Multi-objective Optimization of Knitted Fabric Comfort and Ultraviolet Radiation Protection by Evolutionary Algorithm

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Abstract The present work does a simultaneous maximization of air permeability and ultraviolet radiation protection of single jersey cotton knitted fabrics. As these two objectives are conflicting in nature, i.e., not a single combination of knitting parameters does exist which produce concurrent maximum air permeability as well as maximum ultraviolet radiation protection. Therefore, it has several optimal solutions from which a trade-off is needed depending upon the requirement of user. In this work, the optimal solutions are obtained with an elitist multi-objective evolutionary algorithm based on Non-dominated Sorting Genetic Algorithm II (NSGA-II). These optimum solutions may lead to the efficient exploitation of knitting parameters to produce fabrics with optimum protection from ultraviolet radiation and comfort.

Keywords Air permeability · Genetic algorithm · Fabric comfort · NSGA-II · Pareto optimal solutions · Ultraviolet protection factor

1 Introduction

Of late, the concept of mass production in textile industry is changing rapidly toward engineered production. This has been empowered mainly due to the advent of various machine learning techniques such as ANN, genetic algorithm (GA).

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K.N. Das et al. (eds.), *Proceedings of Fourth International Conference on Soft Computing for Problem Solving*, Advances in Intelligent Systems and Computing 335,
DOI 10.1007/978-81-322-2217-0_26

Apparel textiles protect our skin from the solar ultraviolet (UV) radiation. The UV protection ability of a textile fabric is expressed by the ultraviolet protection factor (UPF). Heavy cotton fabrics can provide good protection against UV radiation. However, during summer season heavy fabrics are not good from a comfort point of view as the air permeability is very low. The simultaneous maximization of fabric air permeability as well as UPF is conflicting in nature. For these two conflicting objectives, each of them corresponds to a different optimal solution. A single solution which is the best with respect to both the objectives may not exist. Rather, we can visualize a set of optimal solutions where a gain in UPF calls for a sacrifice in air permeability.

In single objective optimization, there is only one optimal solution, but in multi-objective optimization, there are multiple optimal solutions termed as Pareto optimal solutions or non-dominated solutions in which all solutions are equally important. For clarity, these solutions are joined with a curve. The curve formed by joining these points is termed as Pareto optimal front [1]. Depending upon the requirement of the user, any one solution from the Pareto optimal front can be selected. There have been few researches on application of multi-objective optimization in textile field. Settle and Langenhove [2] studied the multi-objective optimization to maximize yarn tensile strength at minimum cost. Skordos et al. [3] studied multi-objective optimization problem to optimize shear and drape behavior of woven fabric. Ghost et al. [4] developed Non-dominated Sorting Genetic Algorithm II (NSGA-II) technique of multi-objective optimization to maximize cotton strength at minimum raw material quality.

In this work, an attempt has been made for simultaneous maximization of two conflicting objectives viz. air permeability and UPF of single jersey cotton knitted fabrics. Since evolutionary algorithm finds multiple optimal solutions in one single simulation run, it becomes a unique technique in solving multi-objective optimization problems. Here, NSGA-II developed by Deb [1] is used to solve the proposed multi-objective optimization problem. The following sections present experimental, multi-objective optimization by NSGA-II, results and discussion, and conclusion. The "experimental" section contains the details of variables and their levels that affect the air permeability and UPF of a single jersey fabric. The design of experiment, experimental details, and the results are shown in this section. In the "multi-objective optimization by NSGA-II" section, the development of NSGA-II algorithm for multi-objective optimization of two conflicting objects, i.e., air permeability and UPF is discussed. In the section "results and discussion," the Pareto optimal solutions of air permeability and UPF are shown and discussed.

2 Experimental

Four variables such as loop length, carriage speed, input tension, and yarn count were considered for the preparation of knitted fabric samples. Each variable was considered at three levels. The coded levels of variables and their corresponding actual values are given in Table 1. Altogether, 36 single jersey fabric samples were prepared using Shima Seiki knitting machine according to the Box and Bhenken orthogonal design of experiments as shown in Table 2. The Box and Bhenken design [5] is a response surface design that is used to optimize various process parameters of a process. This method is often employed after identification of controllable factors and to find the factor levels that optimize the response. In orthogonal Box and Bhenken design, the design can be blocked orthogonally. A 4-factor 3-level orthogonal Box and Bhenken design is shown below:

$$\begin{bmatrix} \pm 1 & \pm 1 & \pm 1 & 0 \\ \pm 1 & \pm 1 & 0 & \pm 1 \\ \pm 1 & 0 & \pm 1 & \pm 1 \\ 0 & \pm 1 & \pm 1 & \pm 1 \end{bmatrix}$$

Air permeability Tester (FX 3300, TEXTEST AG) was used to measure the air permeability at 100 Pa air pressure according to ASTM D737.

