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ORIGINAL CONTRIBUTION

Multi-objective Optimization of Yarn Characteristics Using Evolutionary Algorithms: A Comparative Study

Shankar Chakraborty[1] · Sunny Diyaley[2]

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Abstract In cotton spinning industries, attainment of the most desired yarn characteristics mainly depends on different parameters of the ring or rotor spinning process. Thus, it is often required to determine the optimal parametric settings of a spinning process with the help of some optimization tools. In this paper, two multi-response optimization problems are considered and subsequently solved using four popular evolutionary algorithms, i.e. artificial bee colony algorithm, ant colony optimization algorithm, particle swarm optimization algorithm and non-dominated sorting genetic algorithm-II for searching out the global optimal settings of ring and rotor spinning processes. As the process parameters' settings derived using single response optimization solutions are often impractical to maintain, it is always recommended to set them based on the results of multi-response optimization techniques. It is observed that among these four algorithms, particle swarm optimization excels over the others with respect to the derived optimal solution, consistency of the solution and convergence speed. The developed scatter diagrams also help in investigating the effects of changing values of different process parameters on various yarn qualities.

Keywords Spinning · Yarn characteristic · Parameter · Optimization · Evolutionary algorithm

✉ Shankar Chakraborty
s_chakraborty00@yahoo.co.in

1 Department of Production Engineering, Jadavpur University, Kolkata, West Bengal, India

2 Department of Mechanical Engineering, Sikkim Manipal Institute of Technology, Majitar, Sikkim, India

Introduction

One of the important production processes in any textile industry is the spinning process. Using cotton fibres as the input material, yarns are usually produced through a ring or rotor spinning process. Out of the total volume of staple yarn manufactured around the world, approximately 60–70% is the outcome from the ring spinning process and rotor spinning caters the remaining volume. As compared to ring spinning process, rotor spinning involves lesser labour force, lower maintenance cost, lesser floor space, lesser spare parts and lower energy consumption. It has also been observed that in rotor spinning process, labour productivity is improved and lesser waste is generated. With respect to quality, rotor spinning process produces more even yarn with minimum count variation and imperfections. Yarn breakage rate is also lower in rotor spinning as compared to ring spinning. However, rotor-spun yarns are weaker in strength against ring-spun yarns due to some structural differences [1].

In both the ring and rotor spinning processes, quality of the resulting yarn plays a significant role in determining its end application. It is the task of the spinning industry personnel to produce a good quality yarn with minimum possible cost. Thus, there must be a trade-off between these two conflicting objectives. In textile industries, quality of a yarn is often evaluated with respect to its several characteristics, like specific strength, unevenness, hairiness, imperfections, breaking elongation etc. It is worthwhile to mention here that these yarn characteristics are often conflicting in nature, such as maximum yarn strength against minimum yarn imperfections. In order to achieve these yarn characteristics, it is always recommended to determine the optimal settings of the concerned ring or rotor spinning process which are often available from the manufacturers' data handbooks or are determined in consultation with the spinning experts. Due to scarcity of the experts and high consultation time involved, it is advised to deploy some mathematical tools and techniques which would ultimately help in predicting the settings of different spinning process parameters so as to attain the target yarn characteristics. Thus, determination of the optimal spinning process parameters, to have the most preferred yarn characteristics, can simply be formulated as a mathematical optimization problem. In a single objective optimization problem, each of the yarn characteristics is optimized separately and for each of them, there would be individual parametric settings. These settings often do not match with each other and it becomes impossible/impractical to operate a spinning process at different settings to achieve all the desired yarn characteristics. As the manufactured yarn has multiple quality characteristics which need to be simultaneously fulfilled, it is always advised to employ a multi-objective optimization tool which would determine a single best parametric setting for the considered spinning process which would be feasible to maintain. At that setting, all the yarn characteristics are simultaneously optimized. Several evolutionary algorithms are now available which have already proven their ability to solve multi-objective optimization problems with an aim to search out the global optimal solutions.

Literature Review

Sette et al. [2] proposed a novel approach to simulate and optimize the fibre-to-yarn production process while combining neural network with genetic algorithm (GA), and also achieved simultaneous optimization of yarn qualities as a function of the optimal input parameters. Sette and Van Langenhove [3] presented a model while taking into consideration different machine settings and fibre quality parameters as the inputs, and yarn tenacity and elongation as the responses. A constrained optimization algorithm was later adopted to optimize the blend of fibre qualities for having the best yarns. Van Langenhove and Sette [4] developed a complex model while integrating different fibre properties, process parameters and spinning results. Based on the developed model, a specific blend could be determined and the corresponding machine settings could also be identified for the optimal yarn strength and elongation. Based on the Box–Behnken design plan, Ishtiaque et al. [5] optimized three ring-frame process parameters, i.e. spindle speed, top roller pressure and traveller mass for better yarn quality and production. Majumdar et al. [6] presented various techniques of modelling, optimization and decision making intended for design of functional clothing. Arain et al. [7] developed a multi-response optimization model to identify the best rotor speed and yarn twist level for optimal rotor yarn strength and unevenness, and minimum yarn hairiness and imperfections. Feng et al. [8] quantitatively studied and optimized the relationship between various spinning parameters and properties of the fine modified yarns while employing fractional factorial design and response surface methodology (RSM). While applying Monte Carlo simulation techniques, Ochola and Mwasiagi [9] studied the influences of different cotton fibre properties on the strength of ring- spun yarn. Jeyaraj et al. [10] applied GA as a multi-response optimization tool for determining the optimal combinations of five parameters in a colour fast finishing process for attaining the target values of five quality characteristics. Ghosh et al. [11] first formulated an artificial neural network (ANN)-based input–output relation between different cotton fibre properties and yarn strength, and then derived the optimal solutions using non-dominated sorting genetic algorithm II (NSGA-II). El Messiry et al. [12] investigated the effects of varying values of different fibre properties while controlling noil percentage on the structural parameters of compact single and ply yarns, and also determined the optimal combing noil percentage for production of quality compact yarns. Fattahi and Hoseini Ravandi [13] applied robust regression and extra sum squares methods to predict and evaluate yarn characteristics from various fibre properties. The optimal equations with appropriate variables were also developed along with their relative importance. Das and Ghosh [14] formulated a relationship between raw material and yarn properties which was subsequently optimized using simulated annealing technique in order to maximize yarn strength. Hasanuzzaman et al. [15] studied the effects of three spinning process parameters, i.e. spindle speed, roving twist multiplier and yarn twist multiplier on several yarn quality characteristics, and also determined the optimal combination of those process parameters while applying desirability function approach. Eldeeb et al. [16] optimized the spinning and plying processes of raw and finished conventional ring-spun and compact yarns. A graphical method was subsequently employed to determine the range of alpha single and alpha plied twist factor to achieve the target yarn characteristics. Bagwan and Patil [17] determined the effects of opening roller speed on different properties of open-end yarn. Majumdar et al. [18] derived the Pareto optimal solutions using NSGA-II optimization technique so as to obtain the effective knitting and yarn parameters to engineer knitted fabrics having optimal comfort properties and desired level of ultraviolet protection. Mukhopadhyay et al. [19] developed a regression model correlating different slub yarn parameters (i.e. slub length, slub thickness and slub frequency) with abrasive damage of fabric in terms of fabric mass loss and appearance deterioration. A set of optimal parametric combinations was subsequently derived using multi-objective evolutionary algorithms. It is clearly observed from the above cited literature review that ANN-based models and GA have extensively been utilized in textile industries in order to predict/optimize various yarn characteristics based on different ring/rotor spinning process parameters. But, the application of GA tool may often lead to near or sub-optimal solutions. Thus, in this paper, four popular evolutionary algorithms in the form of artificial bee colony (ABC) algorithm, ant colony optimization (ACO) algorithm, particle swarm optimization (PSO) algorithm and NSGA-II are applied for searching out the parametric settings of ring as well as rotor spinning process for global optimal values of various considered yarn characteristics. The optimization performance of these algorithms is also compared with respect to the value of the derived solution, consistency of the solution and computational speed.

