# Multi-Objective Optimization of Rotorcraft Compact Spinning Core-Spun Yarn Properties

Parvaneh Kheirkhah Barzoki, Morteza Vadood*, and Majid Safar Johari

*Abstract*- **One way to improve the properties of staple yarns is to employ core–compact yarn spinning system. This type of yarn is used in a wide range of applications and up to now many researchers have studied its production process and properties. However, there is a lack of researches regarding the optimization of the properties of rotorcraft compact spinning (RoCos) core-spun yarns based on the spinning parameters. Therefore, in this paper, the influence of some spinning parameters including the pre-tension of filament, yarn count and type of sheath fiber on the properties of RoCos core-spun yarns was investigated. To achieve the goals of this research, the physical and mechanical properties of RoCos core-spun yarns including the tenacity, hairiness and abrasion resistance were measured, and then modeled by artificial neural network (ANN). Finally, to optimize all measured properties at the same time the ANN models and non-dominated sorting genetic algorithm (NSGAII) method were applied as a hybrid model. The results showed that the presented method could be successfully used to determine the spinning parameters to produce RoCos yarns with desired properties. The optimized values of hairiness, tenacity and abrasion resistance for an ideal yarn were observed at yarn count of 41.5 tex, filament pre-tension of 125 g and for sheath fiber of viscous/polyester.**

***Keywords*: rocos, core-spun yarn, artificial neural network, non-dominated sorting genetic algorithm, multi-objective optimization**

## I. INTRODUCTION

Core spinning system has two distinct categories: core and sheath. The core is usually made of filament yarns and the sheath part is made of staple fibers. The main aim of using the core-spun yarns is to mix the advantage of different properties of both components. Core yarns are used in different fields and up to now some studies have been accomplished about core yarns production system [1-5]. Bhatnagar [6] studied the effects of twist, pre-tension, and feed positions of the core filament on properties of core-spun yarns. Yuan *et al.* [7] studied the effects of changing compound spinning conditions such as the tension ratio between filaments and staple fibers, and position where the filaments were fed into the staple fibers. These kinds of yarns have various properties which can be predicted with different models. In recent decades, ANN models have been employed in many published works to predict the properties of various yarns and many other characteristics of textile materials precisely [8-11].

On the other hand, in many engineering problems, objectives under consideration conflict with each other, so the optimization of a particular solution with respect to a single specified objective may cause to obtain unacceptable results regarding the other objectives. A reasonable solution to a multi-objective problem is to investigate a set of solutions, each of which satisfies the objectives at an acceptable level without being dominated by any other solution [12]. Multi-objective formulations are realistic models for many complex engineering optimization problems. Customized genetic algorithms have been demonstrated to be particularly effective to determine excellent solutions to these problems [13-18].

In case of textile engineering, Chen *et al.* [19] used multi-objective optimization method for carbon fiber drawing process. They proposed a new synergetic immune clonal selection algorithm (SICSA) to obtain the optimal process parameters, such as linear density, tenacity, and breaking elongation ratio. Han and Wang [20] proposed multi-objective genetic algorithm based on the numerical simulation of the polymer flow to optimize the geometry parameters of the coat-hanger die with uniform outlet velocity and minimal residence time. Gu [21] discussed about the feasibility of adopting multiple objective

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optimization to design blended fabric. In this research, he illustrated that multiple objective optimization is feasible for designing textile proucts. Recently Majumdar et al. [22] derived a simultaneous optimal solution of two objectives, namely air permeability and thermal conductivity for both single jersey and 1×1 rib knitted fabrics with desired ultraviolet (UV) protection. In this work, Pareto-optimal solutions were derived by an elitist multi-objective evolutionary algorithm based on non-dominated sorting genetic algorithm (NSGAII), and the effective knitting and yarn parameters for engineer knitted fabrics with optimal comfort and desired level of UV protection were obtained.

Due to the lack of information on prediction and multi optimization about the RoCos (Rotorcraft Compact Spinning) core-spun yarns, in present study the relation between the controllable factors and physical and mechanical properties of RoCos yarns was modeled, and then the best controllable factors for an ideal yarn were determined using multi optimization method. To this aim, using ANN the tenacity, abrasion resistance and hairiness of yarn were modeled, and NSGAII technique of multi-objective optimization has been implemented with the aim to maximize the tenacity and abrasion resistance and to minimize the hairiness, simultaneously.