The UPF of fabric specimen was determined by the in vitro method, according to the AATCC 183:2004 standard. In this method, the measurement of basic properties of the fabric viz. fabric density, yarn diameter, and open area portion is determined with photo analysis. The values of UV transmission were then calculated using a spectrophotometer. The transmission values obtained were then used to calculate the in vitro UPF [6].

The UV transmittance analyzer (Labsphere 2000F) was used for measuring the UPF of fabric samples. The UV transmittance was measured in a step of 1 nm wavelength by passing UV rays through the fabric. The UPF of fabric was calculated by using Eq. (1). For each experimental run, 10 samples were tested for UPF and the average value was taken.

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

where $E(\lambda)$ is relative erythemal spectral effectiveness, $S(\lambda)$ is solar spectral irradiance ($\mathrm{Wm^{-2}\,nm^{-1}}$), $\Delta\lambda$ = measured wavelength interval (nm), and $T(\lambda)$ = average spectral transmittance of the sample.

Air permeability and UPF values of the fabric samples corresponding to different experimental runs are given in Table 2. The regression coefficients were determined

Table 1 Actual values of the variables corresponding to coded levels

Variables	Coded level		
	−1	0	+1
Loop length (X_1), mm	6.6	7.0	7.41
Carriage speed (X_2), m/s	0.25	0.6	0.95
Input tension (X_3), gf	6	8	10
Yarn count (X_4), Ne	5	7.5	10

Table 2 Orthogonal Block Box Bhenken design for 4 variables

Experimental No.	Level of variables				Air permeability ($cm^3/cm^2/s$)	UPF
	X_1	X_2	X_3	X_4		
1	−1	−1	−1	0	116.6	11.65
2	−1	−1	+1	0	116	11.25
3	−1	+1	−1	0	110.07	11.47
4	−1	+1	+1	0	113	11.69
5	+1	−1	−1	0	162	8.42
6	+1	−1	+1	0	160	8.66
7	+1	+1	−1	0	161.6	8.73
8	+1	+1	+1	0	174.6	8.22
9	0	0	0	0	138.1	9.33
10	−1	−1	0	−1	42.16	22
11	−1	−1	0	+1	226.4	5.37
12	−1	+1	0	−1	41	25.1
13	−1	+1	0	+1	235.7	5.21
14	+1	−1	0	−1	62.43	17.5
15	+1	−1	0	+1	278	4.2
16	+1	+1	0	−1	62.59	16.98
17	+1	+1	0	+1	290.2	4.05
18	0	0	0	0	121.9	10.49
19	−1	0	−1	−1	44.5	19.58
20	−1	0	−1	+1	240.7	5.06
21	−1	0	+1	−1	42.37	23.41
22	−1	0	+1	+1	259.2	4.18
23	+1	0	−1	−1	65.67	16.32
24	+1	0	−1	+1	316.9	3.95
25	+1	0	+1	−1	68.67	14.53
26	+1	0	+1	+1	319.9	3.93
27	0	0	0	0	144	10.16
28	0	−1	−1	−1	53.5	17.48
29	0	−1	−1	+1	289.8	4.06
30	0	−1	+1	−1	46.66	22.26
31	0	−1	+1	+1	260	4.3
32	0	+1	−1	−1	49.24	21.84
33	0	+1	−1	+1	297.2	4.24
34	0	+1	+1	−1	45.45	20.12
35	0	+1	+1	+1	286	4.09
36	0	0	0	0	133	10.23

based on the experimental results. The coefficients were tested for significance at the 95 % confidence level. Only significant terms were taken into consideration for a further investigation of the results. The response surface equation for air permeability and UPF is given in Table 3 along with the R^2 values and mean accuracies. The R^2 denotes the co-efficient of determination that indicates how well data fit to a statistical model.

It is evident from the Table 3 that air permeability of the knitted fabric is the function of variables X_1, X_3, and X_4, whereas UPF is a function of variables X_1 and X_4 only. Hence, the variable X_2 has no influence on air permeability and the variables X_2 and X_3 have no effect on UPF.

3 Multi-objective Optimization by NSGA-II

3.1 Objective Functions

Both the objective functions, which correspond to air permeability and UPF, respectively, as given in Eq. (2), are subjected to maximization.

$$\left.\begin{array}{ll}\text{Objective 1 : Maximize} & 134.25 + 22.29X_1 + 111.49X_4 + 9.60X_1X_4 + 10.36X_3^2 + 25.9X_4^2 \\ \text{Objective2 : Maximize} & 10.05 - 1.69X_1 - 7.69X_4 + 1.32X_1X_4 + 2.05X_4^2\end{array}\right\} \tag{2}$$

The above multi-objective optimization problem is solved using NSGA-II.

