

# Optimization of woven fabric parameters for ultraviolet radiation protection and comfort using artificial neural network and genetic algorithm

Abhijit Majumdar<sup>1</sup> · Apurba Das<sup>1</sup> · Piyali Hatua<sup>1</sup> · Anindya Ghosh<sup>2</sup>

Received: 4 March 2015 / Accepted: 9 August 2015 / Published online: 21 August 2015  
© The Natural Computing Applications Forum 2015

**Abstract** Optimization of woven fabric parameters for ultraviolet protection factor (UPF) and comfort properties has been attempted using hybrid artificial neural network (ANN)–genetic algorithm (GA) system. ANN was used for developing the prediction models, and GA was employed as an optimization tool. Four feasible combinations of UPF, air permeability and moisture vapor transmission rate (MVTR) were chosen from the Pareto charts of UPF–air permeability and UPF–MVTR. Penalty function method was adopted to form a single objective function by combining the objectives and constraints related to UPF, air permeability and MVTR. The developed ANN–GA hybrid system was executed to obtain the solution set of input parameters for achieving the targeted fabric properties. To validate the developed ANN–GA-based fabric parameter optimization system, four fabric samples were woven using the solution sets of input parameters and functional properties of these engineered fabrics were evaluated. The targeted and achieved values of fabric properties of four validation samples were in reasonably good agreement.

**Keywords** Artificial neural network · Fitness function · Genetic algorithm · Optimization · Ultraviolet radiation

## 1 Introduction

Ozone layer depletion in the atmosphere has caused significant rise in the amount of ultraviolet radiation (UVR) reaching the earth. This in turn has increased the incidence of skin cancers, specially in countries with high solar exposure such as Australia and South Africa. Covering the skin by clothing is the most common and convenient way of solar UV protection [1–3]. There are various parameters which influence the UV protection capability of fabrics and clothing. These parameters include fiber type, yarn structure, fabric cover factor, fabric areal density, fabric thickness, finishing process, coloration process and presence of UVR absorbers. Fabric cover indicates the percentage of fabric area which is actually covered by the constituent yarns. Increased cover and areal density of fabrics facilitates the blocking and absorption of incident UV rays.

UV protection characteristics of a fabric are generally measured by using a spectrophotometer according to in vitro method. Ultraviolet protection factor (UPF) is the parameter that expresses the UV protective capability of a fabric. UPF value of 20 implies that only 1/20 part or 5 % of the incident rays can pass through the fabric [4–6]. Along with sufficient UV protection, clothing should also allow the transmission of fluids like air and moisture vapor to ensure comfort to the wearer. However, improved UPF attained by enhancing the fabric cover causes deterioration in comfort properties and vice versa. Therefore, clothing should be engineered in such a manner that desired levels of all these properties (UPF, air permeability and moisture vapour transmission rate or MVTR) are achieved simultaneously. Designing a fabric to meet these multiple functional properties, which are conflicting to each other, is a very challenging task. This type of problems is known as multi-objective optimization where more than one objective is to be met simultaneously [7, 8].

---

✉ Abhijit Majumdar  
majumdar@textile.iitd.ac.in

<sup>1</sup> Indian Institute of Technology Delhi, Delhi 110016, India

<sup>2</sup> Government College of Engineering and Textile Technology, Berhampore 742101, India

Functional properties of woven fabrics are mainly governed by the basic constructional parameters like blend proportion of fibers, ends per inch, picks per inch and linear densities or count (mass per unit length) of warp and weft yarns. At present, trial and error approach, which takes the leverage of human expertise and thumb rules, is generally adopted for producing fabrics to meet the targeted functional properties. As the quality requirements of fabrics are becoming stringent in a customer-centric market, it has become essential to have a robust scientific approach for fabric parameter optimization. A fabric parameter optimization should essentially possess two sub-systems, namely a predictive model and an optimization tool. Traditional techniques like regression model and linear or goal programming can be used for attempting simple fabric optimization problems. For handling complex fabric optimization problems, advanced soft computing techniques can be invoked. Among the soft computing techniques, artificial neural network (ANN) has been used extensively for modeling complicated systems. Besides genetic algorithm (GA) has been successfully employed as an efficient searching algorithm in multi-objective optimization problems [9]. The main advantage of GA is that it works with a number of solution points (population) in each iteration instead of point-by-point searching. Therefore, GA has a greater probability to converge at global solution [7, 8, 10].

In recent years, textile materials have received significant attention as engineered materials. Attempts have been made to develop computational models for thermal resistance, moisture transmission and impact resistance of woven fabrics [11–13] using finite element modeling. ANN–GA has been used as a computational platform in various domains of materials engineering including processes of powder metallurgy of pure iron [14], injection molding of plastic [15] and laser welding of stainless steel [16]. Zhou et al. [17] applied ANN and GA for material selection for sustainable products. Lin [18] utilized GA to search four woven fabric parameters for obtaining desired fabric weight at minimum cost. Karthikeyan and Sztandera [19] used hybrid ANN–GA algorithm-based system to identify a suitable set of mechanical properties of fabric for a required tactile comfort score.

In the present research, fabric parameter optimization for ultraviolet protection and comfort properties (air permeability and MVTR) has been attempted using hybrid ANN–GA system. ANN has been used to predict the fabric functional properties (UPF, air permeability and MVTR) using fiber blend proportion in yarn, yarn count (warp and weft) and thread density (ends per inch and picks per inch) as inputs. These models have been used to define the fitness function of GA. Finally, GA has been used to search the

optimum combination of fabric construction parameters for attaining targeted functional properties.