Evolutionary Algorithms

Evolutionary algorithm is a domain term used to describe computer-based problem solving systems based on the deployment of computational models of evolutionary processes. There are several variants of evolutionary algorithm. The common underlying principle behind all these techniques is the natural selection causing a rise in the fitness of the population (survival of the fittest). For example, in a maximization problem, a set of candidate solutions is randomly created and their abstract fitness measures are computed. Based on these fitness values, some of the better candidates are chosen to seed the next generation while applying crossover and/or mutation of them. Execution of crossover and mutation operations leads to a set of new candidates replacing the old ones with poor fitness values. This process is continued until a candidate with the desired quality is achieved or a predetermined number of iterations is complete.

ABC Algorithm

The ABC algorithm is based on the intelligent foraging behaviour of honey bees [20]. In this algorithm, colonies of artificial bees are categorized into three elements, i.e. employed bees, onlooker bees and scout bees [21]. The idea of position and quality of food source is known by the employed bees, and with this information, they start waggle dance which is an indication of the quality of food source. The onlooker bees present in the hive watch the waggle dance to have the information about the food sources and get attracted towards them. The nectar content of a food source is related to the nature of dance of the employed bees and it represents the fitness value correlating the quality of the solution. The onlooker bees now become the employed bees and start consuming nectar from the best food source. When this food source becomes abandoned, the employed bees start finding out a new food source and become scout bees. After obtaining a new food source, these scout bees act as employed bees. The cycle is repeated till the best food source position is obtained which becomes the optimal solution. The ABC algorithm consists of four main phases, i.e. initialization phase, employed bee phase, onlooker bee phase and scout bee phase. In the first phase, settings of different control parameters and vectors of the population of foods are initialized. The initial solutions are then subjected to repeated cycles which indicate the search process of the employed, onlooker and scout bees. In the next phase, searching of the neighbouring food sources with more nectar content is performed by the employed bees. These neighbour food sources remain present in their memory which are further employed for evaluation of the fitness values. The fitness value is calculated for each new food source and subsequently, a greedy selection process is applied. During the onlooker bee phase, information about the food sources are being shared with the onlooker bees waiting in the hive and further food sources are chosen probabilistically by them. Scout bee phase deals with searching the new solutions in place of the abandoned solutions while making the scouts free. The employed bees, whose solutions cannot be improved, are set as scout bees and are abandoned. These scout bees further search for new solutions randomly which results in more exploitation of the poor food source and gets abandoned. Thus, the negative feedback of such behaviour leads to a balanced positive feedback.

ACO Algorithm

This algorithm works on the principle of foraging behaviour of real ants [22, 23]. Near-blind ants have the ability of establishing the shortest route from their nest to the food source and back to the nest. This behaviour of ants fascinates the researchers to develop the ACO algorithm. The medium for communication used by these ants is called pheromone, a substance secreted by them. They use the pheromone trails to communicate between themselves. The ants follow these trails and the probability of trails is increased by more deposition of pheromone by other ants which were moving on that route. There is a cooperative search behaviour of the ants leading to inspiration of solving large complex optimization problems. There are three main operations in this algorithm which include construction of ant-based solution, pheromone update and daemon action. In the first operation, artificial ants are constructed which represent the solutions and the solutions are chosen probabilistically according to the pheromone level. It results in forcing the algorithm to search in the area of better solution. In the operation of pheromone update, there is an increase in the amount of pheromone which results in good solution or a decrease for a bad solution by evaporation. Centralized actions are implemented in the third operation which cannot be performed by a single ant. Moreover, a global criterion is collected and adopted as a decision whether the additional deposition of pheromone is required or not. The selection of a solution by the artificial ants mainly depends on the selection probability which is proportional to the pheromone trail.

