Modeling Ultraviolet Protection Factor of Polyester-Cotton Blended Woven Fabrics Using Soft Computing Approaches

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ABSTRACT

Ultraviolet protection factor (UPF) of woven fabrics is modeled by using two soft computing approaches, namely adaptive network based fuzzy inference system (ANFIS) and artificial neural network (ANN). Three fabric parameters: proportion of polyester in weft yarns, weft count, and pick density are used as input parameters for predicting fabric UPF. Two levels (low and high) of membership function for each of the input parameters are used to reduce the complexity of ANFIS. The eight linguistic fuzzy rules trained by ANFIS are able to explain the relationship between fabric parameters and UPF. A comparison between ANFIS and ANN models is also presented. Both the models predict the UPF of fabrics with very good prediction accuracy in the testing data sets.

Keywords: Ultraviolet protection factor, polyester-cotton blend, artificial neural network, adaptive network based fuzzy inference system.

INTRODUCTION

Ultraviolet (UV) rays are a proven human carcinogen, though controlled exposure to sunlight is beneficial for the synthesis of vitamin D. UV rays mainly affect skin, immune system, and eye [1]. Sunburn, erythema, cancer of the lip, basal cell, and squamous cell carcinoma are some of the most common skin diseases caused by UV radiation. Eye diseases includes photokeratitis, photo conjunctivitis, and cataracts [2, 3]. Clothing, sunscreen, sunglasses, umbrellas, and hats are commonly used for sun protection [4-7]. UV protection capability of a fabric or clothing is expressed by ultraviolet protection factor (UPF). UPF of woven fabric depends on fiber properties, yarn properties, fabric properties, finishing process, color, and presence of UV absorbers [8, 9]. Among the fabric parameters, UPF is largely influenced by cover, areal density, and thickness [10-14]. However, these parameters are interdependent on each other. Moreover, at higher level of cover and areal density, a small increase of these fabric parameters leads to a drastic increase in UPF, bringing in the nonlinearity [15]. Therefore, it becomes difficult to develop predictive models for UPF using linear systems. Several researchers have attempted to predict UPF from single fabric parameter like cover factor, porosity, thickness, and areal density by using simple regression models [10-14]. However, these parameters are secondary in nature and dependent on independent parameters like yarn count and thread density. Unfortunately, prediction models based on independent fabric parameters as inputs are seldom available in the literature. Algaba and Riva [16] used independent fabric parameters (weave, yarn count, and thread density) as input variables to model the UPF of woven fabrics.

Conventional mathematical and statistical models often fail to capture the input-output relationship of real world problems, having noisy data. In contrast, soft computing models are capable of capturing any kind of functional relationship from input-output data. Soft computing techniques mimic the behavior of biological systems like the human brain or natural evolution. Artificial Neural Network is a very powerful modeling tool which can approximate any kind of functional relationship. However, it does not reveal the underlying logic based on which decisions are taken. In contrast, fuzzy logic presents linguistic rules which interpret the relationship between inputs and outputs. However, developing the fuzzy rules is difficult and it often requires the tacit knowledge of the domain expert. Therefore, the hybridization of ANN with fuzzy logic can combine the benefits of both soft computing systems. The adaptive network based fuzzy inference system proposed by Jang [19] is a popular hybrid system for mapping nonlinear relationships among input-output variables. Hadizadeh et al. [20] predicted the initial load-extension behavior of plain woven fabrics in warp and weft directions by ANFIS. Malik et al. [21] predicted the strength transfer efficiency of warp and weft yarns by ANFIS from yarn strength and fabric construction parameters. They reported good prediction accuracy of the model and better understanding of the relationship between the different input and output variables. Ertrugal and Ucar [22] used both the ANN and ANFIS to predict bursting strength of cotton knitted fabrics from fabric weight, yarn strength, and yarn elongation. In a subsequent study, Ucar and Ertrugal [23] predicted circular knitting machine parameters like machine gauge and diameter using multiple linear regression and neuro-fuzzy method. Park and Kang [24] tried to evaluate seam pucker from five shape parameters utilizing neuro-fuzzy algorithm coupled with three dimensional image analysis. In a recent study, Behera and Guruprasad [25] developed ANN and ANFIS models to predict the bending property of cotton plain woven fabrics.

