, it is difficult to study the effect of one parameter without changing the other. Therefore, a system is required which can predict the tactile prickle comfort parameters of the fabric by considering the collective influence of all the fabric parameters at the same time. This is where artificial neural network can be effectively put to use. An artificial neural networks (ANNs) has proved useful for many prediction-related problems in textiles research such as: the prediction of characteristics of textiles; identification, classification and analysis of defects; process optimization; and marketing and planning (Mukhopadhyay, 2002; Mukhopadhyay, et al. 2003). Researchers have already tried to use neural networks to predict various comfort-related properties such as human sensory perceptions and overall comfort of wear fabric (Ti T. Li et al., 2012; Wong, 2003).

Therefore, in this paper an artificial neural network is used to predict the tactile prickle discomfort sensation behavior of different wear fabric, when the fabric weaving and construction handle parameters are given as inputs. The ANNs system consisted of one network with one output. The networks were trained with a training data set and then tested with a set of untrained values of fabric parameters. The total prickle score (TPS) values obtained from the network were compared with actual values obtained from the subjective evaluation score result of total prickle score (TPS) values.

MATERIALS AND METHODS

Experimental Materials:

Fifty-six samples of several fabrics such as cotton, cashmere, linen, hemp, ramie, jute, wool, wool/cotton, cotton/ polyester and wool/polyester, woolen fabrics were used for the present study. The samples were collected from different sources, including markets and factories. It involved a wide range of end users, and thus they differed a lot in fiber content, density, thickness, weight and fabric weave type.

Characteristic Parameters:

The characteristic parameters of input layers are the major factors for determining the recognition rate. In this study the proposed method with KES-F instruments, which measure the handle properties of the wear fabrics (Kawabata et al., 1991). The KES-F system consists of subsystems which have the function of measuring different handle properties such as surface property, compression property, bending property, thickness and weight properties.

For this study they choose five parameters from KES-F parameter namely, bending, competition, surface, thickness and weight. Wear fabric when in contact with human skin, many parameters influence the pleasant situation of human comfort such as fabric bending (rigidity and hysteresis) when human worn fabric especially the bending of protruding single fiber from the fabric surface. Therefore, when wear fabric has low bending and hysteresis, it may become discomfort especially for wear fabric prickle. The second KES-F parameter compression of wear fabric, also have large influence on clothing comfort and discomfort. Furthermore, wear fabric surface friction and geometrical roughness play very important parameter for wear fabric comfort, when it is worn next to human skin. Also wear fabric weight and thickness are very important for fabric tactile comfort because the weight and thickness have high influence on fiber bending and hysteresis. Therefore, for all this reason they those five parameters and the details of ten categories of five mechanical properties for wear fabrics are given in the Table (1).

Table 1: The mechanical properties of wear fabrics measured on KES–F system

Property	Symbol	Parameter measured	Unit	Device
Bending	B	Bending rigidity, the average slope of the linear regions of the bending hysteresis curve to ±1.5 cm^{-1} curvature	[gf cm^2/cm]	KES-FB2
	2HB	Bending hysteresis, the average width of the bending hysteresis loop at ±0.5 cm^{-1} curvature	[gf cm/cm]	
Surface	MIU	Coefficient of fabric surface friction	[–]	KES-FB4
	MMD	Mean deviation of MIU	[–]	
	SMD	Geometrical roughness	[μ m]	
Compression	LC	Linearity of compression–thickness curve	[–]	KES-FB3
	WC	Compression energy per unit area	[gf cm/cm^2]	
	RC	Compressional resilience, the ability of recovering from compressional deformation	[%]	
Thickness	T	Fabric thickness at 50 N/m^2	[mm]	KES-FB3
Weight	W	Fabric weight per unit area	[mg/cm^2]	Digital Balance

MEASUREMENT OF MECHANICAL PROPERTIES AND SUBJECTIVE EVALUATION OF WEAR FABRIC

Wear Fabric Mechanical Properties:

Fabric mechanical properties namely; surface (friction), compression, bending, thickness and weight were measured by test methods which were discovered by Kawabata, S. and Niwa M.

(Kawabata et al., 1991). Mechanical properties were measured under the conditions of high sensitivity. All measurements were performed at 65±2% relative humidity and 20±1 ºC. For each sample, 5 measurements were performed. In order to evaluate total hand value of the samples, paired comparison methods were carried out.

Wear Fabric Subjective Evaluation:

Subjective evaluation of prickliness felling score was performed via forearm experiment to test the samples covered in a box which could not be seen by the evaluators. A total of 31 students who had textile education (age: 19-38), participated in the evaluation. The human perception score of prickliness was measured by the 1-7 prickle rating scale. This scale was developed by TMT research group in Donghua University, the range of prickliness values varied between 1 and 7, where 7 corresponds the least prickle value, and 1 to the most prickle value. The questionnaires were composed of 7 questions; not prickle at all, very slight prickle, slight prickle, moderate prickle, strong prickle, very strong prickle and extremely strong prickle. High deviations obtained from the subjective evaluation were not included in the evaluation process. The range of mechanical properties as measured using the KES-F module and total prickle score (TPS) values is given in Table (2).