PSO Algorithm

This optimization algorithm is based on the social behaviour of animals and birds. It deals with the random motion of intelligent swarm to find out the optimal objective function defined in a given search space [24]. In this algorithm, the group is known as swarm and it consists of number of individuals called as particles. These particles fly in an *n*-dimensional space and each particle is treated as a point in this space. Each particle represents a candidate solution which keeps track of the information of the best coordinates in the problem space and till then, these coordinates are the best solution, termed as personal best (*pbest*). The position of the particles must be checked which may have better solution than a particular particle as it keeps track on the neighbouring particles. The term local best (*lbest*) denotes the particle with better coordinates than the first particle. Now, after comparison with all the particles, the particle with the best coordinate value is termed as the global best (*gbest*) which represents the best solution for an optimization problem. Velocity update and position update are the two main parameters in this algorithm [25]. Each particle in a new generation is accelerated towards the previous best position of the particle, and the new velocity of particle is calculated based on its current velocity, distance from its previous best position and distance from the *gbest* position. The next position of the particle is calculated based on the new velocity component in the search space. The process is repeated until minimum error is achieved. It follows some fundamental steps. In the first step, the population size is specified with random generation of initial positions and velocity of particles. The objective function value is then calculated for each particle. The *pbest* value is set as the current position and among all the particles, *pbest* value with the best objective function is stored as the *gbest* value. In the next step, new positions of particles in the solution space are determined and the particles migrate towards the *gbest* value. For each new position of particle, new objective function value is calculated. Depending on this new position, the *pbest* value is replaced by the current *pbest* value. This replacement is performed only if the new position is better than the previous position. From each *pbest* value, a new *gbest* value is selected. If this new *gbest* value is better than the previous *gbest* value, there is a replacement of previous *gbest* value by the current *gbest* value and is stored. These steps are repeated for a predetermined number of iterations.

NSGA-II Algorithm

The application of GA is based on the principle of natural genetic systems and it works with a population of feasible solutions. The NSGA, which has been proven to be an effective evolutionary multi-objective optimization tool, is an extension of GA. This algorithm also adopts three biological operators, i.e. selection, crossover and mutation. The principles of crossover and mutation operators in NSGA are same as those of GA, but the selection operator works differently. The principle of shared fitness is adopted in the selection procedure, which is calculated by the ranking process and non-dominated sorting of the individuals. The non-dominated sorting of individuals is obtained from the current population while assigning a large dummy fitness value. The same fitness value is also provided to the individuals selected so that they have equal reproductive potential. The individuals are then shared with their dummy fitness values. This sharing procedure involves the process of using degraded fitness values in a selection operation. The degraded fitness values are calculated by dividing the original fitness value of an individual by a quantity proportional to the number of individuals around it. This results in the coexistence of multiple optimal points in the population. Now, processing of the rest of the population occurs by neglecting the non-dominated individuals after the sharing process is terminated. A new set of points obtained is assigned with a new dummy fitness value which is kept smaller than the minimum shared dummy fitness of the previous front. The process continues until the entire population is classified into several fronts. The new population is reproduced according to the dummy fitness values. The entire activity in NSGA results in searching for non-dominated regions, quick convergence of the population towards non-dominated regions and development of schemata representing the Pareto optimal regions.

In order to overcome the demerits of NSGA with respect to high computational complexity and lack of elitisms, NSGA-II was developed for obtaining the set of Pareto optimal solutions in constrained multi-objective optimization problems. It has the advantage of arriving at the true Pareto-optimal solutions using elite-preserving operator maintaining diversity and without specifying any additional parameter [26, 27]. The two main aspects of NSGA-II are a fast non-dominated sorting of the population and a large crowding distance. In this algorithm, based on the range of problem and constraints, a population is initialized at first.

Non-dominated solution is then sorted out from the initial population based on its rank. After completion of this sorting process, crowding distances are calculated for all the solutions. Selection of the parents is based on the rank and comparison of crowding distance in the population. Crowding distance is mainly preferred for selection of the required parents if they are less than the number of individuals of specific rank. Offspring are then generated from the selected parents using genetic operators, like crossover and mutation. The increase in values of crossover probability and mutation probability causes population to converge to a global optimal solution. But, these phenomena may also result in disruption of the near optimal solution and may cause non-convergence to a global optimum. Therefore, by maintaining lower values of crossover probability and mutation probability for higher fitness solution, and higher values of crossover probability and mutation probability for lower fitness solution may overcome the above problem while preserving better solutions of the population. After combining the initial offspring population and initial population, a new population is created, and based on the rank and crowding distance, the best individuals are identified from the population. The process is repeated until the maximum number of generation is reached or the specified termination criterion is met so that the new solution obtained is better than the previous one.

Illustrative Problems

Problem 1

In order to study the effects of rotor speed and yarn twist level on four yarn (30 tex) characteristics, i.e. yarn strength (YS) (in cN/tex), unevenness (YU) (in CV_m%), hairiness (YH) and imperfections (YI), Arain et al. [7] developed a multi-response optimization model based on RSM technique which was subsequently optimized using desirability function approach. During the experiment, rotor speed (x_1) was set at four different levels, i.e. 70,000, 80,000, 90,000 and 100,000 rpm, and twist level (x_2) had also four levels, i.e. 500, 550, 600 and 700 twist per metre. As the outcomes of the experiment, four second-order regression equations were formulated as presented below:

$$Y(YS) = -23.568 + 0.00035x_1 + 0.05271x_2 - 1.92333E^{-9}x_1^2 - 3.27182E^{-5}x_2^2 \quad (1)$$

$$Y(YU) = 25.8516 - 3.28901E^{-4}x_1 + 2.10938E^{-9}x_1^2 \quad (2)$$

$$Y(YH) = 15.5734 - 2.17571E^{-4}x_1 - 0.00234x_2 + 1.26251E^{-9}x_1^2 \quad (3)$$