In this work, ultraviolet protection factor of plain woven fabrics were modeled using ANFIS and ANN. Polyester is the best UV absorbing material among textile fibers, due to the presence of its large conjugate aromatic polymer chain, but it is quite uncomfortable in summer due to its lower moisture absorption capacity. On the other hand, cotton fabrics are very popular as summer garments despite having the poorest UV absorbing capacity. Hence, polyester-cotton blended fabrics often yield the optimum characteristics as summer clothing. Therefore, Polyester-cotton blended yarns were used in this study. Three parameters related to weft yarns, namely proportion of polyester (%), count (Ne), and pick density (cm^{-1}) were used as input variables.

MATERIALS AND METHODS

Materials

Yarns made of 100% polyester, 100% cotton, and two different polyester-cotton blends (namely 50:50 and 65:35) were used in this study. Three different yarn counts namely 20, 30 and 40 were taken for each of the four blends making a total of twelve (4 × 3) types of yarn. All the yarns were spun using a ring spinning system. Fabrics were woven by varying the pick density at three levels (16, 20 and 24 cm^{-1}) from each of the 12 types of yarn. Accordingly, 36 (3 × 12) fabric specimens, differing in proportion of polyester (%), weft count (Ne) and pick density (cm^{-1}), were produced. The yarn and fabric parameters and their levels are summarized in *Table I*. All the fabric specimens were produced on an air jet loom (Mythos). Warp count and end density were kept constant at 40 Ne and 40 cm^{-1}, respectively, for all the fabrics. The grey fabric samples were then desized, scoured, and bleached with the same recipe so as not to influence the UPF of the fabrics.

TABLE I. Parameters and levels used in experiments.

Parameters	Levels of parameter	Details
Proportion of polyester in weft (%)	4	0, 50, 65 and 100
Weft count (Ne)	3	20, 30 and 40
Pick density (cm^{-1})	3	16, 20 and 24

Testing

The UPF of fabric samples was measured by the *in-vitro* method, according to the AATCC 183:2004 standard using UV transmittance analyzer (Labsphere 2000F). UV transmittance was measured in a step of 1 nm wavelength by passing the UV rays through the fabric. The UPF of fabric was calculated by using Eq. (1). An average of 10 readings was taken for each fabric specimen.

$$UPF = \frac{\sum_{290}^{400} E(\lambda)S(\lambda)\Delta\lambda}{\sum_{290}^{400} E(\lambda)S(\lambda)T(\lambda)\Delta\lambda} \qquad (1)$$

where *E(λ)* is relative erythemal spectral effectiveness, *S(λ)* is solar spectral irradiance [W m^{-2} nm^{-1}], *Δλ* is measured wavelength interval [nm] and *T(λ)* is average spectral transmittance of the specimen.

Outline of Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS possesses the benefits of two soft computing methods, namely ANN and fuzzy logic. In fuzzy logic, a fuzzy set contains elements with only partial membership ranging from 0 to 1 to represent uncertainty or fuzziness in the absence of distinct boundaries between the sets. For a variable, fuzzy sets are created by dividing the universe into a number of sub-regions, named in linguistic terms like high, moderate, and low. Once the fuzzy sets are chosen, a membership function for each set is created. A membership function is a mathematical expression that converts the input between 0 to 1 to indicate the belongingingness of an element to a particular fuzzy set. Membership function (MF) can have various forms, such as triangular, trapezoidal, sigmoid, and Gaussian. The fuzzy rules are then used to interpret the relationship between input (premise) and output (consequent) fuzzy sets. The output of each rule is also a fuzzy set. All output fuzzy sets are then aggregated into a single fuzzy set. Finally the aggregated fuzzy set is resolved to a crisp output number by dint of "defuzzification".