Table 2: Range of the mechanical properties as measured using KES-F module and TPS measured by subjective evaluation test

Property	**Minimum value**	**Maximum value**
B	0.031	0.500
2HB	0.026	0.704
MIU	0.124	0.248
MMD	0.010	0.059
SMD	5.890	14.29
LC	0.130	0.350
WC	0.121	1.200
RC	50.00	85.70
T	0.557	1.870
W	13.60	55.80
TPS	1.645	6.871

ARCHITECTURE OF NEURAL NETWORKS

Principle Of Artificial Neural Networks (ANNs):

ANNs can be defined as an interconnection of neurons, such that the neuron outputs are connected through weights, along with biases to all other neurons. Like its biological counterpart, an ANNs is simply composed of many neurons and inter-connections with weights. These mathematical units are conventionally constructed with three layers, i.e. input, hidden and output layers, according to the function as shown in Figure (1). The hidden layer usually contains one or several layers, and the number of neurons in each layer can be different (Hagan, 1996; H. S., 1999). For the convenience of description, the structure of the ANNs is expressed as

$$N_{in} - \left(N_1 - N_2 - N_3 ... N_h\right)_h - N_{out} \qquad (1)$$

Where, N_{in} and N_{out} refer to the number of input and output parameters, respectively. h denotes the number of hidden layers, and N_1, N_2 and N_h are the number of neurons in each hidden layer.Therefore, each layer, except the input layer, takes the output of the preceding layer as an input, which is modulated by transfer function and weights in the neuron for the output to the next layer. This procedure can be described as

$$Xj^{(n)} = f(\sum_i Wji^{(n)} Xi^{(n-1)}) \qquad (2)$$

Where, f(x) is a transfer function which is usually nonlinear. $Xj^{(n)}$ is the output of node j in the n*th* layer, and $Wji^{(n)}$ represents the weight from node i in the *(n-1)th* layer to node j in the n*th* layer. The ANNs works like a ‘‘black box’’. An input vector is imported to the nodes in the input layer, and the results are then expected to export at the output layer through a series of computation in the hidden layer. The learning algorithm is based on a gradient search to optimize the performance function of the network, which is generally evaluated by mean squared errors between the predicted and desired values.

$$E = \frac{1}{2L}\sum_{t=1}^{L}[d(t) - p(t)]^2 \qquad (3)$$

Where, L equals the number of training samples, $d(t)$ is the desired output value, and $p(t)$ refers to the target output value predicted by the ANNs for the t*th* sample. For the purpose of minimizing E, the weights of the inter-connections are adjusted during the training procedure until the expected error level is achieved or the maximum iteration is reached. It should be noted here that the sensitivity factor propagates (S) backwards from the last layer to the first layer [S (n+1) → S (n) → …. → S(2) → S(1)], hence the name back-propagation algorithm is used (Graupe, 1997; Hagan MT, 1996; Haykin S., 1999).

The architecture, transfer function, training algorithm and other parameters of the neural network should be carefully set and modified during optimization. Thus, the well-trained neural network can be used to obtain the solutions of new input data in the same domain of the experimental database. This process can be summarized in the following four stages: 1) Collect and preprocess the experimental data; 2) Train the ANN, and optimize its configuration; 3) Evaluate the performance of the ANN, return to stage if the performance is not satisfactory; 4) Use the trained ANN for simulation or prediction.

For the present study, fabric mechanical properties B, 2HB, MIU, MMD, SMD, LC, WC, RC, T and W were selected as input variables, and total prickle score (TPS) values were chosen as output parameters as shown in Figure 1. In ANNs analysis, a multilayer feed forward network with ten hidden layers trained by back propagation algorithm was used to predict the (TPS) values of the wear fabric. Several analyses were done and it was observed that ten hidden layered neural networks gave minimum error and higher estimation of coefficient. In the input layer of the network, ten inputs were used. In the hidden layers of the network, twenty neurons were selected. As the purpose of the study was to estimate the TPS value of wear fabric, one output, TPS, takes parts in the output layer. While linear transfer function was used in the input and output layers of the neural network, a nonlinear hyperbolic transfer function was used in the hidden layers. The training of the network was performed in two phases. In the first stage, back propagation algorithm was applied for 1000 epochs. Learning rate and momentum coefficient used in the back-propagation algorithm were set to 0.01 and 0.001 respectively, since decreasing the learning rate improve the performance of network. Furthermore, the training time increased. In the second stage of the training, conjugate gradient descent algorithm was applied for 1000 epochs. Increasing the number of epochs for the second phase of the training improves the training and testing performances. The details of the architecture and the set parameters for training and testing phases are as shown in Table 3.

A typical artificial neural network (ANNs) structure and a neuron within a neural network of the 56 wear fabric samples, 41 (≈75%) samples were chosen as the training set, while the rest 15 (≈25 %) were chosen for the testing set at random. A nonlinear hyperbolic transfer function [$f(x) = e^x - e^{-x}/e^x + e^{-x}$] served in the hidden layers, and a linear transfer function $f(x) = x$ was used in the input and the output layers to avoid limiting the output value to a small range.