$$Y(YI) = 2516.21 - 0.06916x_1 + 0.40028x_2 + 4.43751E^{-7}x_1^2 \quad (4)$$

Based on the experimental data and at 50% quality level, Arain et al. [7] obtained a composite desirability score of 1.0 at 77,800 rpm rotor speed and 700 yarn twist per metre with the optimal response values as yarn strength = 12.7 cN/Tex, yarn unevenness = 13 CV_m%, yarn hairiness = 4.6 and yarn imperfection = 101. Now, in order to search out the global optimal values of the considered yarn characteristics (responses), ABC, ACO, PSO and NSGA-II algorithms are separately employed to optimize the four RSM-based equations with respect to the constraints as imposed by the chosen limiting values of rotor speed and yarn twist level, i.e. $70{,}000 \leq x_1 \leq 100{,}000$ and $500 \leq x_2 \leq 700$. Here, the responses are first individually optimized. Among these responses, yarn strength needs to be maximized so as to withstand the stress generated during the subsequent weaving or knitting process. On the other hand, minimization of yarn unevenness, hairiness and imperfections are required for providing a perfect appearance to the end products. The results of single response optimization derived while employing ABC, ACO, PSO and NSGA-II algorithms in MATLAB (R2013a) are exhibited in Table 1. For ABC algorithm, various control parameters are set as maximum number of iterations = 500, population size (colony size) = 500, number of onlooker bees = 500 and acceleration coefficient upper bound = 1. For ACO algorithm, the corresponding control parameters are fixed as maximum number of iterations = 500, population size (archive size) = 500, sample size = 40, intensification factor (selection pressure) = 0.5 and deviation distance ratio = 1. On the other hand, for PSO algorithm, the corresponding values of different control parameters are set as maximum number of iterations = 500, population size (swarm size) = 500, inertia weight = 1, inertia weight damping ratio = 0.99, personal learning coefficient = 1.5 and global learning coefficient = 2. Similarly, for NSGA-II algorithm, the values of various control parameters are maximum number of iterations = 500, population size = 500, crossover probability = 0.9, mutation probability = 0.07 and tournament selection process. From the results of single response optimization, it is interestingly noticed that for all the evolutionary algorithms under consideration, the derived response values are significantly improved with respect to those as attained by the past researchers based on desirability function approach. Amongst these algorithms, it is observed that PSO algorithm outperforms the others with respect to the derived optimal solution and consistency of the solution in terms of standard deviation (SD) value. The superiority of PSO algorithm can also be well validated

Table 1 Results of single response optimization problem for example 1

Optimization method	Response	Mean	SD	Optimal value	Parameter	
					Rotor speed	Yarn twist
ABC algorithm	Yarn strength	13.1948	0.0080	13.1951	90,800	700
	Yarn unevenness	12.9999	0.0037	12.9988	77,950	623
	Yarn hairiness	4.5624	0.0014	4.5619	86,104	700
	Yarn imperfection	21.7348	0.5002	21.6618	77,832	500
ACO algorithm	Yarn strength	13.0909	0.0020	13.0911	91,542	682
	Yarn unevenness	12.9317	0.0114	12.9304	78,018	595
	Yarn hairiness	4.5630	0.0101	4.5618	86,166	700
	Yarn imperfection	23.0545	0.4655	23.0301	83,250	507
PSO algorithm	Yarn strength	13.2180	0.0150	13.2200	90,988	700
	Yarn unevenness	12.9108	0.0076	12.9104	77,999	523
	Yarn hairiness	4.5536	0.0403	4.5455	90,121	630
	Yarn imperfection	20.6333	0.4230	20.5699	77,925	500
NSGA-II algorithm	Yarn strength	13.1627	0.0216	13.1672	91,480	693
	Yarn unevenness	12.9243	0.0223	12.9207	77,963	615
	Yarn hairiness	4.5978	0.0956	4.5743	90,175	698
	Yarn imperfection	52.2836	22.6050	27	79,992	514

from the convergence diagrams for all the four responses, as shown in Fig. 1.

As in this example, PSO algorithm emerges out as the most attractive single response optimization tool, the corresponding scatter plots are generated in Figs. 2 and 3 for this algorithm in order to show the variations in yarn strength, unevenness, hairiness and imperfections with varying values of rotor speed and yarn twist level. These plots provide a better insight into how a response behaves with variations in several input parameters, as opposed to surface plots, where only variation of a response with respect to a particular input parameter is depicted whilst other parameters are kept constant. It is observed from Fig. 2a that yarn strength gradually increases with the increment in rotor speed and after reaching its maximum value at rotor speed of around 90,000 rpm, it starts going on decreasing. On the other hand, for non-beneficial or smaller-the-better type of responses, they all start decreasing with the increasing values of rotor speed and after arriving at their corresponding minimum values, they follow the increasing trends. Similarly, in Fig. 3a, with the increasing values of yarn twist level, yarn strength shows a steadily increasing trend. For yarn unevenness, it can be revealed from Fig. 3b that yarn twist level has basically no effect on it. In Fig. 3c, yarn hairiness is observed to decrease with the increasing values of yarn twist level and in Fig. 3d, yarn imperfections exponentially increase with the varying values of yarn twist level. The reasons behind these variations in yarn strength, unevenness, hairiness and imperfections with changes in rotor speed and yarn twist level were well explained by Arain et al. [7].

In multi-objective optimization of the same problem, instead of treating the four responses individually, all of them are simultaneously optimized. For this, the following objective function is developed.

$$\begin{aligned}\mathrm{Min}(Z_1) = w_1\left[\frac{Y(\mathrm{YU}) - \mathrm{YU}_{\min}}{\mathrm{YU}_{\max} - \mathrm{YU}_{\min}}\right] \\ + w_2\left[\frac{Y(\mathrm{YH}) - \mathrm{YH}_{\min}}{\mathrm{YH}_{\max} - \mathrm{YH}_{\min}}\right] \\ + w_3\left[\frac{Y(\mathrm{YI}) - \mathrm{YI}_{\min}}{\mathrm{YI}_{\max} - \mathrm{YI}_{\min}}\right] \\ - w_4\left[\frac{\mathrm{YS}_{\max} - Y(\mathrm{YS})}{\mathrm{YS}_{\max} - \mathrm{YS}_{\min}}\right]\end{aligned} \tag{5}$$

where $Y(\mathrm{YU})$, $Y(\mathrm{YH})$, $Y(\mathrm{YI})$ and $Y(\mathrm{YS})$ are the second-order response surface equations for unevenness, hairiness, imperfections and yarn strength respectively; $\mathrm{YU}_{\min}$, $\mathrm{YH}_{\min}$, $\mathrm{YI}_{\min}$ and $\mathrm{YS}_{\min}$ are the minimum values of unevenness, hairiness, imperfections and yarn strength respectively; $\mathrm{YU}_{\max}$, $\mathrm{YH}_{\max}$, $\mathrm{YI}_{\max}$ and $\mathrm{YS}_{\max}$ are the maximum values of unevenness, hairiness, imperfections and yarn strength respectively; and w_1, w_2, w_3 and w_4 are the weights assigned to unevenness, hairiness, imperfections and yarn strength respectively. These minimum and maximum values of the responses are obtained from the single objective optimization results. The weight values can be anything provided that $w_1 + w_2 + w_3 + w_4 = 1$ and it depends on the priorities of the considered yarn characteristics as set by the spinning industry personnel. Here, equal weights for all the four responses, i.e. $w_1 = w_2 = w_3 = w_4 = 0.25$ are considered, and the results obtained after solving this multi-objective optimization problem using ABC, ACO, PSO and NSGA-II algorithms are provided in Table 2.