## II. ANN

ANN models are very useful in modeling nonlinear and complex systems. ANN includes three layers namely: input, hidden and output layers. Neurons in each layer are connected by associated weights to other neurons in the next layer. The input data is received in input layer and the output is obtained in the output layer by mathematical operations through hidden layers. The number of hidden layers and neurons in each hidden layer are the most important parameters in ANN model [23].

## III. NSGAII

Generally, in the method of multi-objective optimization, there are some optimal solutions known as Pareto-optimal or non-dominated solutions, so that each solution can be considered as a response. The Pareto-optimal solutions plotted regarding the related objectives are called Pareto-optimal fronts. NSGAII is one of the most used methods for multi optimization and its purpose is to find a set of solutions as much as close to Pareto-optimal front simultaneously with maximum variety. All operations in NSGAII are the same as those in genetic algorithm (GA) including crossover and mutation, except for the fitness assignment method which is modified by fast non-domination sorting and crowding distance sorting [17, 24, 25].

### *A. Fast Non-Domination Sorting*

The population generated by GA is sorted into a hierarchy of subpopulations based on non-domination method. In this method each objective for a solution is compared with the corresponding objectives in other solutions as follows (for example a solution with two objectives):

$$S_i \begin{Bmatrix} O_1 > O_1 \\ O_2 \geq O_2 \end{Bmatrix} S_j \quad \text{or} \quad S_i \begin{Bmatrix} O_1 \geq O_1 \\ O_2 > O_2 \end{Bmatrix} S_j \qquad (1)$$

Where, S is the solution, O is the objective, and indices i and j are the i$^{th}$ and j$^{th}$ solutions, respectively. Based on the upper constraint j$^{th}$ solution is dominated by i$^{th}$ one, otherwise it is non-dominated. Therefore, the whole population is divided into different ranks such as solutions in Rank 1 which are better than ones in Rank 2 and solutions in Rank 2 which are better than ones in Rank 3 and so on.

### *B. Crowding Distance*

After sorting the population, the crowding distance is assigned to each individual for each rank. To this aim, regarding each objective, the fitness values of objective functions for solutions are sorted in descending order. The crowding distance operator helps in distributing the solutions uniformly to the ranks rather than bunching up at several good points. The individuals of the next generation are selected using tournament selection function based on the rank and crowding distance. In tournament function two individuals are compared and that with better rank is selected, and if two individuals have the same rank one with higher crowding distance is selected.

## IV. MATERIAL AND METHOD

In this study, 56 different types of yarn samples were produced on a compact-core spinning system. A blended

TABLE I
PROPERTIES OF SHEATH FIBERS

| Elongation (%) | Tenacity (cN/tex) | Percentage of fiber blending (%) | Denier | Length (mm) | Type of sheath fiber |
|---|---|---|---|---|---|
| 20 | 18.63 | 45 | 1.5 | 38 | Viscose |
| 45 | 40.21 | 55 | 1.4 | 34 | Polyester |
| 6 | 27.46 | 100 | 1.24 | 27 | Cotton |

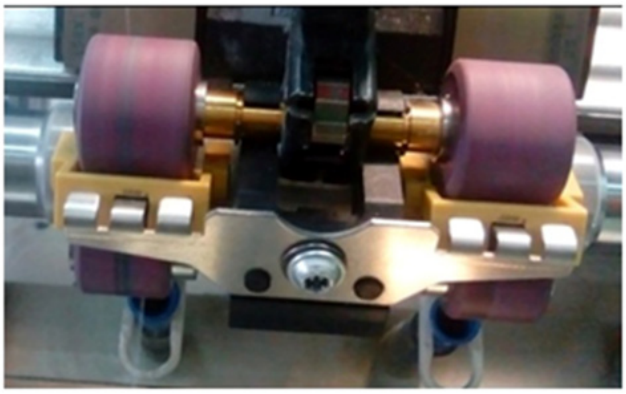

Fig. 1. Rotorcraft compact spinning roller (RoCoS).

viscose/polyester and cotton fibers were used as the sheath fiber with properties presented in Table I. Multifilament nylon (30 monofilaments: elongation-at-break and tenacity of monofilament were 26% and 4600 cN/Tex, respectively) with count of 100 denier was used as the core filament.

The cotton and viscose/polyester roving count were 0.72 and 1.09 Ne, respectively. To produce the samples, RoCos system was installed on SKF lab spinner instead of delivery top roller (Fig. 1).