## 2 Woven fabric and fabric cover

Woven fabric is an interlaced structure made up of two sets of yarns, namely warp (singular: end) and weft (singular: pick). Figure 1 depicts the structure of a plain woven fabric which is produced by regularly recurring interlacement between longitudinal warp (gray) and transverse weft (black) yarns. The basic construction parameters of a woven fabric are blend proportion of fibers in warp and weft yarns, warp count ( $N_e$ ), weft count ( $N_e$ ), ends per inch and picks per inch.  $N_e$ , an indicator of yarn diameter, is the unit of yarn count, and it represents the number of hanks (840 yards) which can be produced from 1 pound of yarn. Higher value of yarn count implies finer yarn and vice versa as indicated by Eq. 1.

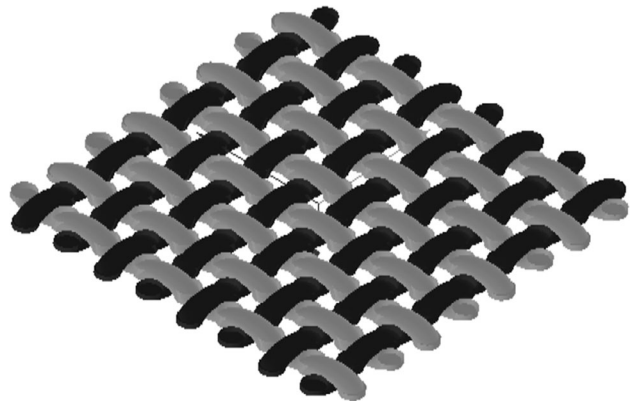
$$\text{Yarn diameter (in.)} \simeq \frac{1}{28\sqrt{N_e}} \quad (1)$$

The transmission of ultraviolet rays, air and moisture vapor through the fabrics largely depends on fabric cover. Figure 2 depicts the repeat unit of a plain woven fabric and the pore between the warp and weft yarns. Fractional fabric cover is expressed by Eq. 2.

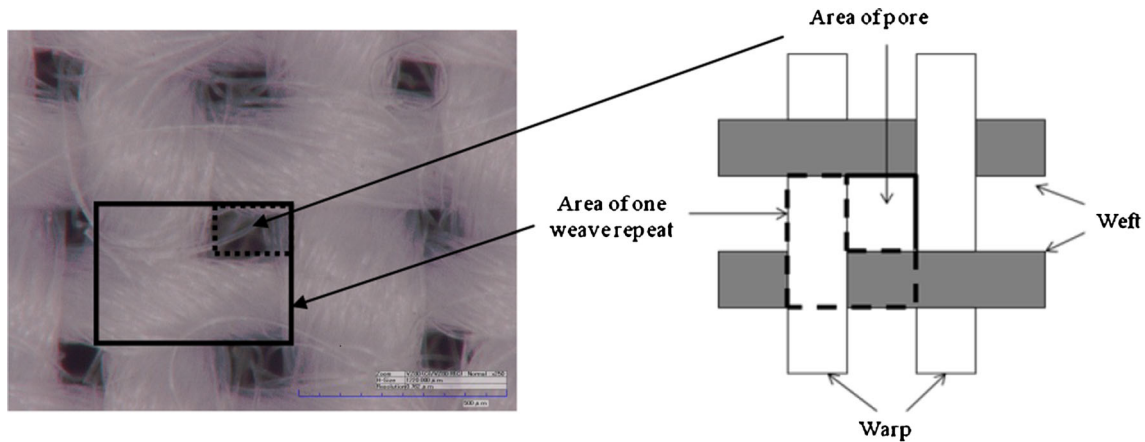
Fractional fabric cover

$$= \frac{\text{Area of one weave repeat} - \text{area of the pore within that repeat}}{\text{Area of one weave repeat}} \quad (2)$$

Fractional warp cover is defined as the ratio of area covered by the warp yarns to the total area of the fabric. This can be expressed by  $\frac{d_1}{p_1}$  and similarly fractional weft cover can be expressed by  $\frac{d_2}{p_2}$ , where  $d_1$  is diameter of warp yarn,  $d_2$  is diameter of weft yarn,  $p_1$  is end spacing and  $p_2$  is pick



**Fig. 1** A plain woven fabric



**Fig. 2** A repeat unit of plain woven fabrics

spacing. End spacing ( $p_1$ ) and pick spacing ( $p_2$ ) imply the distances between two consecutive warp yarns and weft yarns, respectively, and they are the reciprocals of end density (ends per inch) and pick density (picks per inch), respectively. The fractional fabric cover is the ratio of area covered by the warp and weft yarns together to the total area of the fabric and it can be expressed by Eq. 3.

$$\begin{aligned} \text{Fractional cover of fabric} &= \frac{d_1 p_1 + d_2 p_2 - d_1 d_2}{p_1 p_2} \\ &= \frac{d_1}{p_2} + \frac{d_2}{p_1} - \frac{d_1 d_2}{p_1 p_2} \end{aligned} \quad (3)$$

### 3 Materials and methods

#### 3.1 Sample preparation

Among the textile fibers, polyester is known to be the best UV-absorbing material due to its large conjugate aromatic polymer chain. However, 100 % polyester fabric is generally uncomfortable due to its lower moisture absorption capacity. On the contrary, cotton fibers possess very good moisture absorption capacity. However, cotton is the poorest UV-absorbing textile fiber. Hence, the polyester–cotton blended fabrics can yield the best characteristics in terms of UV protection and comfort. Therefore, apart from 100 % cotton and 100 % polyester, two polyester–cotton blends (50:50 and 65:35) were used in this study.