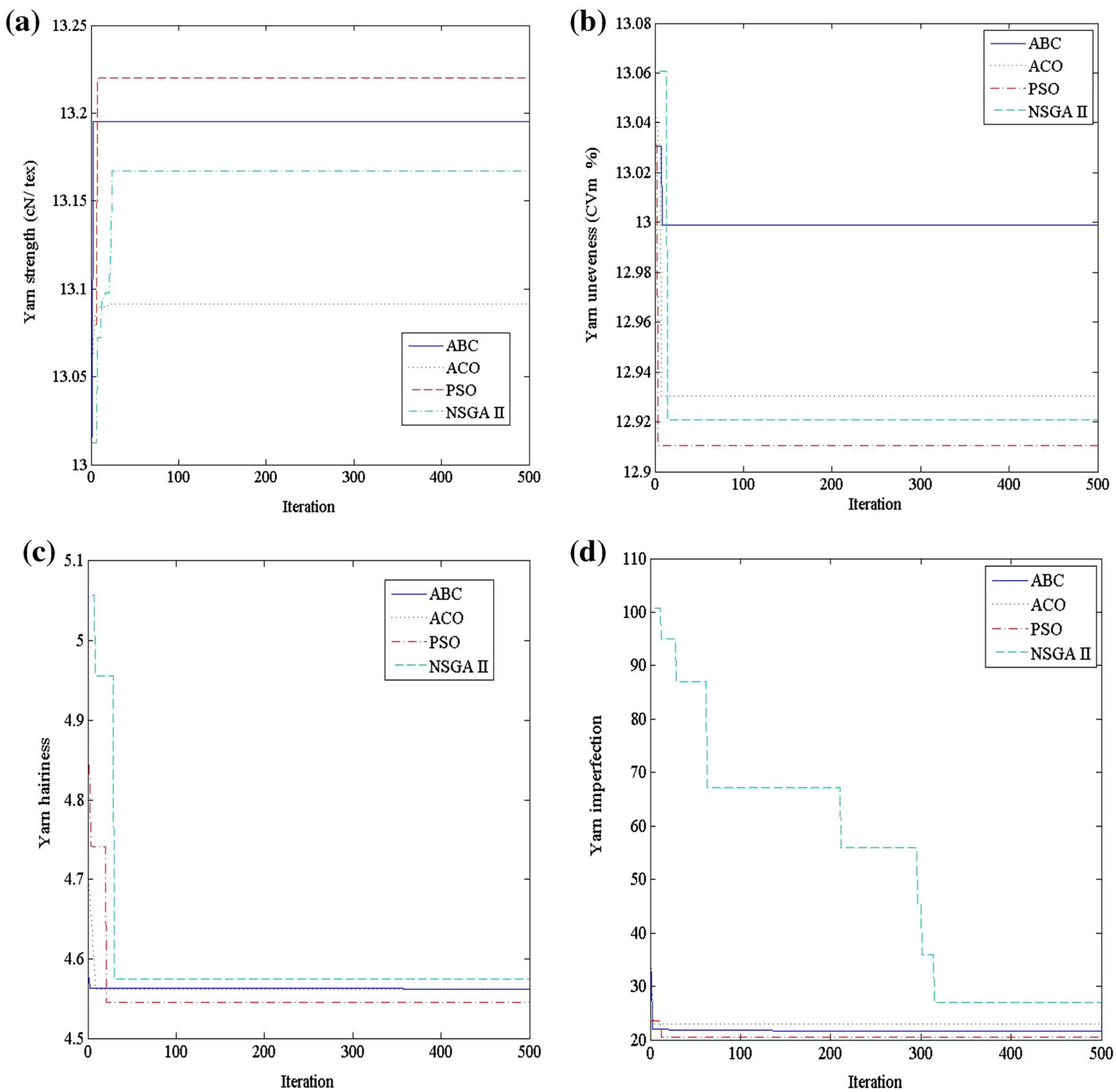

Fig. 1 Convergence diagrams of ABC, ACO, PSO and NSGA-II algorithms for four responses

It is observed that among the four considered evolutionary algorithms, PSO algorithm again supersedes the others with respect to the derived objective function value and consistency of the solution. Thus, it can be concluded that using PSO algorithm, at 83,053 rpm rotor speed and 700 yarn twist per metre, an optimal combination of yarn strength = 13.0994 cN/Tex, yarn unevenness = 12.0859 CV_m%, yarn hairiness = 4.5539 and yarn imperfections = 82 is attained. There are improvements in yarn strength, yarn unevenness and yarn hairiness values at that optimal parametric setting as compared to those derived by Arain et al. [7]; but yarn imperfections are drastically reduced from 101 to 82.

Problem 2

In this example, the experimental data of Hasanuzzaman et al. [15] are considered for single as well as multi-response optimization of yarn characteristics. Based on the Box–Behnken design plan, Hasanuzzaman et al. [15] conducted 15 experiments in order to investigate the effects of three process parameters, i.e. spindle speed (x_1), yarn twist multiplier (yarn TM) (x_2) and roving TM (x_3) on breakage rate per 100 spindle per hour (BR), specific strength (SS) (gm/tex), yarn irregularity (IR) (%), breaking extension (BE) (%), hairiness index (HI) and imperfection per km (IM). It is worthwhile to mention here that SS and BE are the beneficial (larger-the-better) type of quality characteristics, and the remaining four are non-beneficial (smaller-the-better) responses. Each of those process