In order to produce different types of compact-core yarns, core filament should be pre-drawn before entering the front rollers (RoCos roller). Filament also should be fed to compactor groove of RoCos roller and to this aim, a guide rod and a pre-tensioner were used. Fig. 2 illustrates the process of core-compact yarn production and Table II exhibits the machine parameters for producing RoCos yarns.

In this study, the tenacity, hairiness and abrasion resistance were considered as the physical and mechanical properties of compact-core yarns, and to determine the effect of controllable factors on these properties, 7 levels of filament pre-tension (25, 50, 75, 100, 125, 160 and 180 g), 4 levels of yarn count (41.5, 43.5, 48 and 59 tex) and two kinds of sheath fibers (cotton and polyester/viscose) were chosen. The list of yarn samples and considered controllable factors are presented in Table III.

The Instron testing machine (Model: M10-8201-1) was

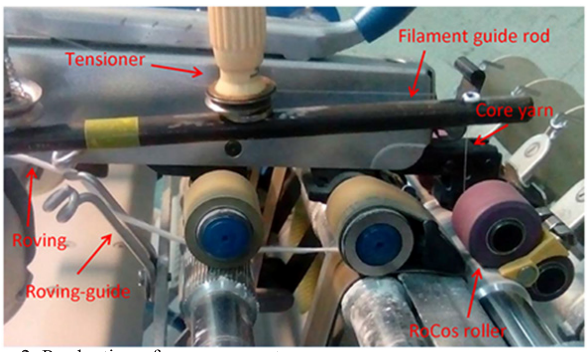


Fig. 2. Production of core-compact yarns.

TABLE II
MACHINE PARAMETERS

| Setting parameters | Value |
|---|---|
| Twist per meter | 900 |
| Spindel speed (rpm) | 22000 |
| Ring diameter (mm) | 36 |
| Traveler* ISO No. | 50 |

* Traveler type: J

used to measure the tenacity of yarns with a gauge length of 25 cm according to ASTM D2256, and the speed of testing was selected according to the breaking time of 20 s. For measuring hairiness (number of hairs longer than or equal to 3 mm), a Shirley hairiness tester (Model SDL096/8) was used based on ASTM D5647. The measurement was carried out on 20 m of each yarn sample at the speed of 60 m/min. Abrasion resistance was determined by a Shirley abrasion tester (Model: Y027) according to ASTM D6611. In order to determine the tenacity, each test was repeated 10 times, and for abrasion resistance and hairiness it was 5 times. All experiments were conducted at the condition of 30 ºC and 60 RH%.

## V. RESULT AND DISCUSSION

### *A. ANN Model*

To find the best set of ANN parameters to predict each property, the trial and error method was applied. Regarding the literature review, the number of hidden layers and neurons in each hidden layer were considered between 1 to 3 and 1 to 10, respectively. The activation functions for all hidden and output layers were considered tangent hyperbolic and linear functions, respectively. Obviously, the input parameters to ANN models are the pre-tension of filament, yarn count and the kind of sheath fibers. The ANNs were trained with the error back propagation algorithm using Trainlm function. 20% of data for test, 20% for validation and the rest were selected for training set, randomly. As the initial weights in ANN were selected randomly, each ANN topology was created five times and the best obtained result was considered for that topology. To evaluate the accuracy of the created ANNs, besides the correlation coefficient (R-value) two more indexes namely MSE (mean square error) and MAPE (mean absolute percentage error) were calculated between ANN outputs and corresponding actual values for testing set (Eqs. (2) and (3)).

$$\mathrm{MAPE} = 100 \times \frac{1}{n} \times \sum_{i=1}^{n} \left| \frac{y_i - x_i}{x_i} \right| \tag{2}$$