3.2 Development of NSGA-II for Multi-objective Optimization

The goal of the NSGA-II algorithm is to find a set of solutions, which is as close as possible to the Pareto optimal front and as diverse as possible simultaneously. Except for the fitness assignment method, the basic structure of NSGA-II is similar to that of GA [2]. The steps involved in this algorithm are briefly explained [3, 4, 7–9].

Table 3 Response surface equations for various parameters

Parameter	Response surface equation	Co-efficient of determination (R^2)	Mean accuracy (%)
Air permeability	$134.25 + 22.29X_1 + 111.49X_4 + 9.60X_1X_4 + 10.36X_3^2 + 25.94X_4^2$	0.991	92.80
UPF	$10.0 - 1.69X_1 - 7.69X_4 + 1.32X_1X_4 + 2.05X_4^2$	0.974	94.58

Step 1: Initialization of random binary population

A binary coded population of size N is randomly generated. Each individual of the population represents 3 parameters or inputs. In this work, 8 bits are chosen for each parameter, thereby making a total string length of an individual equal to 24. The binary coded parameters are then converted into real value by a linear mapping using the following expression:

$$x_i = x_i^L + \frac{\left(x_i^U - x_i^L\right)}{\left(2^{\mathrm{ls}_i} - 1\right)} \times x_i^D \tag{3}$$

where x_i is the real value of the ith input parameter, x_i^L and x_i^U are the lower and upper limits of the ith input parameters, respectively, ls_i is the string length of the ith input parameter, and x_i^D is the decoded value of the ith parameter. This real valued population consists of a set of 3 parameters is used in making solutions of the two objective functions viz. air permeability and UPF.

Step 2: Fast non-dominated sorting

The population is sorted based on their non-domination levels. In this technique, two entities are calculated, first one is the domination count (n_i) that represents the number of solutions, which dominates the solution i, and the second one is S_i that represents the number of solutions which are dominated by the solution i. This is accomplished by comparing each solution with every other solution and checked whether the solution under consideration satisfies the rules given below

$$\left.\begin{array}{l} Objective1_i > Objective1_j \ \ and\ Objective2_i \geq Objective2_j \ or \\ Objective1_i \ \geq Objective1_j \ \ and\ Objective2_i \ > Objective2_j \end{array}\right\} \tag{4}$$

where Objective1_i and Objective1_j are the fitness values of 1st objective for the ith and jth solutions, respectively. Similarly, Objective2_i and Objective2_j are the fitness values of 2nd objective for the ith and jth solutions, respectively. If the rules are satisfied; then, the solution j is dominated else non-dominated. Thus, the whole population is divided into different ranks. Ranks are defined as the several fronts generated from the fast non-dominated sorting technique such that Rank-1 solutions are better than the Rank-2 solutions and so on.

Step 3: Crowded tournament selection

Once the populations are sorted, crowding distance is assigned to each individual belonging to each rank. This is because the individuals of the next generation are selected based on the rank and the crowding distance. This crowding distance ensures a better spread among the solutions.

A better spread means a better diversity among the solutions. In order to calculate crowding distance, fitness of the objective functions for the solutions belonging to a particular rank is sorted in descending order with respect to each objective. An infinite distance is assigned to the boundary solutions, i.e., for the first and nth solutions, if n number of solutions belong to a particular rank. This ensures that the individuals in the boundary will always be selected and hence result in better spread among the solutions [5]. For other solutions belonging to that rank, the crowding distances are initially assigned to zero. For $r = 2$ to $n - 1$ solutions, this is calculated by the following formula:

$$I(r)m = I(r)m + \frac{f_m(r-1) - f_m(r+1)}{f_m^{\max} - f_m^{\min}} \quad (5)$$

where $I(r)m$ is the crowding distance of the rth individual for mth objective, $m = 1$ and 2, $f_m(r - 1)$ is the value of the mth objective for $(r - 1)$th individual, and $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values of the mth objective, respectively.