Table 3: Details of the neural network architecture

Parameter	**Value**
Learning algorithm	Feed forward back propagation
Number of input neurons	10
Number of hidden layers	1
Number of hidden neurons	10

Number of output neurons	1
Number of Epochs	2000
Mean square of error (termination criteria)	0.01
Activation function	Hyperbolic tangent
Total data set	56 (11 fabrics x 5 samples)
Training data set	41 (<75 percent of 55)
Training data set	15 (<25 percent of 55)

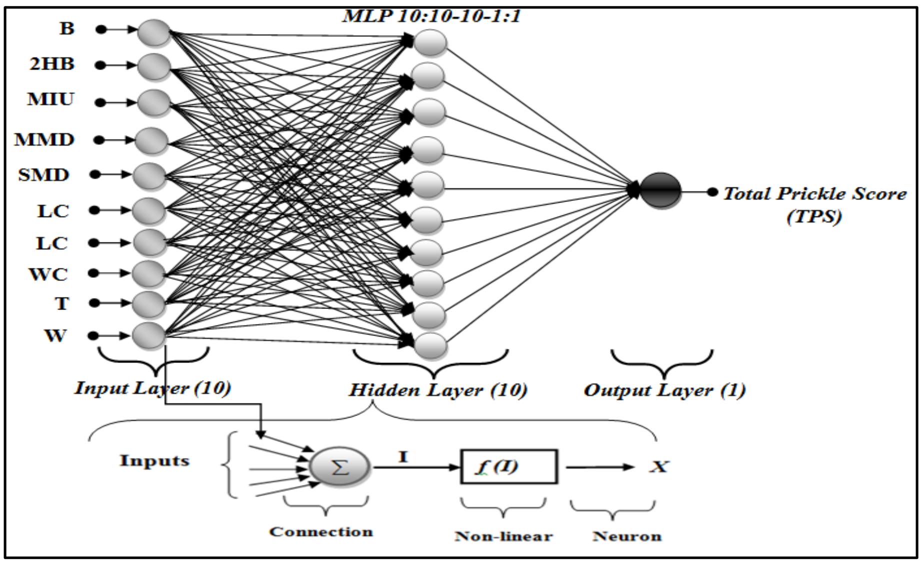

Figure 1: The architecture of neural networks (ANNS)

RESULTS AND DISCUSSION

Predictions of Total Prickle Score (TPS) Values:

The whole data was split into two parts, namely, training set and testing set. The proportions of these data sets are ≈ (75 and 25) %, respectively. Following the training phase, the neural network is tested for its performance using the test data. The data of input layer was entered into the established BP neural network using MATLAB program for simulation training value as shown on Figure 2. The comparison between output value and subjective evaluation value were listed in Table (4) and Figure (3). The data in Table (4) and Figure (3) illustrate that relative errors between output value from neural network and subjective evaluation value is below 5.0%. Therefore, the BP neural network method is considerably accurate for evaluating prickle instead of subjective appraisal. Therefore, from the results, we had seen that no significant difference between actual and predicted values of total prickle score TPS, refer to good training performance process of ANNs designed with low error as shown in Figure 2.

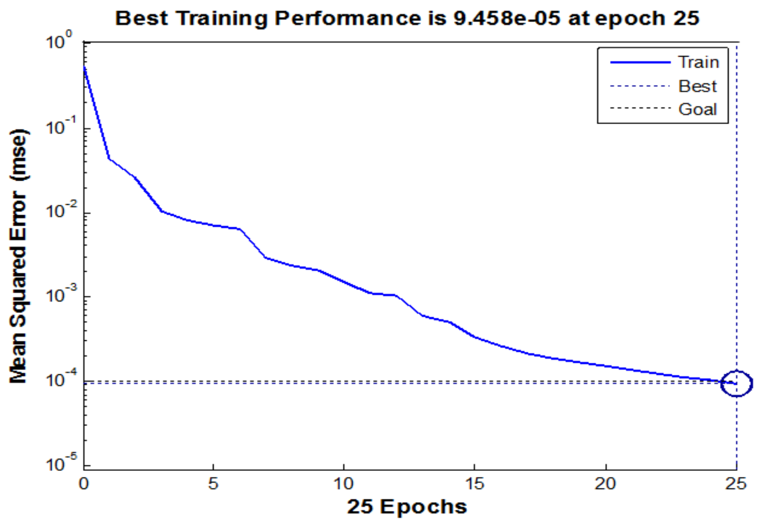

Figure 2: Training performance process of ANNs designed to predicted the wear fabric prickle score

Table 4: Actual and predicted result data of TPS

Test data number	Subjective evaluation (Actual) value (TPS)	Output (Predicted) value from ANNs	Error value (%)
1	1.871	1.809	3.426
2	5.290	5.226	1.231
3	6.097	5.892	3.475
4	6.134	6.039	1.580
5	2.190	2.102	4.202
6	1.710	1.637	4.440
7	1.935	1.877	3.116
8	5.419	5.375	0.825
9	6.110	5.911	3.565
10	2.161	2.018	2.145
11	4.581	4.431	3.377
12	6.210	5.937	4.593
13	1.677	1.66	1.049
14	2.925	2.834	3.202
15	6.742	6.478	4.074