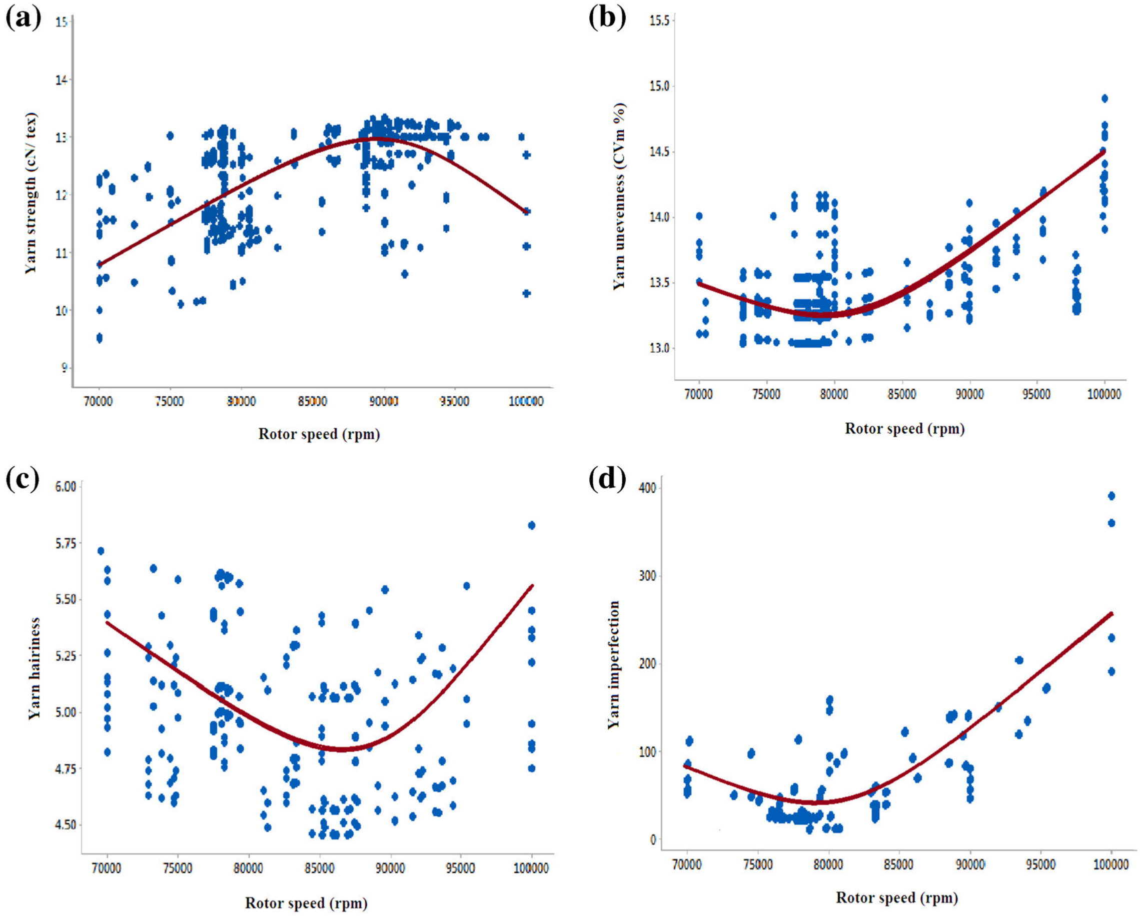

Fig. 2 Variations in responses with changing values of rotor speed

parameters was set at three different levels, i.e. spindle speed 15,000, 17,000 and 19,000 rpm; yarn TM 3.7, 3.9 and 4.1; and roving TM 1.1, 1.3 and 1.5. Using desirability function approach, an optimal parametric combination of spindle speed = 17,020 rpm, yarn TM = 4.1 and roving TM 1.3 was derived for BR = 5.81433, SS = 16.5792 gm/tex, IR = 8.6359%, BE = 3.86991%, HI = 5.67938 and IM = 87.5435 with an overall desirability of 0.664. Based on the experimental observations and using RSM technique, the following six second-order regression models were also developed showing the relationships between the process parameters and yarn characteristics.

$$Y(\mathrm{BR}) = 6.46 + 4.36x_1 - 1.33x_2 - 0.44x_3 - 1.15x_1x_2 + 1.81x_1^2 + 0.63x_2^2 \quad (6)$$

$$Y(\mathrm{SS}) = 16.15 + 0.43x_2 + 0.12x_3 - 0.26x_1^2 \quad (7)$$

$$Y(\mathrm{IR}) = 8.62 - 0.068x_2 - 0.32x_3 + 0.095x_1x_2 - 0.085x_1x_3 + 0.22x_1^2 + 0.071x_2^2 \quad (8)$$

$$Y(\mathrm{BE}) = 3.72 - 0.18x_1 + 0.045x_2 - 0.46x_3 + 0.10x_2^2 + 0.13x_3^2 \quad (9)$$

$$Y(\mathrm{HI}) = 5.81 + 0.047x_1 - 0.14x_2 - 0.066x_3 - 0.080x_1x_2 - 0.068x_2x_3 - 0.067x_3^2 \quad (10)$$

$$Y(\mathrm{IM}) = 83.38 + 5.12x_1 - 3.38x_2 + 7.50x_3 + 5.00x_1x_2 + 7.58x_2^2 + 27.33x_3^2 \quad (11)$$

Now, this problem is first solved applying ABC, ACO, PSO and NSGA-II algorithms while optimizing each of the responses separately with the constraints set as $15{,}000 \le x_1 \le 19{,}000$, $3.7 \le x_2 \le 4.1$ and $1.1 \le x_3 \le 1.5$. Table 3 provides the detailed solutions for these individual optimization problems. It is interestingly revealed that for all the considered evolutionary algorithms, there are improvements in the derived yarn characteristics and PSO algorithm provides the best optimization performance. For these algorithms too, the settings of various control parameters remain the same as those of the first example.