Step 4: Crowded tournament selection

A crowded comparison operator compares two solutions and returns the winner of the tournament. A solution i wins a tournament with another solution j if any of the following conditions are true:

(i) If solution i has a better rank than j
(ii) If they have the same rank but solution i has larger crowding distance than solution j

Step 5: Recombination and Selection

The offspring and current population are combined, and selection is done in order to obtain the population of the next generation. The offspring are generated by 2-point crossover with a probability of 0.9 and bitwise mutation with a probability of 0.1. The elitism is ensured, as the best population from the offspring and parent solutions are selected for the next generation. The $2N$ solutions are then sorted based on their non-domination, and crowding distances are calculated for all the individuals belonging to a rank. In order to form the population of the current generation, the individuals are taken from the fronts subsequently unless it reaches to the desired population number (N). The filling starts with the best non-dominated front (Rank 1 solutions), with the solutions of the second non-dominated front, followed by the third non-dominated front, and so on. If by adding all individuals in a front, the population exceeds N, and then individuals are selected based on their crowding distance. The steps are repeated until maximum generation number is reached.

4 Results and Discussion

NSGA-II starts with randomly generated 200 initial populations (N), and it ranks the individuals based on the dominance. The fast non-dominated sorting procedure finds out the non-domination frontiers (ranks) where individuals of the frontier set are non-dominated by any solution. By using this procedure, the scattered initial solutions make four frontiers after 12 generations. Hence, the whole initial scattered solutions are now grouped into four ranks. After finding the frontiers, the crowding distance is calculated for each individual by applying Eq. 5. The crowding distance selection operator helps NSGA-II in distributing the solution uniformly to the frontier rather than bunching up at several good points. Subsequently, step 1 to step 5 of NSGA-II are repeated and the solutions of four frontiers are converged into a single Pareto front at the end of 103 generations leading to the final set of solutions.

The Pareto optimal front for air permeability and UPF of the single jersey knitted fabrics is illustrated in Fig. 1, which contains 140 non-dominated solutions. As none of the solutions in the Pareto front are better than other, any one of them is an acceptable solution. The choice of one solution over other exclusively depends upon the requirement of the end user. Table 4 depicts only few selected Pareto optimal non-dominated solutions. If better fabric comfort at high level of UPF is required, a suitable combination of X_1, X_3, and X_4 could be selected from the Pareto optimal solution.

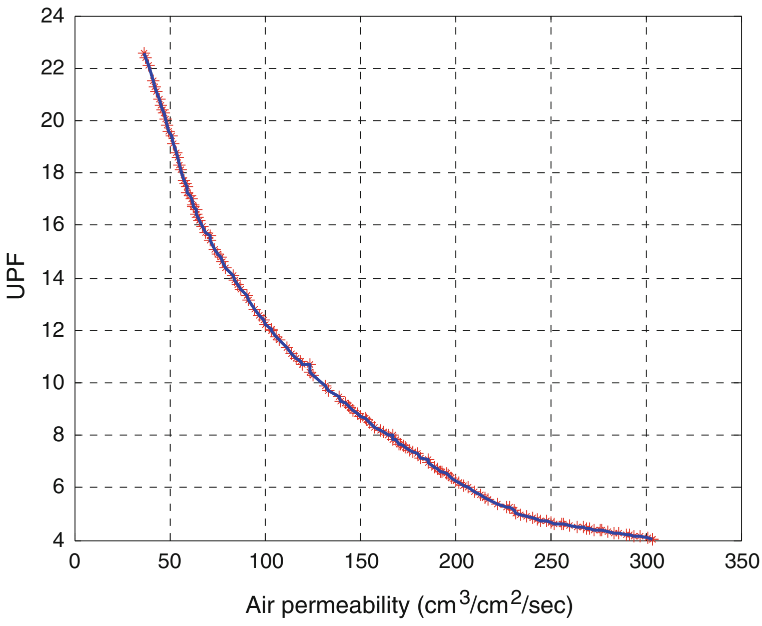

Fig. 1 Pareto optimal front for air permeability and UPF

Table 4 Some selected Pareto optimal solutions

X_1	X_3	X_4	Air permeability ($cm^3/cm^2/s$)	UPF
7.35	8.01	7.95	176.3	7.46
6.63	8.05	9.04	186.79	6.9
6.61	8.04	9.35	202.2	6.18
7.36	8.02	7.84	171.57	7.66
7.33	8.04	7.58	156.38	8.46
7.02	8.04	8.16	167.28	8.07
6.7	8.03	9.14	197.32	6.5
6.63	8.02	8.6	163.9	8.09
7.38	8.01	7.43	151.98	8.63
6.61	8.04	9.37	203.5	6.13

5 Conclusions

The NSGA-II technique of multi-objective optimization has been developed with an aim to maximize simultaneously air permeability and UPF of single jersey cotton knitted fabric. NSGA-II is capable of finding the Pareto optimal solutions for production of fabrics with optimal comfort and UPF. These optimum solutions may lead to the efficient utilization of knitting parameters to produce desired quality of fabrics.

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