The yarn counts were 20, 30 and 40 Ne for each of the three blends (100 % cotton, 100 % polyester and 50:50 polyester–cotton). Polyester–cotton yarn (65:35) of 30 Ne was also used for preparing validation sample. At first, 13 plain woven square fabrics having same proportion of polyester, yarn count and thread density in warp and weft were woven following Box and Behnken design of

**Table 1** Parameters and their levels used for fabric sample preparation

Parameters	Levels	Details
Proportion of polyester (%)	3	0, 50 and 100
Yarn count (Ne)	3	20, 30 and 40
Thread density on loom (in. <sup>-1</sup> )	3	50, 60 and 70

experiment plan for three factor and three level. To increase the diversity in the sample pool, weft-related parameters, namely proportion of polyester in weft, weft count and pick density, were then varied randomly for each of the aforesaid 13 fabrics to produce another 29 non-square fabrics making the sample pool of 42 plain woven fabrics. All the fabrics were woven on SL 8900S CCI Tech single rigid rapier loom. The fabric parameters and their levels are given in Table 1. The range of thread density was chosen selectively as 50–70 in.<sup>-1</sup> keeping in mind the weaveability and fabric cover of the fabric samples. All gray fabric samples were processed through preparatory wet treatments, i.e., enzymatic desizing, alkaline scouring and peroxide bleaching.

#### 3.2 Testing

The actual end and pick densities were measured in the fabric samples after wet treatment using counting glass (pick counter) according to ASTM D3775-08. The UPF of fabric samples was measured in UV transmittance analyzer (Labsphere 2000F) according to the AATCC 183:2004 standard. Equation 4 was used for calculating UPF.

$$\text{UPF} = \frac{\sum_{290}^{400} E(\lambda)S(\lambda)\Delta(\lambda)}{\sum_{290}^{400} E(\lambda)S(\lambda)T(\lambda)\Delta(\lambda)} \quad (4)$$

where  $E(\lambda)$  is relative erythema spectral effectiveness,  $S(\lambda)$  is solar spectral irradiance (W/m<sup>2</sup>/nm),  $\Delta\lambda$  is

measured wavelength interval (nm) and  $T(\lambda)$  is average spectral transmittance of the specimen.

The air permeability of the fabric samples was measured in TEXTEST air permeability tester (FX3300). Air permeability was calculated from the rate of air flow through known area of fabric at a specified air pressure differential according to standard BS 5636. Moisture vapor transmission rate of the fabric samples was measured in WVTR testing instrument (Labthink, W3/060). Water method as specified in ASTM E96/E96M-13 was followed during MVTR testing. MVTR was calculated from the rate of loss of mass of water at a constant humidity differential and temperature through known area of fabric. The temperature and humidity of the controlled chamber were kept at 32.2 °C and 50 %, respectively.

## 4 Results and discussion

### 4.1 Development of ANN models for UPF, air permeability and MVTR

Overall proportion of polyester fiber in fabric was calculated for all the samples using yarn counts and actual thread densities. Overall proportion of polyester fiber in fabric, warp count, weft count, end density and pick density were the five input parameters to the ANN models. The output of ANN models were UPF, air permeability and MVTR. Total 42 datasets were randomly divided into 36 and six datasets for training and testing, respectively. Separate ANN models were developed for UPF, air permeability and MVTR. Only one hidden layer with four nodes was used for all the models. Tan-sigmoid transfer function was used for both hidden and output layers. Levenberg–Marquardt algorithm was used for training of ANN models. The learning rate was kept at 0.3, and mean-squared error (MSE) was set at 0.01 as stopping criteria. Table 2 presents the mean values and ranges of input parameters and functional properties of 42 fabric samples. The ranges of UPF, air permeability and MVTR are 4–202, 2–199 and 2214–2550, respectively, implying that the dataset is covering a huge range of functional properties of woven fabrics.

While selecting ANN models, emphasis was given on trend analysis results along with the commonly used performance criteria, namely coefficient of determination ( $R^2$ ) and mean absolute percentage error (MAPE). Trend analysis was performed by increasing the value of a particular input parameter, in steps, while keeping all other parameters constant at their mean value and observing the effect on the output variable. Only those models which produced logical trend analysis results were considered further. Finally, three ANN models were chosen after extensive training and trend analysis. The models were named as ANN<sub>UPF</sub>, ANN<sub>AP</sub> and ANN<sub>MVTR</sub> for UPF, air permeability and MVTR, respectively. The prediction performances of the developed models are summarized in Table 3. The coefficient of determination ( $R^2$ ) values are very high (around 0.99) in all the cases except for testing dataset of MVTR. The MAPE values are hovering between 10 and 13 % which is at the higher side. However, these models were accepted for fabric parameter optimization endeavor as the trend analysis results were plausible implying that the models have been able to capture the roles of various input parameters on the outputs.

The overall trend analysis results of ANN<sub>UPF</sub> model is shown in Fig. 3. It is noticed that UPF increases with increasing end and pick densities when all other input parameters are kept constant at respective mean values. The UPF decreases with finer warp and weft yarns, i.e., higher Ne values. UPF increases with increasing proportion of polyester in the fabric. All these trends are in agreement with the findings of previous researches, and thus, it can be inferred that the ANN<sub>UPF</sub> model has correctly learned the input–output relationships. The trend analysis results of other two models, i.e., ANN<sub>AP</sub> and ANN<sub>MVTR</sub>, also demonstrated logical relationship between the input and output parameters.