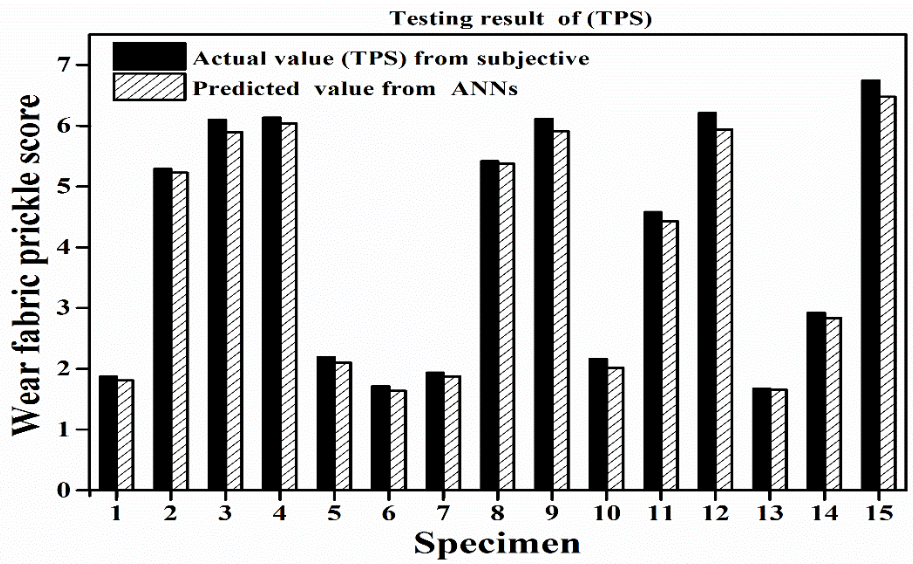

Figure 3: Compression between prediction and actual data of total prickle score (TPS) using ANNs engine

COMPARISON OF TOTAL PRICKLE SCORE OF ANNS AND REGRESSION WITH SUBJECTIVE JUDGMENT EVALUATION TEST

Ten input parameters, of wear fabrics, were experimentally measured. The above-prepared samples are considered as control and using those input parameters, the output parameters total prickle scores (TPS) were predicted. Using the results from the subjective evaluation test, mean square error was used to compare and verify which method is a good agreement with the subjective test result of neural networks and regression analysis as shown in Table (5). From this investigation, mean square errors (MSE) for TPS_{sub}-TPS_{ANN} and TPS_{sub}-TPS_{REG} are 0.0841 and 0.152, respectively. It was found that the results of subjective assessment were more consistent with neural networks method rather than the regression method because MSE of TPS_{sub}-TPS_{ANN} is smaller than MSE of TPS_{sub}-TPS_{REG}. The summary statistics of ANNs are given in Table 5, it can be seen that even the error values of testing are lower and estimation coefficient values are higher compared to the results of regression analysis. The difference between the RMSE of testing and RMSE error of regression is 0.1619. Since TPS values range is 1.6 to 6.8, this difference in RMSE causes 3-5 % improvement in the estimation of total prickle score values with ANNs methods as shown in Figure (4), correlation between subjective and ANNs total prickle score was high R^2= 0.9472.

Table 5: Summary statistics of total, training, and testing set

Summary Statistics of models	Total	Training	Testing	Regression
Mean Square Error	0.0621	0.0850	0.0241	0.1520

Root Mean Square Error	0.2251	0.1419	0.3514	0.5192
Absolute Error Mean	0.1531	0.1436	0.3001	0.4335
Mean Percentage of Absolute Error	0.0650	0.0416	0.0929	0.1767
Correlation	0.9985	0.9472	0.9845	0.8791
Regression	0.8761	0.9201	0.8715	0.7431

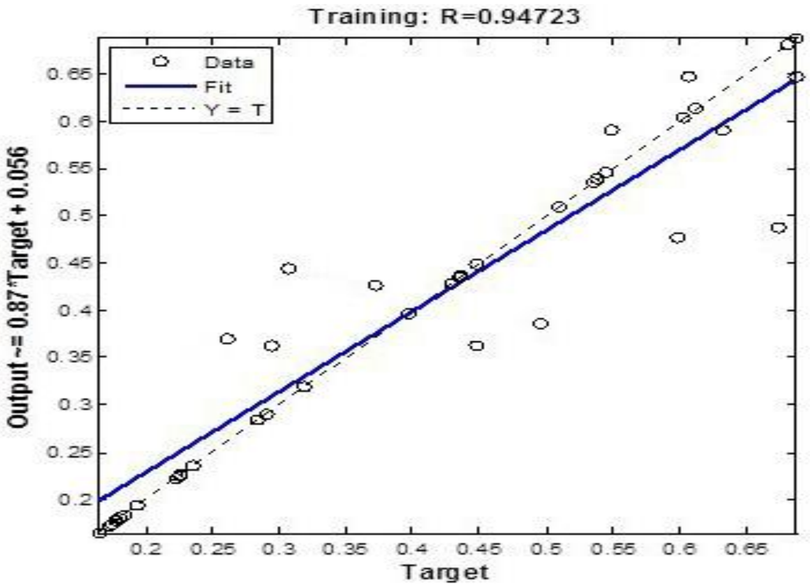

Figure 4: The correlation between subjective and ANNs total prickle score

Predictions of TPS Value Using Reduced Attributes:

In order to minimize the "curse of dimensionality" and reduce the computational resources, an attempt is made to reduce the number of attributes and design an engine that can predict the human perception of total prickle score using the reduced attributes. Also, to reduce the number of attributes, a subset evaluation algorithm was used. The WEKA software is used for the subset evaluation with the "best first" search algorithm. Subset evaluation is based on the worth of a subset of attributes by considering the individual predictive ability of each feature along with the degree of redundancy between them. Best first approach is used as the search method in selecting the attributes. While evaluating the subset contribution, a 10 cross-validation was set to avoid over-fitting. At the end of the validations, seven attributes are identified as the best contributing parameters and are listed below:

1. B (Bending rigidity)
2. 2HB (Bending hysteresis)
3. MIU (Coefficient of fabric surface friction)
4. MMD (Mean deviation of MIU)