$$\mathrm{MSE} = \frac{1}{n} \times \sum_{i=1}^{n} (y_i - x_i)^2 \tag{3}$$

TABLE III
LIST OF YARN SAMPLES AND CONTROLLABLE FACTORS

| No. | Filament pre-tension (g) | Yarn count (tex) | Type of sheath fiber | No. | Filament pre-tension (g) | Yarn count (tex) | Type of sheath fiber |
|---|---|---|---|---|---|---|---|
| 1 | 25 | 41.5 | Viscose/polyester | 29 | 25 | 48 | Viscose/polyester |
| 2 | 50 | 41.5 | Viscose/polyester | 30 | 50 | 48 | Viscose/polyester |
| 3 | 75 | 41.5 | Viscose/polyester | 31 | 75 | 48 | Viscose/polyester |
| 4 | 100 | 41.5 | Viscose/polyester | 32 | 100 | 48 | Viscose/polyester |
| 5 | 125 | 41.5 | Viscose/polyester | 33 | 125 | 48 | Viscose/polyester |
| 6 | 160 | 41.5 | Viscose/polyester | 34 | 160 | 48 | Viscose/polyester |
| 7 | 180 | 41.5 | Viscose/polyester | 35 | 180 | 48 | Viscose/polyester |
| 8 | 25 | 41.5 | Cotton | 36 | 25 | 48 | Cotton |
| 9 | 50 | 41.5 | Cotton | 37 | 50 | 48 | Cotton |
| 10 | 75 | 41.5 | Cotton | 38 | 75 | 48 | Cotton |
| 11 | 100 | 41.5 | Cotton | 39 | 100 | 48 | Cotton |
| 12 | 125 | 41.5 | Cotton | 40 | 125 | 48 | Cotton |
| 13 | 160 | 41.5 | Cotton | 41 | 160 | 48 | Cotton |
| 14 | 180 | 41.5 | Cotton | 42 | 180 | 48 | Cotton |
| 15 | 25 | 43.5 | Viscose/polyester | 43 | 25 | 59 | Viscose/polyester |
| 16 | 50 | 43.5 | Viscose/polyester | 44 | 50 | 59 | Viscose/polyester |
| 17 | 75 | 43.5 | Viscose/polyester | 45 | 75 | 59 | Viscose/polyester |
| 18 | 100 | 43.5 | Viscose/polyester | 46 | 100 | 59 | Viscose/polyester |
| 19 | 125 | 43.5 | Viscose/polyester | 47 | 125 | 59 | Viscose/polyester |
| 20 | 160 | 43.5 | Viscose/polyester | 48 | 160 | 59 | Viscose/polyester |
| 21 | 180 | 43.5 | Viscose/polyester | 49 | 180 | 59 | Viscose/polyester |
| 22 | 25 | 43.5 | Cotton | 50 | 25 | 59 | Cotton |
| 23 | 50 | 43.5 | Cotton | 51 | 50 | 59 | Cotton |
| 24 | 75 | 43.5 | Cotton | 52 | 75 | 59 | Cotton |
| 25 | 100 | 43.5 | Cotton | 53 | 100 | 59 | Cotton |
| 26 | 125 | 43.5 | Cotton | 54 | 125 | 59 | Cotton |
| 27 | 160 | 43.5 | Cotton | 55 | 160 | 59 | Cotton |
| 28 | 180 | 43.5 | Cotton | 56 | 180 | 59 | Cotton |

Where, y and x are the ANN output and corresponding actual values, respectively. The obtained results revealed that the use of MAPE index leads to higher accuracy in prediction. Table IV. shows the best topology of ANNs for each measured properties and Fig. 3 depicts the ANN outputs based on the MAPE index along with corresponding actual values in testing group for different properties.

*B. NSGAII algorithm*

After determining the best topology of ANN for each property, the value of tenacity and abrasion resistance and hairiness can be predicted accurately by inserting the pre-tension of filament, yarn count and the kind of sheath fiber to the ANN models. Therefore, at this step, the optimization of all properties at the same time is possible. Clearly, for an ideal yarn the tenacity and abrasion resistance should be maximum and hairiness should be minimum. Considering that GA minimizes the fitness function, in this step three objectives are defined as follows (Eq. (4)) and each solution contains all objectives.

$$\begin{aligned}&\text{Objective}_1=\text{Tenasity}_{\text{value}}\\&\text{Objective}_2=\text{abrasion resistance}_{\text{value}}\\&Objective_3=\frac{1}{Hairiness_{value}}\end{aligned} \tag{4}$$

TABLE IV
THE BEST TOPOLOGY OF ANN FOR EACH INVESTIGATED PROPERTIES BASED ON MAPE

| Measured properties | Hidden layer (best topology of ANN) | Accuracy index between ANN output with best topology and corresponding actual values for testing group | | |
|---|---|---|---|---|
| | | MAPE | MSE | R-value |
| Tenacity | [8 3]* | 0.0626 | 0.8500 | 0.9929 |
| Hairiness | [6 6] | 0.0997 | 0.3283 | 0.8374 |
| Abrasion resistance | [2 4 4] | 0.1744 | 1.8600 | 0.7587 |