ANFIS is a multilayered adaptive network [*Figure 1*] in which each node performs a particular function on incoming signals. The formula for the node functions vary from node to node. Mainly two types of nodes, namely circle and square are used in a network to reflect different adaptive capabilities [*Figure 1*]. A square node is an adaptive node having parameters while a circle node is a fixed node having no parameter. These parameters are updated according to given training data to achieve a desired input-output mapping [19]. The learning capability of ANN is used to tune the fuzzy membership function parameters using input-output data sets. Generally two learning methods, namely back propagation learning and hybrid learning, are used for training of the model. In hybrid learning, ANFIS uses back propagation learning (gradient descent method) to determine premise parameters (related to the input fuzzy sets) and least mean squares estimation to determine the consequent parameters (related to the output fuzzy sets). A step in the hybrid learning procedure is composed of two passes. In the first pass (forward pass), functional signals go forward and the consequent parameters are estimated by an iterative least mean square procedure, while the premise parameters remain fixed. In the second pass (backward pass), the error propagates backward to update the premise parameters by gradient descent method, while the consequent parameters remain fixed. This procedure is then iterated until the error criterion is satisfied or preset number of cycles is reached [25].

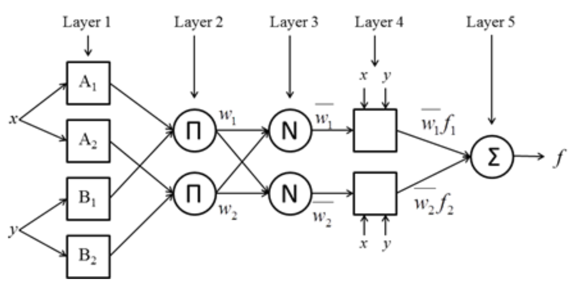

FIGURE 1. ANFIS architecture.

ANFIS Structure

Figure 1 illustrates the ANFIS architecture having five layers assuming two inputs *x* and *y* and one output z. A common first order Sugeno fuzzy model with two rule set can be represented as follows:

Rule 1: If x is A_1 and y is B_1; then $f_1=p_1x+q_1y+r_1$,
Rule 2: If x is A_2 and y is B_2; then $f_2=p_2x+q_2y+r_2$.

Layer 1: Every node in this layer is an adaptive node with a node function as shown below:

$$O_{1,i} = \mu_{A_i}(x) \text{ for } i=1,2 \text{ or} \tag{2}$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i=3,4 \tag{3}$$

where x and y are the input to node i, A_i and B_{i-2} are fuzzy sets associated with inputs x and y, respectively, $\mu_{A_i}(x)$ is the membership of x in fuzzy set A (=A_1, A_2). $O_{1,i}$ is the output at layer 1 of ANFIS for the *i*th node. Here, the MF for A can be any appropriate parameterized MF, such as the generalized Gaussian function:

$$\mu_A(x) = e^{\frac{-(x-\mu)^2}{2\sigma^2}} \tag{4}$$

where $\{\mu, \sigma\}$ is the parameter set containing mean and standard deviation of the distribution, respectively. As the values of these parameters change, the Gaussian function varies accordingly, thus exhibiting various shapes of MFs for fuzzy set A. Parameters in this layer are referred to as premise parameters.

Layer 2: Every node in this layer is a fixed node labeled Π, whose output is the product of all the incoming signals:

$$O_{2,i} = \mu_{A_i}(x)\mu_{B_i}(y) = w_i \text{, for } i=1,2 \tag{5}$$

Each node output represents the firing strengths of a fuzzy rule. In general, any other T-norm operators that perform fuzzy AND can be used as the node function in this layer.

Layer 3: Every node in this layer is a fixed node labeled N. The i^{th} node calculates the ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths. For convenience, outputs of this layer are called normalized firing strengths.

$$O_{3,i} = \frac{w_i}{w_1 + w_2} = \overline{w_i} \tag{6}$$

Layer 4: Every node *i* in this layer is an adaptive node with a node function as shown below:

$$O_{4,i} = \overline{w_i f_i} = \overline{w_i}(p_i x + q_i y + r_i) \tag{7}$$

where w_i is a normalized firing strength from layer 3 and $\{p_i, q_i, r_i\}$ is the parameter set of this node. Parameters in this layer are referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals:

$$O_{5,i} = \sum \overline{w_i f_i} = \frac{\sum w_i f_i}{\sum w_i} \tag{8}$$

TABLE II. Number of ANFIS parameters for three input variables each having Gaussian membership function with two levels.