5. SMD (Geometrical roughness)
6. T (Fabric thickness)
7. W (Fabric weight)

Consequently, when the bending rigidity nature of the fabric is in contact with human skin, it influences the tactile prickle comfort and human subject perception is reflected by the B, and 2HB properties. The next major influential stimulation is the frictional property of the wear fabric, which is reflected in the MIU property. Similarly, the subset evaluation with the search algorithm changed to genetic search was run and it yielded the same set of attributes. The new neural network is then trained using the selected attributes (seven attributes) as the input and the total prickle score (TPS) the main output as shown in Figure 5 and training process performance as shown on Figure (6). The coefficient of determination in this case is around 0.9986 as shown in Figure (7). While using all the 10 attributes, the R^2 value was around 0.9472 as shown in Figure 4 and with a loss of 0.05, when the numbers of attributes are reduced to seven attributes hence giving us more evidence.

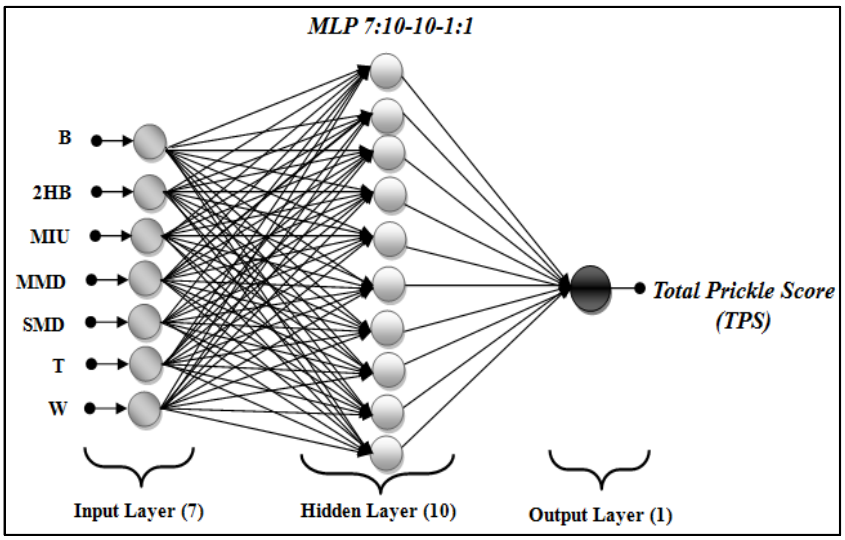

Figure 5: The architecture of neural networks after reduced attributes

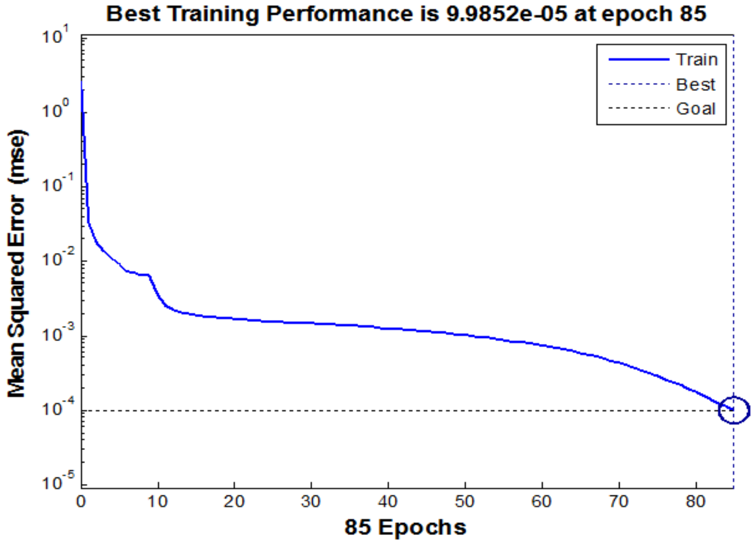

Figure 6: Training process of ANNs designed to predicted the wear fabric prickle score after reduction attributes

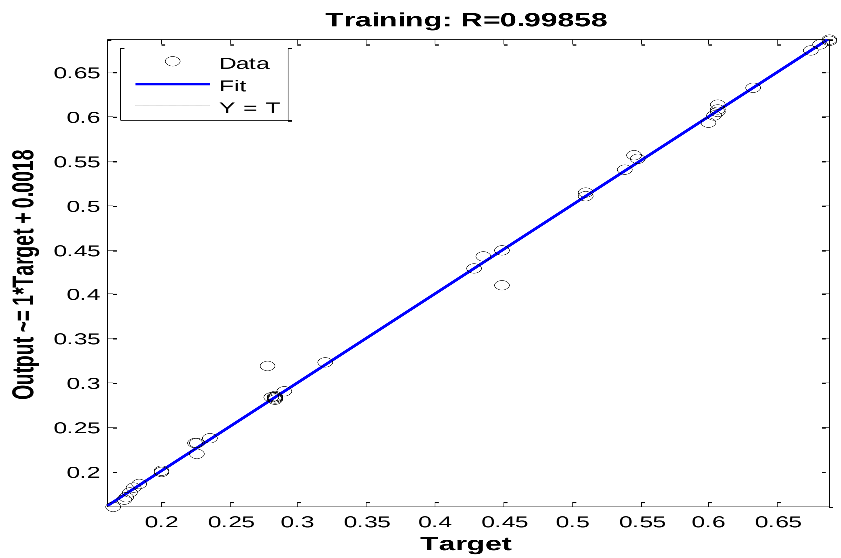

Figure 7: The correlation between subjective and ANNs total prickle score using reduced attributes

Further, the comparison between output value and subjective evaluation value were listed in Table 6 and Figure 8 after attribute reduction. Therefore, the data in Table (6) and Figure (8) illustrate that relative errors between output value from neural network and subjective evaluation value is below 3.0%. Hence, from the results, we had seen that no significant difference between actual and predicted values of total prickle score TPS after reduction.