### 4.2 Selection of feasible combinations of target properties

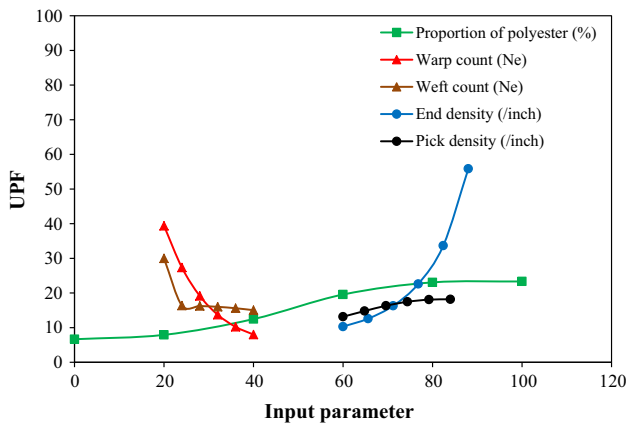
Pareto chart provides various combinations of achievable objectives in a multi-objective problem. In this study, Pareto charts were developed for selecting the achievable

**Table 2** Input and output fabric parameters for ANN models

	Input parameters					Output parameters		
	Proportion of polyester in fabric (%)	Warp count (Ne)	Weft count (Ne)	End density in fabric (in. <sup>-1</sup> )	Pick density in fabric (in. <sup>-1</sup> )	UPF	Air permeability (cm <sup>3</sup> /cm <sup>2</sup> /s)	MVTR (g/m <sup>2</sup> 24 h)
Minimum	0	20	20	56	57	4	2	2214
Maximum	100	40	40	88	84	202	199	2550
Mean	52	29	31	71	69	36	57	2417

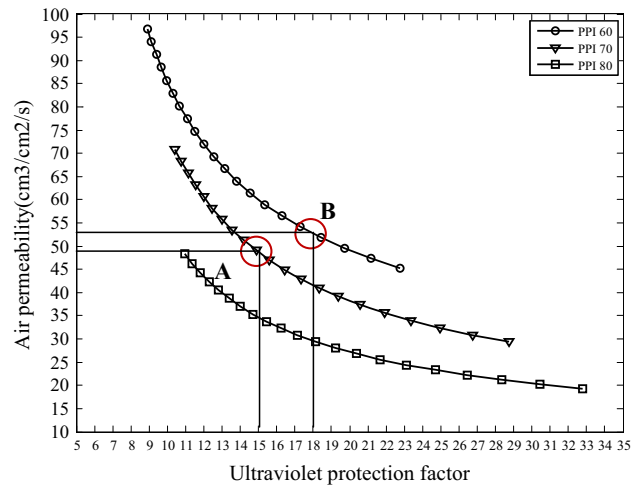
**Table 3** Prediction accuracy of developed ANN models

Model	Performance parameter	Dataset	
		Training	Testing
ANN <sub>UPF</sub>	$R^2$	0.997	0.988
	MAPE (%)	11.40	10.35
ANN <sub>AP</sub>	$R^2$	0.993	0.989
	MAPE (%)	12.90	10.77
ANN <sub>MVTR</sub>	$R^2$	0.988	0.436
	MAPE (%)	0.24	1.84

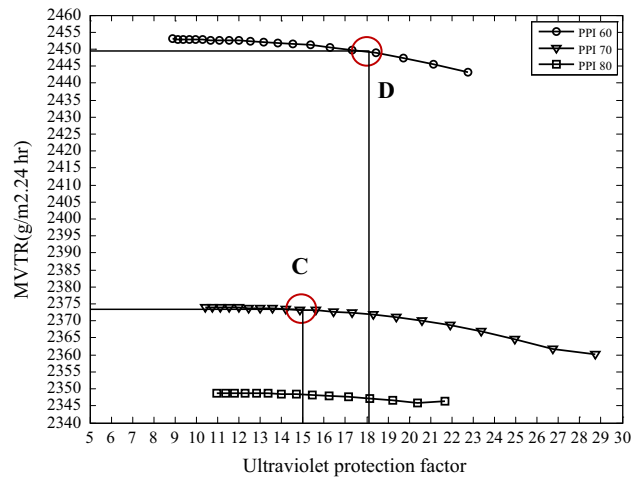


**Fig. 3** Trend analyses of ANN<sub>UPF</sub> model

combinations of UPF, air permeability and MVTR for validation samples by considering two functional properties at a time. Figure 4 depicts the Pareto chart for UPF and air permeability when warp and weft counts were kept constant at 30 Ne and proportion of polyester was kept constant at 50 %. Three lines in the figure represent the achievable levels of UPF and air permeability at three pick density levels, namely 60, 70 and 80 in.<sup>-1</sup>. It is noticed that air permeability decreases as UPF increases at all pick density levels. Two points (A, B) were chosen from this Pareto chart for UPF and air permeability for 30 Ne warp and weft counts and 50 % proportion of polyester (Fig. 4). These points are (15, 48) and (18, 53) where the first and second values represent UPF and air permeability, respectively. The associated MVTR values were obtained from the UPF–MVTR Pareto chart for 30 Ne warp and weft counts and 50 % proportion of polyester as shown in Fig. 5. The points are C (15, 2374) and D (18, 2449) where the first and second values represent UPF and MVTR, respectively. Then two sets of achievable combinations of UPF, air permeability and MVTR were obtained by amalgamating the achievable binary combinations of functional properties. These combinations are (15, 48,



**Fig. 4** Selection of UPF and air permeability from Pareto chart



**Fig. 5** Selection of UPF and MVTR from Pareto chart

2374) and (18, 53, 2449) where the first, second and third values represent UPF, air permeability and MVTR, respectively. Similarly, from the Pareto charts of UPF–air permeability and UPF–MVTR for 20 Ne and 30 Ne yarn counts and 65 % proportion of polyester, another two sets of achievable combinations of functional properties were chosen. Total four combinations of functional properties, as given in Table 4, were selected for validation samples.