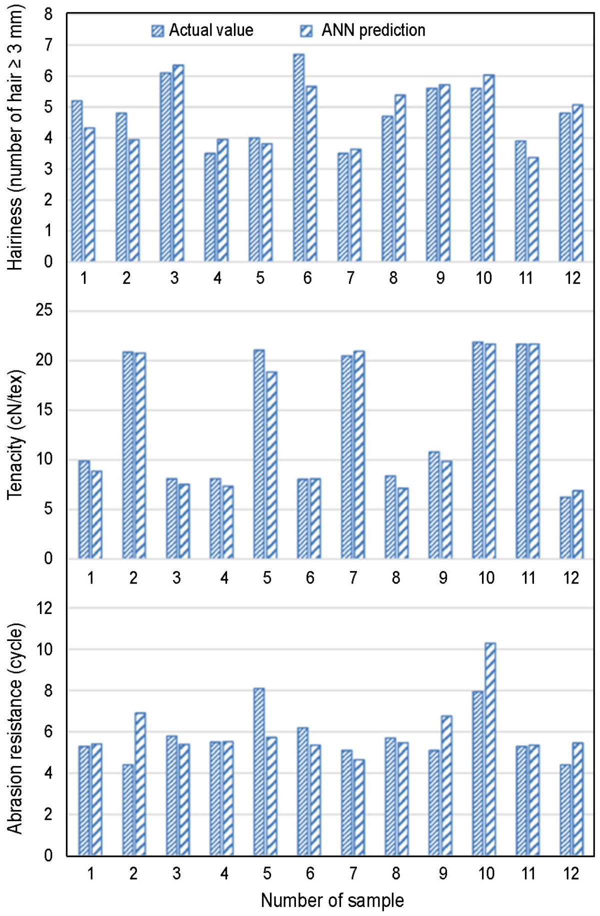


Fig. 3. ANN outputs based on the MAPE index along with corresponding actual values for different properties (testing group).

NSGAII starts with randomly generated 100 initial populations and it ranks the individuals based on the dominance. The fast non-dominated sorting procedure finds out the non-domination ranks where individuals of a particular rank are non-dominated by any solution. In the next step, the crowding distance is calculated for each individual. NSGAII steps are repeated and the Pareto-optimal front is obtained at the end of 100 generations leading to the final set while the crossover and mutation rate are 0.8 and 0.2, respectively. Fig. 4 shows the 3D scattered Pareto-optimal front for tenacity, hairiness and abrasion resistance. The coordinates of some points on the axes are displayed for better comprehension of point's position. As can be seen in Fig. 4, while the tenacity and abrasion

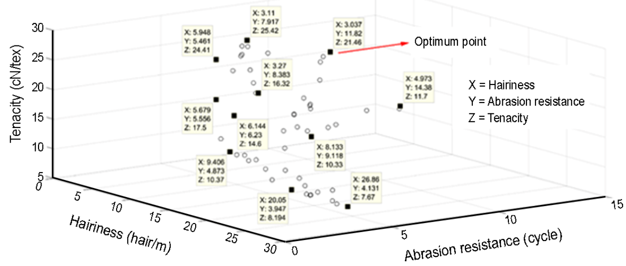


Fig. 4. Result of implementation NSGAII (the optimal Pareto front for measured properties).

resistance increase, the hairiness decreases. In this study, the Pareto-optimal front contains 56 solutions for RoCos core-compact yarn. It must be noted that the corresponding values of the filament pretension, yarn count and kind of sheath fibers for each point in Fig. 4 are presented by NSGAII.

As all the solutions in the Pareto front are better than all those in the others, at least in terms of one objective, any one of them is an acceptable solution. The choice of one solution over other depends completely on the end user requirements. For better understanding the relation between three optimized mentioned properties, the Pareto-optima fronts are illustrated in 2D-dimensional figures (Figs. 5 to 7).

In Figs. 5 and 6, the trends between the parameters are very clear; one is decreasing while the other is increasing. However, a specified trend is not observed in Fig. 7, because

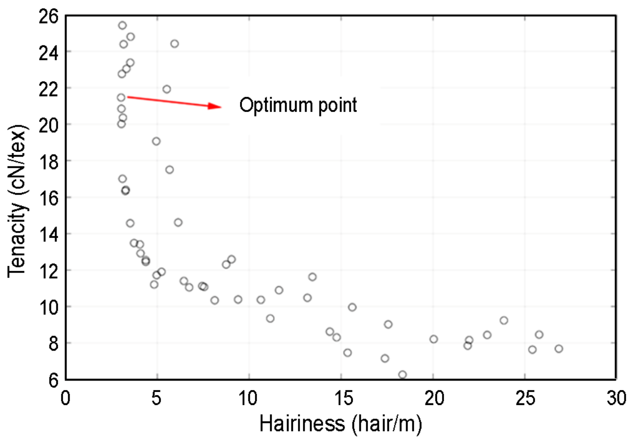


Fig. 5. Optimal Pareto front for hairiness and tenacity for RoCos core-compact yarn.