Table 6: Details of the test data and the predicted result of TPS

Test data number	**Subjective evaluation (Actual) value (TPS)**	**Output (Predicted) value from ANNs**	**Error value (%)**
1	1.871	1.830	2.181
2	5.290	5.253	0.699
3	6.097	5.991	1.739
4	6.134	6.148	-0.228
5	2.190	2.069	5.525
6	1.710	1.744	-1.988
7	1.935	2.061	-6.512
8	5.419	5.367	0.960
9	6.110	6.154	-0.720
10	2.161	2.138	1.064
11	4.581	4.481	2.183
12	6.210	6.252	-0.676
13	1.677	1.684	-0.417
14	2.925	2.869	1.915
15	6.742	6.675	0.994

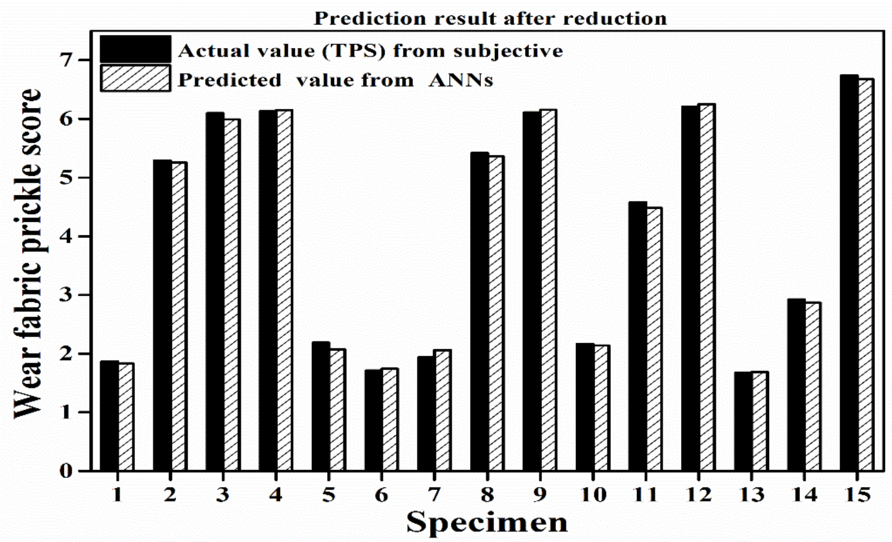

Figure 8: Compression between prediction and actual data of total prickle score (TPS) using ANNs engine after reduction attributes

The configuration of adopted architecture of the neural network for wear fabric overall hand evaluation was shown in Figure (7) and (9). Therefore, from Figure (7) and (9) the predicted and subjective total prickle score (TPS) values for both training and testing sets were compared. The correlation coefficient R^2 of the predicted (training and testing) and subjective TPS values are 0.9975 ($p<0.001$) and 0.9874 ($p<0.001$), respectively.

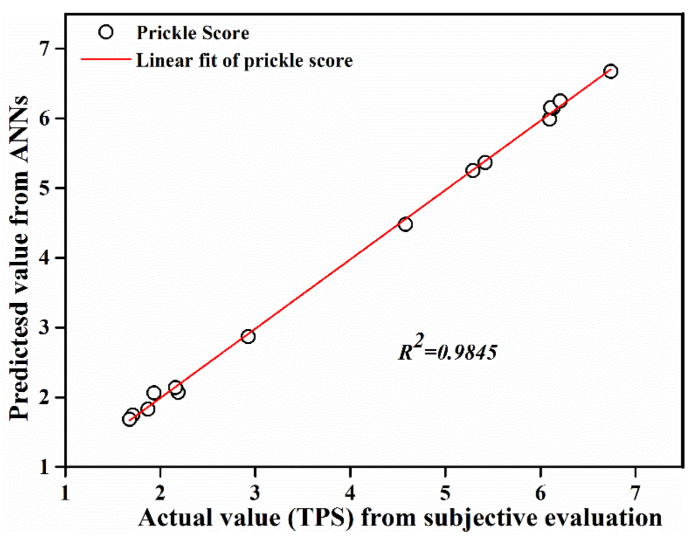

Figure 9: The correlation between Predicted and actual total prickle score (TPS) for testing data after reduction attributes of ANNs

NEURAL NETWORK ANALYSIS

To examine the significance levels of each variable taking place in the network, sensitivity analysis was performed (Yeung, et al., 2010). Sensitivity expresses the relative contribution of each variable to the overall prediction of the network. Therefore, this analysis gives an idea about the significance levels of each variable in the network. The sensitivity is calculated as the ratio of the error with missing value substitution to the original error. If this ratio is high, the deterioration will be high which means that the network is more sensitive to that particular variable. After all sensitivities of all variables have been calculated, the variables can be ranked by their importance. The ranks indicate the order of variables by the magnitude of the quotient. The variable ranked first is the most important. The results of the sensitivity analysis carried out for seven input quantities based on the neural network are summarized in Table (7).