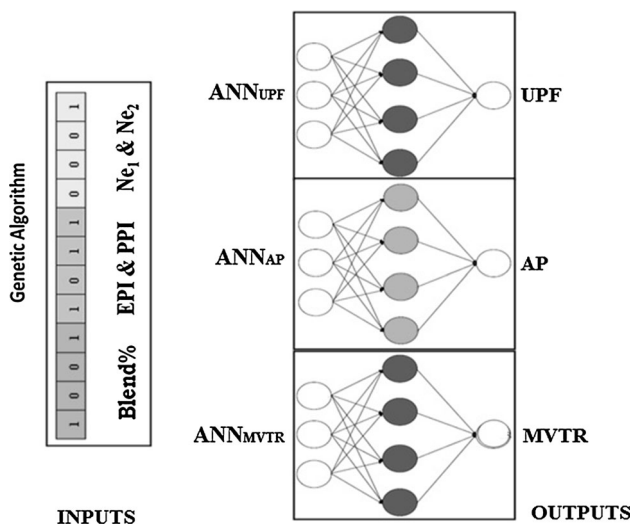
**4.3 Optimization by ANN–GA hybrid approach**

The schematic representation of hybrid ANN–GA is shown in Fig. 6. Genetic algorithm works with population of potential solutions for producing a better solution of the given problem in iterative steps. First, it encodes a potential solution into a chromosome-like data structure. Initial population is formed by generating a large number of such



**Table 4** Specification of validation samples

Sample no.	UPF	Air permeability (cm <sup>3</sup> /cm <sup>2</sup> /s)	MVTR (g/m <sup>2</sup> 24 h)
V <sub>1</sub>	15	48	2374
V <sub>2</sub>	18	53	2449
V <sub>3</sub>	15	68	2376
V <sub>4</sub>	30	23	2358



**Fig. 6** Schematic representation of hybrid ANN-GA

chromosomes. Then, genetic operators are applied to direct the initial population toward the optimal solution in successive iterations. Popular genetic operators are reproduction/selection, crossover, mutation, etc.

In this study, GA was amalgamated with ANN for searching the best combination of fabric construction parameters for achieving the targeted fabric functional properties. The process is comprised of several steps as follows.

**Encoding** As GA works on a genetic space, the search space was converted to a genetic space. The five input variables were overall proportion of polyester in fabric (%), warp count (Ne), weft count (Ne), end density (in.<sup>-1</sup>) and pick density (in.<sup>-1</sup>). The search space for the five input parameters were [0, 100], [20, 40], [20, 40], [56, 88] and [57, 84], respectively. For each input variable, 14 bits were used and thus the total length of the chromosome was 70 bits. Initial population consisting of such chromosomes was generated randomly. The population size was taken as 1000. Figure 7 shows an example of binary coding. Here, a solution point comprising five input parameters is converted into a 30-bit chromosome using binary coding.

**Fitness evaluation** Each individual chromosome or solution point was then evaluated using the objective function known as fitness function. In this study, one objective, i.e., UPF, and two constraints, i.e., air permeability and MVTR, were considered. Therefore, the following optimization problem was formulated.

$$\text{Minimize } f(x) = \left( \frac{\text{UPF}_T - \text{UPF}_P}{\text{UPF}_T} \right)^2 \tag{5}$$

Subject to the constraints

$$g(x) = \text{AP}_T - \text{AP}_P = 0 \tag{6}$$

$$-50 \leq h(x) = \text{MVTR}_T - \text{MVTR}_P \leq 50 \tag{7}$$

where UPF<sub>T</sub>, AP<sub>T</sub> and MVTR<sub>T</sub> are the targeted values and UPF<sub>P</sub>, AP<sub>P</sub> and MVTR<sub>P</sub> are the predicted values by ANN models for UPF, air permeability and MVTR, respectively.

Penalty function method was adopted for converting the above-mentioned constrained optimization problem to an unconstrained optimization problem having single objective. If a constraint is violated, the objective function is penalized by an amount based on the extent of constraint violation. As there are multiple constraints, normalization was done to improve the performance of penalty method as shown below.

$$P(x, K) = f(x) + \Omega \left( K, \frac{g(x)}{\text{AP}_T}, \frac{h(x)}{\text{MVTR}_T} \right) \tag{8}$$

where *K* is a set of penalty parameters which controls the extent of penalty and  $\Omega$  is a bracket penalty operator. The value of *K* was set to 10,000 by trial and error.