Layer number	Layer type	Number of nodes	Number of parameters
0	Inputs	Number of inputs = 3	0
1	Fuzzification	No. of fuzzy sets per input × no. of inputs = 2×3=6	No. of parameters per fuzzy set × no. of fuzzy sets =2×6=12
2	Rules	(No. of fuzzy sets per input)$^{\text{no. of inputs}}$ = 2^3	0
3	Normalization	(No. of fuzzy sets per input)$^{\text{no. of inputs}}$ = 2^3	0
4	Constant function	(No. of fuzzy sets per input)$^{\text{no. of inputs}}$ = 2^3	No. of fuzzy rules × number of constants per rule =8 ×1=8
5	Summation	1	0

Modeling with ANFIS and ANN

Three input variables namely proportion of polyester (%), weft count (Ne) and pick density (cm^{-1}) were used as input parameters and the UPF was the output parameter. For ANFIS, only two fuzzy sets for each of the three input parameters were chosen so that the number of fuzzy rules became 8 (2^3). Gaussian membership function, which is defined by mean and standard deviation, was selected as the input MF and constant function was selected as output MF. For training of the ANFIS model, the hybrid optimization technique was employed. Twenty-seven out of 36 input-output data sets were used for training of ANFIS and ANN models. Nine data sets were kept for the testing of the models. The ANFIS training was done up to 1800 epochs or cycles as it yielded minimum error in testing data sets. The number of nodes and parameters in different layers of ANFIS has been presented in *Table II*.

An ANN model was also developed and evaluated using the same 27 training data sets and nine testing data sets, respectively, as used for ANFIS model. Three input nodes, one hidden layer with four nodes and one node in the output layer were used. Tan-sigmoid transfer function was used for both hidden and output layers. Levenberg-Marquardt algorithm was used for training of ANN. The learning rate was kept at 0.3. Maximum iteration was set at 500 and mean squared error (MSE) were set at 500 and 0.01, respectively, as stopping criteria.

MATLAB® version 7.1 platform was used for developing the ANFIS and ANN models.

RESULTS AND DISCUSSION

Prediction Performance of ANFIS and ANN Models

For assessing the prediction accuracy of the models, mean absolute percentage error (MAPE) and mean squared error (MSE) were calculated using the following expressions:

$$\textit{Mean absolute error (\%)} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\textit{Actual value}_i - \textit{Predicted value}_i}{\textit{Actual value}_i}\right|.100 \tag{9}$$

$$\textit{Mean squared error} = \frac{1}{n}\sum_{i=1}^{n}\left(\textit{Actual value}_i - \textit{Predicted value}_i\right)^2 \tag{10}$$

where i =1, 2, 3….n, n is the number of observations. For comparative analysis of prediction results, a nonlinear regression model was also developed as given below.

$$\begin{aligned} UPF &= -3.268 + 0.048x_1 - 0.087x_2 + 0.838x_3 - 0.002x_1x_2 \\ &+ 0.006x_1x_3 - 0.023x_2x_3 - 0.001x_1^2 + 0.008x_2^2 \end{aligned} \tag{11}$$

where x_1, x_2 and x_3 are proportion of polyester (%), weft count (Ne), and pick density, (cm^{-1}), respectively.

The summary of prediction performance parameters was calculated for ANFIS, ANN and nonlinear regression models and they are presented in *Table III*. The coefficient of determination (R^2), MAPE and MSE were calculated separately for the training and testing data sets. In case of ANFIS, the R^2 values in both the training and testing data sets were very high (0.988 and 0.992 respectively). But the prediction error values (MAPE and MSE) were better for training data sets as the model parameters were optimized using them. It was also observed that there were only three and one sample, respectively, in training and testing data sets where the prediction error crossed 5%. This bolsters the fact that optimum training of the ANFIS model was done. On the other hand, the prediction performance of the ANN model in the training data sets was comparatively better than that of ANFIS model in terms of all the statistical parameters (R^2, MAPE, MSE, number of samples with more than 5% error). However, *Table III* reveals that the R^2 and MAPE of ANN model was similar to that of ANFIS model in the testing data sets. *Table III* also shows that nonlinear regression model exhibited the least prediction accuracy among the three models. For nonlinear regression model, not only the MAPE values were very high in training (6.717) and testing (4.795) data sets but the number of individual samples with more than 5% prediction error was also considerably higher (11 and 2 in training and testing data sets, respectively).

TABLE III. Summary of UPF prediction accuracy ANFIS and ANN models.