Table 7: Sensitivity analysis of the Neural Networks Networks

Input quantity	**B**	**2HB**	**MIU**	**MMD**	**SMD**	**T**	**W**
Quotient	2.38	2.11	5.36	2.71	5.11	4.54	3.42
Rank	6	7	1	5	2	3	4

From the obtained results it has been found that all of the input quantities significantly influence the values of the input quantities of the three-layered perception. The most important parameter affecting on the total prickle score values of the wear fabric as a result of the neural networks is coefficient of fabric surface friction (MIU). The second one is geometrical roughness (SMD) of the wear fabric in that order from Table 8. Based on our study, we can recommend that wear fabric physical properties can be used to predict total prickle score value with the application of the ANNs predictive model that can closely simulate human sensory perception and judgment processes.

CONCLUSION

It has been indicated that the technique of neural networks showed better agreement with the forearm subjective evaluation test method than regression analysis when evaluating the total prickle score (TPS) value. In this study the neural networks method revealed a good coincidence with the results of subjective test assessment. Another advantage of automatic total prickle score (TPS) evaluator that it is simple in application, and was applicable to different textile markets or areas of survey and for a wide range of textile materials. Therefore, it can be stated that the neural network approach suffices an effective tool for simulating the overall hand feeling of textile materials especially prickliness feeling score. Using the dimension reduction algorithms, the numbers of attributes that contribute effectively to the output are chosen. The seven attributes fall under four groups of human tactile sensations such as bending rigidity of the material, compressibility and friction, and the subset evaluation scheme was able to identify these influencing parameters. Thus, the ANNs approach provides a successful platform for cognitive perception analysis of tactile prickling feeling.

REFERENCES

Apurba, D. and Alagirusamy, R., (2010). Science In Clothing Comfort. India: Woodhead Publishing India Pvt. Ltd, pp. 56-87.

Dargahi, J. and Najarian, S. (2004), "Human Tactile Perception As A Standard For Artificial Tactile Sensing—A Review". *The International Journal Of Medical Robotics And Computer Assisted Surgery*, Vol. 1**,** pp. 23-35.

Garnsworthy, R.K., Gully, R.L., Kenins, P., Mayfield, R.J. and Westerman, R. A. (1988), "Identification Of The Physical Stimulus And The Neural Basis Of Fabric-Evoked Prickle", *Journal Of Neurophysiology*, Vol. 59**,** pp. 1083-1097.

Garnsworthy, R.K., Gully, R.L., Kandiah, R.P., Kenins, P., Mayfield, R.J. And Westerman, R.A. (1988), "Understanding The Causes Of Prickle And Itch From The Skin Contact Of Fabrics", *Csiro Division Of Wool Technology Report,* Vol. 64, pp. 56-87.

Garnsworthy, R.K., Gully, R.L., Kenins, P. And Westerman, R.A. (1988), "Transcutaneous Electrical Stimulation And The Sensation Of Prickle", *Journal Of Neurophysiology,* Vol. 59**,** pp. 1116-1127.

Goldstein, E. B. (2010), *Sensation And Perception,* Cengage Brain Vol. 6, pp. 226-257.

Graupe, D. (1997). *Principles Of Artificial Neural Networks,* World Scientific Vol.2, Pp. 7-213.

Hagan Mt, D.H. And Beale M.H. (1996). *Neural Network Design,* Boston, Pws Publishing Company Vol 4, pp. 36-66.

Kawabata, S. And Niwa, M. (1991), "Objective Measurement Of Fabric Mechanical Property And Quality: Its Application To Textile And Clothing Manufacturing", *International Journal Of Clothing Science And Technology,* Vol. 3**,** pp. 7-18.

Li, T.T., Shao, J.Z., Zhou, J.L. And Zhang, T.Z.(2012), "The Evaluation Of Fabric Prickle Based On Bp Neural Network", *Advanced Materials Research,* Vol. 441**,** pp. 645-650.

Li, Y. (2001),“The Science Of Clothing Comfort”, *Textile Progress,* Vol. 31**,** pp. 1-135.

Matsudaira, J.D.W. And Acamaby, G. (1990), “Measurement Of The Surface Prickle Of Fabrics Part Ii: Some Effects Of Finishing On Fabric Prickle”, *Journal Of The Textile Institute,* Vol. 81**,** pp. 300-309.

Matsudaira, J.D.W. And Acamaby, G. (1990), “Measurement Of The Surface Prickle Of Fabrics Part I: The Evaluation Of Potential Objective Methods”, *Journal Of The Textile Institute,* Vol. 81**,** pp. 288-299.

Mukhopadhyay, A. (2002), “Application Of Artificial Neural Networks In Textiles”, *Textile Asian Journal,* Vol. 33**,** pp. 35–39.

Mukhopadhyay, S. And Siddiquee, Q. (2003), “Artificial Neural Networks And Their Use In Textile Technology”, *Asian Textile Journal,* Vol. 12**,** pp. 72–77.

Naebe, M., Lutz, V., Mcgregor, B., Tester, D. And Wang, X. (2013) “ Predicting Comfort Properties Of Knitted Fabrics By Assessing Yarns With The Wool Comfortmeter”, *Journal Of The Textile Institute***,** Vol. 104, pp. 628-633.