The bracket penalty operator ( $\Omega$ ) was as follows:

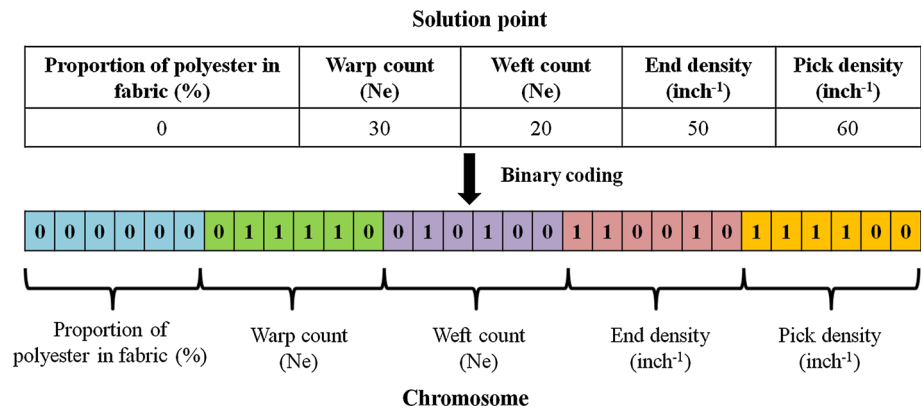
$$\Omega = K \left( \left( \frac{\langle g(x) \rangle}{\text{AP}_T} \right)^2, \left( \frac{\langle h(x) \rangle}{\text{MVTR}_T} \right)^2 \right) \tag{9}$$

where the bracket operator  $\langle g(x) \rangle = g(x)$  when *g*(*x*) is positive or negative and zero otherwise; bracket operator  $\langle h(x) \rangle = h(x)$  when *h*(*x*) ≤ -50 or *h*(*x*) ≥ 50 and zero otherwise.

The bracket penalty operator assigned a positive value and added it with the *f*(*x*) of Eq. 8 when a constraint was violated. As indicated in Eqs. 6 and 7, some penalty was added when the targeted and predicted air permeability was different, i.e., *g*(*x*) was positive or negative. For MVTR, penalty was given if the deviation between targeted and predicted value exceeded ±50.

GA is usually suitable for maximization problems as it follows the Darwinian theory of survival of the fittest. Therefore, the minimization problem was transformed into maximization problem using the following transformation of fitness function.

**Fig. 7** Binary coding of a chromosome



$$F(x) = \frac{1}{1 + P(x, K)} \tag{10}$$

Each of the 1000 individual chromosomes or solution points of the initial population was used as inputs to the developed ANN models for obtaining the predicted UPF, air permeability and MVTR. After that, the fitness of the whole population was calculated using Eq. 10.

**Reproduction or selection** Reproduction or selection operator is the first operator applied on population. Chromosomes are selected from the population according to their fitness value to form a mating pool. In this study, Roulette-wheel selection procedure was adopted. It is a proportionate reproduction operator where a chromosome is selected from the population with a probability proportional to its fitness value  $F_i$ . The probability of selection of  $i$ th chromosome, i.e.,  $p_i$  is expressed as follows:

$$p_i = \frac{F_i}{\sum_{i=1}^n F_i} \tag{11}$$

where  $n$  is the population size.

**Crossover and mutation** After forming the mating pool, crossover operator was applied to create better chromosomes or solution points. Crossover is a recombination operator, and it works in three steps. First, a random pair of chromosomes is selected from the mating pool, then a cross-site is selected randomly along with the chromosome length, and finally, their position values are swapped following the cross-site. Here, uniform crossover with a probability of 0.8 was used. It means that a chromosome of the mating pool had 80 % chance for undergoing crossover operation. Mutation operator is generally applied to introduce new genetic attributes in the population to create diversity. It operates by flipping a bit, i.e., changing 0 to 1 or vice versa in a chromosome. However, there is a danger to lose good solutions due to excessive mutation. Therefore, mutation probability was kept at a very low level (0.005). Thus, new population was generated by modifying the old population using different GA operators.

**Termination criteria** The chromosomes of newly generated population were used as inputs to the developed ANN models for predicting UPF, air permeability and MVTR. The fitness of the chromosomes of new population was then evaluated using the fitness function (Eq. 10). The convergence of this search method was tested by the ratio ( $r$ ) of average fitness value of chromosomes to the maximum fitness value of a chromosome in a generation. The maximum number of generation (800) or minimum  $r$  value (0.95) was the termination criteria for this system. MATLAB<sup>®</sup> version 7.1 was used to write the ANN-GA codes and execute the algorithm.

#### 4.4 Optimization results of hybrid ANN-GA system

The ANN-GA system was run to obtain the solution set of input parameters for achieving the targeted fabric properties of first validation sample  $V_1$ . The entire search domain was chosen for searching except the first input parameter, i.e., overall proportion of polyester in fabric. As the target fabric properties were chosen from the Pareto chart of 50 % polyester blend, the search domain was narrowed down by specifying the proportion of polyester as 50 %. The program was operated for ten runs, and the results are presented partially in Table 5. It is noticed that the UPF and air permeability are achieved with very high accuracy. However, MVTR shows some deviations from the target value of 2374 g/m<sup>2</sup> 24 h. This can be ascribed to the higher allowance of ±50 g/m<sup>2</sup> 24 h that was given for MVTR through bracket operator to lower down its impact in the searching procedure. Although the  $r$  value did not reach stopping criterion level (0.95), the fitness value with the optimized input parameters was above 0.99 except in one case. Searching was stopped when the maximum number of generation (800) was reached. It is pertinent to mention here that the optimization system did not converge to the same point of the search space in different runs though the output fabric parameters were more or less the same. The optimization system resulted different sets of input parameters, in different runs, except for