The deployment of the considered evolutionary algorithms proves that there are scopes for improvements in the derived yarn characteristics with different combinations of the three process parameters. But, in a ring spinning process, it is not at all possible to set the process parameters at

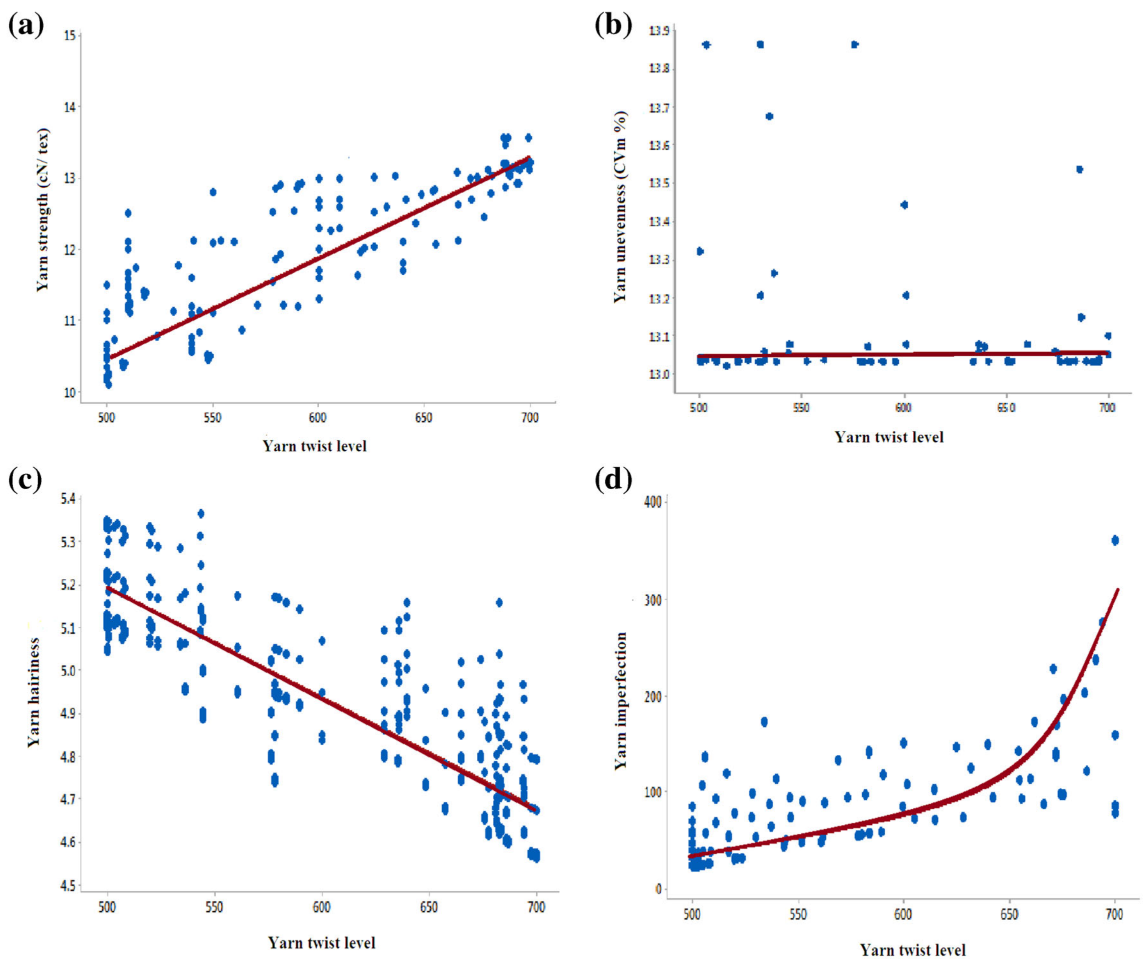

Fig. 3 Variations in responses with changing values of yarn twist level

Table 2 Results of multi-response optimization problem for example 1

Optimization method	Response	Mean Z_1	SD of Z_1	Optimal value	Z_1	Parameter	
						Rotor speed	Yarn twist
ABC algorithm	Yarn strength	3.0721	0.0131	13.0716	3.0654	82,205	700
	Yarn unevenness			12.9287			
	Yarn hairiness			4.5716			
	Yarn imperfection			100			
ACO algorithm	Yarn strength	3.8507	0.2691	13.0160	3.8043	79,171	695
	Yarn unevenness			12.9938			
	Yarn hairiness			4.5853			
	Yarn imperfection			98			
PSO algorithm	Yarn strength	0.6989	0.0048	13.0994	0.6969	83,053	700
	Yarn unevenness			12.0859			
	Yarn hairiness			4.5539			
	Yarn imperfection			82			
NSGA-II algorithm	Yarn strength	6.0988	0.0049	12.7360	6.0965	79,064	525
	Yarn unevenness			12.9333			
	Yarn hairiness			4.5950			
	Yarn imperfection			99			

Table 3 Results of single response optimization problem for example 2

Optimization method	Response	Mean	SD	Optimal value	Parameter		
					Rotor speed	Yarn TM	Roving TM
ABC algorithm	BR	3.4745	0.012	3.4549	15,000	3.9138	1.496
	SS	16.9444	0.0093	16.9471	15,036	3.7	1.112
	IR	8.2828	0.0012	8.2825	17,229	3.967	1.499
	BE	4.6050	0.010	4.6113	15,094	4.096	1.103
	HI	5.4431	0.0048	5.4420	18,919	4.097	1.498
	IM	75.5055	0.038	75.4842	15,001	4.026	1.272
ACO algorithm	BR	3.5523	0.044	3.5414	15,024	3.8617	1.4995
	SS	16.8958	0.0399	16.900	15,164	3.7164	1.1238
	IR	8.2993	0.0009	8.2992	17,231	3.971	1.1105
	BE	4.6175	0.0078	4.6193	15,098	4.0974	1.101
	HI	5.4450	0.0048	5.4414	18,870	4.0993	1.498
	IM	76.2340	0.38	76.1554	15,043	3.9578	1.281
PSO algorithm	BR	3.4573	0.00475	3.4459	15,000	3.928	1.5
	SS	16.9599	0.00167	16.9610	15,002	3.7	1.1
	IR	8.2817	0.00015	8.2816	17,209	3.981	1.5
	BE	4.633	0.0147	4.6350	15,000	4.1	1.1
	HI	5.437	0.0073	5.436	19,000	4.1	1.1
	IM	75.4295	0.0026	75.4293	15,000	4.0105	1.2725
NSGA-II algorithm	BR	3.5095	0.1264	3.4709	15,001	3.922	1.4941
	SS	16.9472	0.012	16.9486	15,024	3.701	1.1014
	IR	8.2838	0.0268	8.2828	17,214	3.981	1.499
	BE	4.6144	0.012	4.6260	15,006	4.099	1.102
	HI	5.4473	0.0054	5.4428	18865	4.1	1.496
	IM	75.543	0.1127	75.4461	15,004	4.012	1.273

different operating levels for achieving different target response values. Thus, it is always recommended to adopt multi-response optimization for this considered problem which would determine one unique setting for all the three process parameters for simultaneous optimization of the six responses. For this purpose, the following multi-response optimization problem is developed and subsequently solved using ABC, ACO, PSO and NSGA-II algorithms.