Model	Performance parameter	Dataset	
		Training	Testing
ANFIS	R^2	0.988	0.992
	MAPE	2.276	2.506
	MSE	0.047	0.173
	Number of samples with more than 5% error	3	1
ANN	R^2	0.999	0.994
	MAPE	1.120	2.590
	MSE	0.007	0.098
	Number of samples with more than 5% error	1	1
Nonlinear regression	R^2	0.973	0.960
	MAPE	6.717	4.795
	MSE	0.319	0.708
	Number of samples with more than 5% error	11	2

TABLE IV. Detailed prediction results of ANFIS and ANN models in testing data sets.

S. No.	Actual UPF	ANFIS		ANN	
		Predicted UPF	Absolute error (%)	Predicted UPF	Absolute error (%)
1	8.31	8.33	0.241	8.27	0.480
2	11.9	12.1	1.681	11.43	3.923
3	17.24	16.9	1.972	16.61	3.682
4	6.62	6.5	1.813	6.44	2.681
5	8.53	8.59	0.703	8.59	0.684
6	10.15	11.3	11.330	10.41	2.549
7	5.84	5.71	2.226	5.52	5.419
8	7.11	7.09	0.281	7.21	1.366
9	8.66	8.86	2.309	8.88	2.523

The detailed prediction performance of both the models in testing data sets is presented in *Table IV*. In case of ANFIS model, the maximum prediction error was as high as 11.3%. However, for ANN model, the prediction error varied from 0.5% to 5.4%. It should be noted that ANFIS demonstrated lower prediction error than ANN model in seven instances out of nine testing data sets. As the performance of models in the testing datasets represents their generalization ability, it can be concluded that ANFIS and ANN had similar prediction accuracy in the unseen testing data sets.

Linguistic Rules of ANFIS Model

Figure 2 shows the eight fuzzy rules which are relating three input variables (proportion of polyester, weft count and pick density) with the output variable (UPF). The membership function of each input variable had two levels, namely low and high. The output variable (UPF) had eight levels of membership function. From *Figure 2* it is observed that when proportion of polyester, weft count, and pick density were 95%, 30 Ne and 20 cm^{-1}, respectively, four fuzzy rules (rules 5 to 8) were active with different strengths indicated by the heights of the black pillars. Final output (UPF) of 8.87 was achieved by defuzzyfying or calculating the weighted average of these four fuzzy sets. It can be inferred from rule 3 that lowest UPF was achieved with lowest proportion of polyester, finest weft count and lowest pick density. Similarly rule 6 implies that highest UPF was achieved with highest proportion of polyester, coarsest weft count and highest pick density. Comparing rules 1 and 2, it can be inferred that UPF increased with increasing pick density, keeping the proportion of polyester and weft count constant. Similarly, it can be said from rules 1 and 3 that UPF increased with coarser weft yarns if the other two parameters were constant. Comparing rule 1 and 5 it can be inferred that UPF increased with the increasing polyester percentage keeping the weft count and pick density constant. These results are in accordance with the established fact which signifies the learning capability of the ANFIS from the experimental data.

Figure 3 depicts the effect of proportion of polyester and weft count on fabric UPF keeping the third parameter (pick density) constant at the mid level (20 cm^{-1}). It can be observed that fabric UPF improved drastically with the increase in the proportion of polyester. This is because of the fact that polyester fiber is having an absorption band in the UV region. UPF increased slowly with increasing yarn coarseness when the proportion of polyester was low. However, UPF increased rather rapidly with the increasing yarn coarseness when the proportion of polyester was high implying positive interaction effect of yarn count and proportion of polyester on UPF. Coarser yarns gave higher fabric cover and thus transmitted lesser UV rays resulting higher values of UPF.