TABLE V
CHARACTERISTICS OF OPTIMUM YARN

| Property | Measured value | Observed values for "Optimum point" |
|---|---|---|
| Tenacity (cN/tex) | 21.77 | 21.46 |
| Abrasion resistance (cycle) | 12.1 | 11.82 |
| Hairiness (hair/m) | 4.8 | 3.03 |

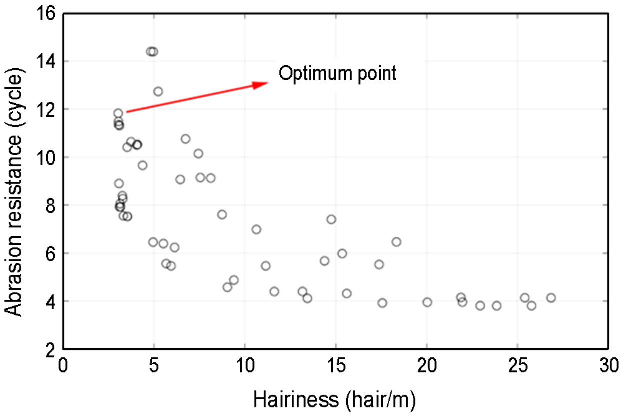

Fig. 6. Optimal Pareto front for hairiness and abrasion resistance for RoCos core-compact yarn.

the tenacity and abrasion resistance should be maximized simultaneously. By obtaining the Pareto-optima solutions, the relation between yarns characteristics becomes clear and a yarn with desired values of hairiness, tenacity and abrasion resistance can be produced with a suitable combination of filament pre-tension, type of sheath fibers and yarn count. For example, a point has been indicated in Fig. 4 as "Optimum point". This point has been highlighted in Figs. 5 to 7, too. As can be seen, this point enjoys from higher values of tenacity and abrasion resistance, while it has low value of hairiness. According to the results obtained from Table III, there is a yarn with characteristics very close to the optimum point characteristics (Table V). The spinning parameters for this yarn were count of 41.5 tex, filament pre tension of 125 g and sheath fiber of polyester/viscous. So, for an ideal yarn in RoCos spinning system, these parameters can be considered for spinning.

The method applied using NSGAII is effective, less subjective, more practical and computationally efficient. The result of this method is a set of trade off solutions, and engineers can select their own desired solution easily without need to use time-consuming and costly experiments.

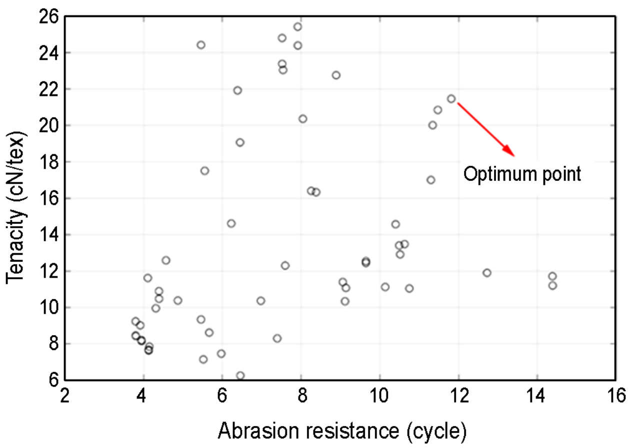

Fig. 7. Optimal Pareto front for abrasion resistance and tenacity for RoCos core-compact yarn.

## VI. CONCLUSION

In this paper, a database was created by considering the influence of spining parameters such as filament pre-tension, yarn count and type of sheath fiber on the tenacity, hairiness and abrasion resistance of compact-core spun yarns.Then, the relation between the spining parameters and measured properties was modeled using ANN, accurately. In the next step, to optimize measured properties simultaneously, NSGAII was applied by the help of ANN models obtained. The results illustrated the relations between the measured properties, therefore, the spining parameters for a core yarn with desired properties could be determined easily. This method is effective, less subjective, more practical and not time-consuming, and can be used to predict the input parametrs for a product with desired properties instead of difficult and expensive experimental testing.

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