$$\begin{aligned}\mathrm{Min}(Z_2) = {} & w_1\left[\frac{Y(\mathrm{B}R) - \mathrm{BR}_{\min}}{\mathrm{BR}_{\max} - \mathrm{BR}_{\min}}\right] + w_2\left[\frac{Y(\mathrm{IR}) - \mathrm{IR}_{\min}}{\mathrm{IR}_{\max} - \mathrm{IR}_{\min}}\right] \\ & + w_3\left[\frac{Y(\mathrm{HI}) - \mathrm{HI}_{\min}}{\mathrm{HI}_{\max} - \mathrm{HI}_{\min}}\right] \\ & + w_4\left[\frac{Y(\mathrm{IM}) - \mathrm{IM}_{\min}}{\mathrm{IM}_{\max} - \mathrm{IM}_{\min}}\right] \\ & - w_5\left[\frac{\mathrm{BE}_{\max} - Y(\mathrm{BE})}{\mathrm{BE}_{\max} - \mathrm{BE}_{\min}}\right] \\ & - w_6\left[\frac{\mathrm{SS}_{\max} - Y(\mathrm{SS})}{\mathrm{SS}_{\max} - \mathrm{SS}_{\min}}\right]\end{aligned} \tag{12}$$

where Y(BR), Y(IR), Y(HI), Y(IM), Y(BE) and Y(SS) are the second-order response surface equations for breakage rate per 100 spindle per hour, yarn irregularity, hairiness index, imperfection per km, breaking extension and specific strength respectively; $\mathrm{BR}_{\min}$, $\mathrm{IR}_{\min}$, $\mathrm{HI}_{\min}$, $\mathrm{IM}_{\min}$, $\mathrm{BE}_{\min}$ and $\mathrm{SS}_{\min}$ are the minimum values of BR, IR, HI, IM, BE and SS respectively; $\mathrm{BR}_{\max}$, $\mathrm{IR}_{\max}$, $\mathrm{HI}_{\max}$, $\mathrm{IM}_{\max}$, $\mathrm{BE}_{\max}$ and $\mathrm{SS}_{\max}$ are the maximum values of BR, IR, HI, IM, BE and SS respectively; and w_1, w_2, w_3, w_4, w_5 and w_6 are the weights allotted to BR, IR, HI, IM, BE and SS respectively. In this multi-response optimization problem, equal weight is assigned to each of the responses, i.e. all the responses are seemed to be equally preferable to the concerned spinning industry personnel. Table 4 provides the optimal solutions as derived for this multi-response optimization problem while employing ABC, ACO, PSO and NSGA-II algorithms. It can be noticed that for all the adopted evolutionary algorithms, the responses are simultaneously optimized at a particular setting of the considered process parameters. It is clearly revealed that in this problem also, the optimization performance of PSO algorithm is the best as compared to the others. For this algorithm, at a parametric combination of spindle speed = 15,000 rpm, yarn TM = 4.010 and roving TM = 1.273, the optimal values of

Table 4 Results of multi-response optimization problem for example 2

Optimization method	Response	Mean Z_2	SD of Z_2	Optimal value	Z_2	Parameter		
						Spindle speed	Yarn TM	Roving TM
ABC algorithm	BR	− 89.226	0.0167	3.9990	− 89.230	15,003	4.002	1.273
	SS			16.6577				
	IR			8.6253				
	BE			4.0122				
	HI			5.5899				
	IM			75.9551				
ACO algorithm	BR	− 89.223	0.0154	3.9725	− 89.237	15,003	4.002	1.274
	SS			16.653				
	IR			8.6178				
	BE			4.0107				
	HI			5.6442				
	IM			75.7559				
PSO algorithm	BR	− 583.45	0.0001	3.7270	− 583.47	15,000	4.010	1.273
	SS			16.671				
	IR			8.6071				
	BE			4.1104				
	HI			5.5358				
	IM			75.5628				
NSGA-II algorithm	BR	− 89.231	0.0197	3.9011	− 89.235	15,004	4.013	1.267
	SS			16.5974				
	IR			8.6181				
	BE			4.0217				
	HI			5.5699				
	IM			75.8872				

the six responses are achieved as BR = 3.7270, SS = 16.671 gm/tex, IR = 8.6071%, BE = 4.1104%, HI = 5.5358 and IM = 75.5628. The developed scatter diagrams (not shown here due to lack of space) depicting the relationships between yarn characteristics and process parameters are also observed to be in well congruence with the observations of Hasanuzzaman et al. [15].

Conclusions

It has been observed that the desired yarn quality characteristics can only be achieved when different parameters of a ring or rotor spinning process are set at their optimal operating levels. As the multiple yarn characterises are often conflicting in nature, it is always desired to search for a single optimal parametric combination for the considered spinning process in order to simultaneously optimize all the yarn qualities. In this paper, four evolutionary algorithms, i.e. artificial bee colony algorithm, ant colony optimization algorithm, particle swarm optimization algorithm and non-dominated sorting genetic algorithm-II are applied for multi-response optimization of various yarn characteristics. It is noticed that particle swarm optimization algorithm provides the best solution with respect to the objective function value, consistency of the solution and convergence speed. In the ring spinning process, in order to simultaneously optimize all the six yarn characteristics, spindle speed, yarn twist multiplier and roving twist multiplier are to be set at 15,000 rpm, 4.010 and 1.273 respectively. On the other hand, in the rotor spinning process, an optimal parametric setting of 83,053 rpm rotor speed and 700 yarn twist per metre concurrently optimizes all the four yarn qualities. The developed scatter diagrams also help in investigating the effects of different spinning process parameters on the final yarn characteristics. These multi-response optimization techniques can also be adopted in any of the intermediate processes of a textile industry where a global optimal parametric setting is needed to achieve a set of conflicting target responses.

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