**Table 5** Results for validation sample  $V_1$  in different runs

Type of parameters	Name of parameter	Optimization run number				
		1	2	3	4	5
Input parameters	Proportion of polyester in fabric (%)	50	50	50	50	50
	Warp count (Ne)	22	22	24	30	36
	Weft count (Ne)	28	35	23	32	37
	End density ( $\text{in.}^{-1}$ )	58	60	61	69	78
	Pick density ( $\text{in.}^{-1}$ )	70	75	63	74	76
Output parameters	UPF	15	15	15	15	15
	Air permeability ( $\text{cm}^3/\text{cm}^2/\text{s}$ )	48	48	48	48	48
	MVTR ( $\text{g}/\text{m}^2$ 24 h)	2359	2385	2402	2359	2361

the proportion of polyester which was fixed at 50 %. It is observed from the Table 5 that warp and weft counts varied within a broad range of 22–36 Ne and 23–37 Ne, respectively. Similarly, the obtained end and pick densities varied within the range of 58–78 and 63–76  $\text{in.}^{-1}$ , respectively. Thus, the hybrid ANN–GA system was accurate in achieving targeted fabric functional properties but lacked repeatability in terms of input parameter combinations. It was therefore important to investigate the reason behind such behavior of ANN–GA system.

All the three fabric functional parameters, namely UPF, air permeability and MVTR, are largely influenced by the fabric cover. Besides, proportion of polyester is also an important parameter for UPF and MVTR. Therefore, logically fabric cover should be more or less the same, in different runs, to attain the targeted UPF, air permeability and MVTR for a constant proportion of polyester in fabric. In the optimization results, it is observed that for 50 % proportion of polyester, ten different combinations of yarn counts and thread densities can actually meet the targeted fabric parameters. Warp, weft and fabric fractional covers were calculated from respective yarn counts and thread densities for all ten runs partially shown in Table 5. It is observed that warp and weft fractional covers are varying, albeit within a small range, following a pattern of mutual compensation. When warp fractional cover decreases, weft fractional cover increases and vice versa. It is paramount to note here that the fabric fractional cover is almost same (0.70) in all the runs. It bolsters that the optimization system is working rationally although it produces different sets of input parameters in different runs for obtaining the same set of fabric properties. From the results and ongoing discussions, it seems that the optimization system cannot distinguish between the two principle directions of fabrics. It is expected as the fabric properties considered in this research are not direction specific.

Even if all the solutions of different runs are assumed to be correct, it would be very difficult to validate these results by manufacturing fabrics using the different solution sets as yarns are available in market only in some

standard counts. To make the situation pragmatic, searching of end and pick densities were attempted considering that the availability of yarns (count and proportion of polyester) in the warehouse is known. Thus, the search domain was narrowed down further by specifying the counts of warp and weft yarns along with the proportion of polyester in fabric. This approach was followed to find out the set of remaining input parameters (end and pick densities) for four validation samples. The solution set of input parameters and targeted fabric properties are shown in Table 6.

#### 4.5 Validation of fabric parameter optimization system

To validate the developed ANN–GA-based fabric parameter optimization system, four fabric samples were woven using the optimized sets of input parameters as shown in Table 6. Then, the samples were tested for actual end density, pick density, UPF, air permeability and MVTR according to the respective standards. The results are presented in Table 7. It is noted that actually obtained end and pick densities in fabrics are quite close to the respective optimized values. The average deviations for these two parameters are only 2.2 and 3.1 %, respectively. It is also observed that the achieved values of fabric functional properties are in good agreement with the respective targeted values. For UPF, maximum, minimum and mean deviations are 19.3 % (for  $V_1$ ), 2 % (for  $V_3$ ) and 8.3 %, respectively. The deviation between targeted and achieved air permeability ranges from 10.4 to 20 % with a mean of 14.9 %. The percent variations are very low (0.8–4.8 %) for MVTR.

## 5 Conclusions

A fabric parameter optimization system based on hybrid ANN–GA has been developed to meet the targeted fabric functional properties like UPF, air permeability and



**Table 6** Optimized input and output parameters for all validation samples

Type of parameter	Name of parameter	Sample no.			
		V <sub>1</sub>	V <sub>2</sub>	V <sub>3</sub>	V <sub>4</sub>
Input parameters	Proportion of polyester in fabric (%)	50 <sup>a</sup>	50 <sup>a</sup>	50 <sup>a</sup>	65 <sup>a</sup>
	Warp count (Ne)	20 <sup>a</sup>	20 <sup>a</sup>	20 <sup>a</sup>	30 <sup>a</sup>
	Weft count (Ne)	40 <sup>a</sup>	30 <sup>a</sup>	30 <sup>a</sup>	30 <sup>a</sup>
	End density (in. <sup>-1</sup> )	61	60	57	77
	Pick density (in. <sup>-1</sup> )	75	63	58	79
Output parameters	UPF				
	Targeted	15	18	15	30
	Optimized	15	18.1	14.9	30
	Air permeability (cm <sup>3</sup> /cm <sup>2</sup> /s)				
	Targeted	48	52.5	68	23
	Optimized	48	52.5	67.7	23.1
	MVTR (g/m <sup>2</sup> 24 h)				
	Targeted	2374	2449	2376	2358
Optimized	2419	2389	2463	2416	