FIGURE 2. Fuzzy linguistic rules relating input variables with fabric UPF

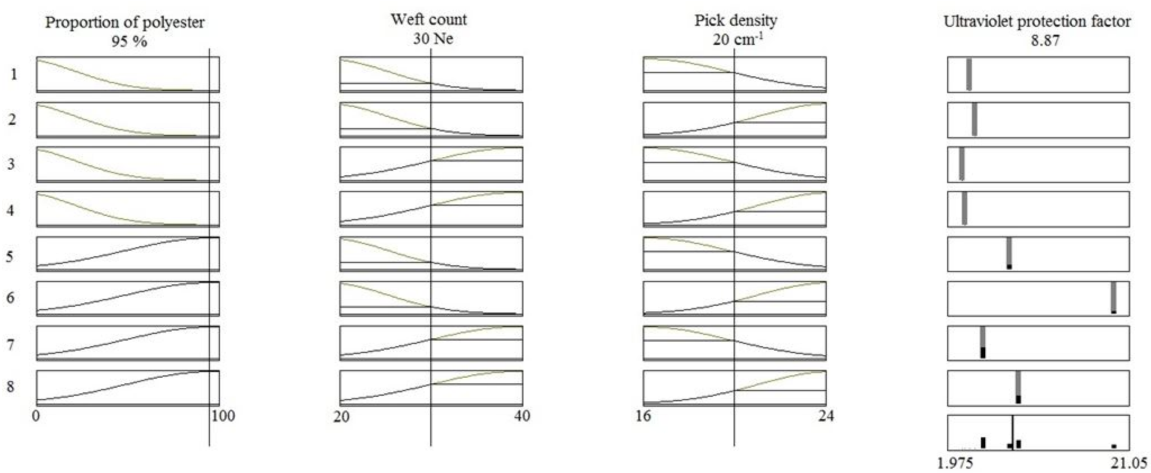

Figure 4 shows the effect of proportion of polyester and pick density on fabric UPF when weft yarn count was kept at its mid level of 30 Ne. Fabric UPF increased consistently with the increasing pick density. It can also be observed that there was a significant synergistic effect of increasing proportion of polyester and higher pick density on fabric UPF. This justifies the positive interaction effect of proportion of polyester and picks density on UPF.

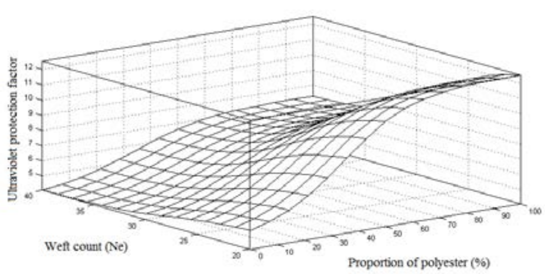

FIGURE 3. Effect of proportion of polyester and weft count on fabric UPF.

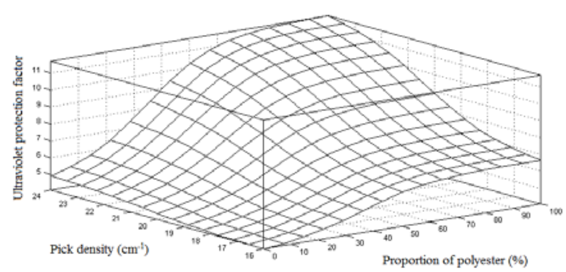

FIGURE 4. Effect of proportion of polyester and pick density on fabric UPF.

CONCLUSION

Fabric UPF has been modeled using adaptive network based fuzzy inference system (ANFIS) and artificial neural network (ANN) models. The prediction performance of both the models was found to be very accurate. Although the performance of ANN was marginally better in the training data sets, the generalization ability of both the models was at par in the unseen testing data sets (R^2= 0.99 and mean absolute error = 2.6%). Eight fuzzy rules were generated and trained by ANFIS which interpreted the influence of fabric parameters on UPF. Higher UPF can be achieved by using higher proportion of polyester, coarser weft, and higher pick density as these combinations are not only favorable for UV protection, but they also have positive interaction effect.

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REFERENCES

[1] MacKie, R.M.; Effects of ultraviolet radiation on human health; *Radiation Protection Dosimetry* 2000, *91*, 15-18.

[2] Gallagher, R.P.; Lee, T.K.; Adverse effects of ultraviolet radiation: A brief review; *Progress in Biophysics and Molecular Biology* 2006, *92*, 119-131.

[3] Halliday, G.M.; Norval, M., Byrne; S.N., Huang, X.X.; Wolf, P.; The effects of sunlight on the skin; *Drug Discovery Today* 2008, *5*(2), e201- e209.

[4] Roy, C.R.; Gies, H.P.; Protective measures against solar UV exposures; *Radiation Protection Dosimetry* 1997; *72*, 231-240.

[5] Wang, S.Q.; Balagula, Y.; Osterwalder, U.; Photoprotection: A review of the current and future technologies; *Dermatologic Therapy* 2010, *23*, 31-47.