Naebe, M., Mcgregor, B.A., Swan, P. And Tester, D. (2014), “Associations Between The Physiological Basis Of Fabric-Evoked Prickle, Fiber And Yarn Characteristics And The Wool Comfortmeter Value”, *Textile Research Journal***,** Doi: 0040517514527372.

Naylor, G.R., Stanton, J.H. And Speijers, J. (2014), “Skin Comfort Of Base Layer Wool Garments. Part 2: Fiber Diameter Effects On Fabric And Garment Prickle”, *Textile Research Journal***,** Doi: 0040517514523174.

Naylor, G.R.S., Veitch, C., Mayfield, R. J. And Kettlewell, R. (1992) “Fabric-Evoked Prickle”, *Textile Research Journal,* Vol. 62**,** pp. 487-493.

Ramsay, D.J., Fox, D.B. And Naylor, G.R.S. (2012) “An Instrument For Assessing Fabric Prickle Propensity”, *Textile Research Journal,* Vol. 82**,** pp. 513-520.

Haykin, S., And Network, N. (1999). *Neural Networks: A Comprehensive Foundation,* India, Pearson Educatio, pp. 36-78..

Naylor, G.R.S. (1992) “The Role Of Coarse Fibres In Fabric Prickle Using Blended Acrylic Fibres Of Different Diameters”, *Wool Technology And Sheep Breeding,* Vol. 40**,** pp. 14-18.

Laing, R. M. And Sleivert, G. G. (2002), “Clothing, Textiles, And Human Performance”, *Textile Progress,* Vol. 32**,** pp. 1-122.

Stanton, J.H., Speijers, J., Naylor, G.R., Pieruzzini, S., Beilby, J., Barsden, E. And Clarke, A. (2014) “Skin Comfort Of Base Layer Knitted Garments. Part 1: Description And Evaluation Of Wearer Test Protocol” *Textile Research Journal*, Doi: 0040517514521114.

Vlattas, C. And Galiotis, C. (1991) “Monitoring The Behaviour Of Polymer Fibres Under Axial Compression”, *Polymer,* Vol. 32, pp. 1788-1793.

Westerman, R., Garnsworthy, R., Walker, A., Kenins, P., Gully, R. And Fergin, P. (1984), “Aspects Of Human Cutaneous Small Nerve Function: Sensations Of Prickle And Itch” *Iups Satellite Symp., Budapest,*Vol. 29, pp. 329-345.

Wong, A.S.W., Li, Y., And Yeung, P.K.W. (2003), “Neural Network Predictions Of Human Psychological Perceptions Of Clothing Sensory Comfort”, *Textile Research Journal,* Vol. 73, pp. 31-37.

Li, Y., And Dai, D.X. (2006). *Biomechanical Engineering Of Textiles And Clothing,* Cambridge , England, Woodhead Publishing Limited, Vol. 1, pp. 17-55.

Yeung, D.S., Cloete, I., Shi, D. And Ng, W. W. (2010). *Sensitivity Analysis For Neural Networks,* Verlag Berlin Heidelberg, Springer, Pp. 32-47.

4 العدد 41 المجلد التطبيقيت والعلم للهندست الجزيرة مجلت – ه 4111 م 9142
103

الشبكات باستخدام المنسوجة الأقمشة من الوخز لخصائص والتحليل التنبؤ الاصطناعية العصبية

1 أسد محمد أحمد ربيع ، 1 الطاهر القادر عبد ياسر ،2 صن شين فنق ، 2 ،
2 يو دونغ ويي ، 1 شبرين على محمد حسن محمود

22 .ب.ص ، مدوي ود ، الجصيسة حامعة ، الصاعات وثنولوحيا هدطة ملية ، 1
الظودان

دوهخوا، حامعة ، الحعليم وشازة ، واليظيج الغصى وثنولوحيا علوم مخحبر 2
الصين شنغهاي،.

الخلاصة

العصبية الشبهات م هموذج وثحليل وثطويس ثصميم إلى الوزقة هره تهدف
المواد م بالوخص الإحظاض لخصائص البشسي الإدزاك لفهم (ANNs (الاصطناعية
القابلة الميهاهينية الخواص حيث م الأحاطيع ثلو ع للحعبير لمي هظام وخلق)الأقمشة(الملبوطة اليظيجية
والغير الموضوعي القياض عمل ثم .للقياض
التهاب مساعاة مع الوخص عملية م للححقق الملبوطة الأقمشة لمخحلف موضوعي
ازثداء عىد)الوخص(بالحنة الحيبؤ ثم ، العمل هرا في .الساحة وخصائص الجلد
الخلفي ز الاهخشا شبنة باطحخدام أَئية الفيز خصائصها خلاى م الملبوض
الميظوحة للأقمشة الملمع خواص قياض ثم .للموذج الحدزيجي والاهحداز
النلي الإحظاض قيم دً ثحد وثم (KES-F (بالأقمشة الخاص مواباثا حهاش بواططة
م العصبية الشبنة فعالية م الححقيق وثم .المحنمين م مجموعة قبل م الملبوطة للأقمشة (TPS (للوخص
وأظهست .العصبون وزقم الطبقات عدد جغيير خلاى
للوخص النلي الإحظاض بقيم ثحيبأ أن مًن ي العنس الاهخشاز شبنة أن النحائج
الشبنة هحائج خلاى وم .الفسوقات بعض وحود مع الملبوطة للأقمشة (TPS (
العصبية هجدها محققة بشهل حيد مع هحائج الاخحباز الراجي.