<sup>a</sup> Fixed parameter

**Table 7** Optimized and achieved values of input and output parameters

Sample no.	Values	Input parameters		Output parameters		
		End density (in. <sup>-1</sup> )	Pick density (in. <sup>-1</sup> )	UPF	Air permeability (cm <sup>3</sup> /cm <sup>2</sup> /s)	MVTR (g/m <sup>2</sup> 24 h)
V <sub>1</sub>	Targeted	–	–	15	48	2374
	Optimized	61	75	15	48	2419
	Achieved	60	73	17.9	43	2351
	Error (%)	1.6	2.7	19.3	10.4	1.0
V <sub>2</sub>	Targeted	–	–	18	53	2449
	Optimized	60	63	18.1	52.5	2389
	Achieved	58	62	18.9	42.4	2332
	Error (%)	3.3	1.6	5.0	20.0	4.8
V <sub>3</sub>	Targeted	–	–	15	68	2376
	Optimized	57	58	14.9	67.7	2463
	Achieved	57	54	15.3	58.9	2356
	Error (%)	0.0	6.9	2.0	13.4	0.8
V <sub>4</sub>	Targeted	–	–	30	23	2358
	Optimized	77	79	30	23.1	2416
	Achieved	80	78	32.1	19.4	2319
	Error (%)	3.9	1.3	7.0	15.7	1.7
Mean error (%)		2.2	3.1	8.3	14.9	2.1

MVTR. ANN was used as the modeling platform and to define the fitness function for GA. Pareto charts were developed using the ANN models to find out the feasible combinations of fabric functional properties. GA was used to search the optimum combination of fabric construction parameters to meet the targeted fabric functional

properties. When GA was used to find four fabric parameters (warp count, weft count, end density and pick density), the optimization system yielded accurate fabric functional properties, but the combinations of input parameters were not repetitive. However, the combinations of input parameters elicited by the optimization system

were found to be rational as they resulted in the same fabric cover which is the governing parameter for UPF, air permeability and MVTR. To tackle the problem of validation, optimization was also done considering known yarn parameters (warp count, weft count and proportion of polyester fibre). In this case, end density and pick density combinations were searched by GA to attain the targeted fabric functional properties. Four validation samples were woven using the solutions sets of end and pick densities. The targeted and achieved functional properties of the validation samples were found to be in reasonably good agreement.

**Acknowledgments** The authors are also thankful to Centre of Excellence for Soft Computing Research, Indian Statistical Institute, Kolkata, and Department of Science and Technology, New Delhi, for providing financial support for this research work.

#### Compliance with ethical standards

**Conflict of interest** The authors declare that they have no conflict of interest.

#### References

- Gies P (2007) Photoprotection by clothing. *Photodermatol Photoimmunol Photomed* 23:264–274
- Kullavanijaya P, Lim HW (2005) Photoprotection. *J Am Acad Dermatol* 5:937–958
- Wang SQ, Balagula Y, Osterwalder U (2010) Photoprotection: a review of the current and future technologies. *Dermatol Ther* 23:31–47
- Dubrovski PD (2010) Woven fabrics and ultraviolet protection. In: Dubrovski PD (ed) *Woven fabric engineering*. New Delhi, Sciyo, pp 273–296
- Akgun M (2010) Ultraviolet (UV) protection of textiles: a review. In: *International scientific conference-UNITECH'10*, Grabrovo
- Hoffmann K, Laperre J, Altmeyer P, Gambichler T (2001) Defined UV protection by apparel textiles. *Arch Dermatol* 137:1089–1094
- Deb K (2001) *Multiobjective optimization using evolutionary algorithms*, 1st edn. Wiley, Chichester
- Gen M, Cheng R (2000) *Genetic algorithms and engineering optimization*, 1st edn. Wiley, New York
- Saridakis KM, Dentsoras AJ (2008) Soft computing in engineering design—a review. *Adv Eng Inf* 22:202–221
- Rajasekaran S, Pai GAV (2010) *Neural networks, fuzzy logic and genetic algorithms: synthesis and applications*, 1st edn. PHI Learning Private Limited, New Delhi
- Siddiqui MOR, Sun D (2013) Finite element analysis of thermal conductivity and thermal resistance behaviour of woven fabric. *Comput Mater Sci* 75:45–51
- Pasupuleti R, Wang Y, Shabalin I, Li LY, Liu Z, Grove S (2011) Modelling of moisture diffusion in multilayer woven fabric composites. *Comput Mater Sci* 50:1675–1680
- Ha-Minh C, Kanit T, Boussu F, Imad A (2011) Numerical multi-scale modeling for textile woven fabric against ballistic impact. *Comput Mater Sci* 50:2172–2184
- Reihanian M, Asadullahpour SR, Hajarpour H, Gheisari K (2011) Application of neural network and genetic algorithm to powder metallurgy of pure iron. *Mater Des* 32:3183–3188
- Yin F, Mao H, Hua L (2011) A hybrid of back propagation neural network and genetic algorithm for optimization of injection molding process parameters. *Mater Des* 32:3457–3464
- Sathiyar P, Panneerselvam K, Abdul Jaleel MY (2012) Optimization of laser welding process parameters for super austenitic stainless steel using artificial neural networks and genetic algorithm. *Mater Des* 36:490–498
- Zhou CC, Yin GF, Hu XB (2009) Multi-objective optimization of material selection for sustainable products: artificial neural networks and genetic algorithm approach. *Mater Des* 30:1209–1215
- Lin JJ (2003) A genetic algorithm for searching the weaving parameters of woven fabrics. *Text Res J* 73(2):105–112
- Karthikeyan B, Sztandera LM (2010) Analysis of tactile perceptions of textile materials using artificial intelligence techniques, Part 2: reverse engineering using genetic algorithm coupled neural network. *Int J Cloth Sci Technol* 22(2/3): 202–210