[6] Kullavanijaya, P.; Lim, H.W.; Photoprotection; *Journal of the American Academy of Dermatolog* 2005, *52*, 937-958.

[7] Gies, P; Photoprotection by Clothing; *Photodermatolgy, Photoimmunolgy & Photomedicine* 2007, *23*, 264-274.

[8] Dubrovski, P.D.; Woven fabrics and ultraviolet protection, In: Dubrovski, P.D.; ed. *Woven fabric engineering*; Sciyo: India, 2010: 273-296.

[9] Das, B.R.; UV radiation protective clothing; *Open Textile Journal* 2010, *3*,14-21.

[10] Dubrovski, P. D.; Golob, D.; Effects of woven fabric construction and color on ultraviolet protection; *Textile Research Journal* 2009, *79*(4), 351–359.

[11] Algaba, I.; Riva, A.; Influence of fibre type and fibric porosity on the UPF of summer fabrics; *AATCC Review* 2004, 26-31.

[12] Algaba, I. M.; Pepio, M.; Riva, A.; Correlation between the ultraviolet protection factor and the weight and thickness of undyed cellulosic woven fabrics; *FIBRES & TEXTILES in Eastern Europe* 2008, *16*(1/66), 85-89.

[13] Majumdar, A.; Kothari, V.K.; Mondal, A.K.; Hatua, P.; Effect of weave, structural parameters and ultraviolet absorbers on *in vitro* protection factor of bleached cotton woven fabrics; *Photodermatology, Photoimmunology & Photomedicine* 2008, *28*, 58–67.

[14] Morihiro, Y; Eri, F; Chie, T; Effects of fiber materials and fabric thickness on UV shielding properties of fabrics; *Journal of Textile Engineering* 2009, *55*, 103-109.

[15] Majumdar, A.; Kothari, V.K.; Mondal AK.; Engineering of cotton fabrics for maximizing in vitro ultraviolet radiation protection; *Photodermatology, Photoimmunology & Photomedicine* 2010, *26*, 290-296.

[16] Algaba, I.M.; Pepio, M.; Riva. A.; Modelization of the influence of structural parameters on the ultraviolet protection factor provided by cellulosic woven fabrics; *Journal of Textile Institute* 2007, *98*(4), 293-300.

[17] Rajasekaran, S; Pai, G.A.V.; *Neural networks, fuzzy logic and genetic algorithms: Synthesis and applications*; PHI Learning Private Limited: New Delhi, 2010.

[18] Majumdar, A.; Soft computing in fibrous materials engineering; *Textile Progress* 2011; *43*(1), 1-95.

[19] Jang, J.S.R.; ANFIS: Adaptive-network based fuzzy inference systems; *IEEE Transactions on Systems, Man and Cybernetics* 1993, *23*(3), 665–685.

[20] Hadizadeh, M.; Tehran, M. A.; Jeddi, A.A.A.; Application of an adaptive neuro-fuzzy system for prediction of initial load-extension behavior of plain-woven fabrics; *Textile Research Journal* 2010, *80*(10), 981-990.

[21] Malik, Z.A.; Malik, M.H.; Hussain, T.; Tanwari, A; Predicting strength transfer efficiency of warp and weft yarns in woven fabric using adaptive neuro-fuzzy inference system; *Indian Journal of Fibre & Textile Research* 2010, *35*, 310-316.

[22] Ertugrul, S.; Ucar, N; Predicting bursting strength of cotton plain knitted fabrics using intelligent techniques; *Textile Research Journal* 2000, *70*(10), 845-851.

[23] Ucar, N.; Ertugrul, S.; Predicting circular knitting machine parameters for cotton plain fabrics using conventional and neuro-fuzzy methods; *Textile Research Journal* 2002, *72*(4), 361-366.

[24] Park, C.K.; Kang, T.J.; Objective Evaluation of Seam Pucker Using Artificial Intelligence Part II: Method of Evaluating Seam Pucker; *Textile Research Journal* 1999, *69*(11), 835-845.

[25] Behera, B.K.; Guruprasad, R; Predicting bending rigidity of woven fabrics using adaptive neuro-fuzzy inference system (ANFIS); *The Journal of The Textile Institute* 2012, *103*(11), 1205–1212.

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