Optimization of Acrylic Dry Spinning Production Line by Using Artificial Neural Network and Genetic Algorithm

M. Vadood, D. Semnani, M. Morshed

Department of Textile Engineering, Isfahan University of Technology, Isfahan 84156-83111, Iran

Received 3 February 2010; accepted 21 August 2010
DOI 10.1002/app.33252
Published online 1 November 2010 in Wiley Online Library (wileyonlinelibrary.com).

ABSTRACT: Acrylic fibers are synthetic fibers with wide applications. A couple of methods can be utilized in their manufacture, one of which is the dry spinning process. The parameters in this method have nonlinear relationships, making the process very complex. To the best of the authors' knowledge, no comprehensive study has yet been conducted on the optimization of acrylic dry spinning production using computer algorithms. In this study, such parameters as extruder temperature in and around the head, solution viscosity, water content in the solution, formic acid content of the solution, and the retention time of the solution in the reactor were measured in an attempt to predict the behavior of the dry spinning process. The color index of the manufactured fibers was used as an indicator of production quality and statistical methods were employed to determine the parameters affecting the process. An artificial neural network (ANN) using the back propagation training algorithm was then designed to predict the color index. ANN parameters including the number of hidden layers, number of neurons in each layer, adaptive learning rate, activation functions, number of max fail epochs, validation and test data were optimized using a genetic algorithm (GA). The trial and error method was used to optimize the GA parameters like population size, number of generations, crossover or mutation rates, and various selection functions. Finally, an ANN with a high accuracy was designed to predict the behavior of the dry spinning process. This method is capable of preventing the manufacturing of undesired fibers. © 2010 Wiley Periodicals, Inc. J Appl Polym Sci 120: 735–744, 2011

Key words: optimization; acrylic dry spinning; artificial neural network; genetic algorithm

INTRODUCTION

Optimization of production process is one of the most important problems in engineering and this object has a vital economical aspect, too.[1] Acrylic fiber is a manmade fiber like wool and has many applications in composites, knitting, and carpet industry and is produced through two methods; wet or dry spinning. Recently, a new method is used that is called dry jet wet spinning, but the most prevalent method is dry spinning because of its high production speed which consists of two main stages; namely polymerization and extruder.[2,3]

In polymerization, the suitable solution for spinning is prepared and, in next stage, it is pumped into the extruder and is converted into the continuous fibers called filament. Afterwards, these filaments cross through the hot air and are collected. So, there are many various parameters such as the amount of formic acid in the polymer (ppm), acrylic polymer basicity (ppm) and viscosity (P) that must be satisfied simultaneously. The relation between these parameters is nonlinear and the performance of the production line directly depends on them.[4] Therefore, the nature of such complex system prevents predicting the final properties of the fibers. Although some modeling methods such as phenomenological, empirical, statistical regression, semi-emprical and numerical models give reasonable responses from the industrial point of view,[5–10] but there is a mathematical modeling entitled artificial neural network (ANN) used widely nonlinear processes recently. There are some considerable efforts in modeling final properties in some textile processes. Sun et al.[11] used ANN with back propagation algorithm to predict the fiber diameter in melt blowing process of polyethylene, and the obtained results show a good agreement with the actual data. The maximum absolute error between the predicted fiber diameter and the actual value was less than 1.5 μm. In another research, Chen et al.,[12] in the melt blowing process of polypropylene, applied ANN to predict the fiber diameter, too. Measured correlation coefficient between the predicted fiber diameters was 0.9424, which confirms the effectiveness of the established ANN model. Some researchers worked on the parison formation, DiRaddo and Garcia-Rejon[13,14] utilized the neural network model to predict final part dimensions from initial parison dimensions and initial parison dimensions from the specified final part thickness, respectively. Huang and Liao[15,16] utilized the ANN method to predict swells of the parison under the effect of sag in the extrusion blow molding

Correspondence to: D. Semnani (d_semnani@cc.iut.ac.ir).

of high density polyethylene (HDPE) and HDPE/polyamide-6 blends. Huang and Lu[17] used two ANN models, one for predicting the length evolution of parison with its drop time and another for predicting the swells along the parison. The comparison of the predicted parison swells using the trained BP network models with the experimentally determined ones showed quite a good agreement between the two. The sum of the squared error for the predictions is within 0.001.

Thus the ANN model can be used as a precision tool to predict the final properties of product in chemical processes. Whereas acrylic fiber are produced and consumed in various Industries too much and there is not any comprehensive investigation on dry spinning of acrylic fiber using ANN model, so in this present research, ANN model was used to predict the acrylic fiber properties and simulate the dry spinning line. So, the prediction of fiber properties can be possible before fiber production and production of undesired fiber can be prevented.

However, the ANN model itself has some technical parameters that have direct effects on the predicting results and should be optimized. There is no order to determine the value of these parameters completely. Therefore, researchers use the trial and error method to find the best option of them in previous works, thus, the obtained values are not necessarily the best options. In other words, there is only one global optimum and it can be one or several local optimum options in search space. After optimizing, the best option of these parameters should be found. Therefore, solving such multiobjective problem and selecting the best option are so difficult. Sette et al.[18] used ANN to predict the behavior of the spinning process and GA to optimize the architecture and the underlying parameters of the ANN, but they focused only on the number of node in the first and second hidden layer, smoothing and learning rate. Curteanu and Leon[19] used the ANN and GA to predict the nylon 66 polymerization separately. They applied GA to optimize the output of a designed formula for the process and topology of ANN, like the number of node and connection weights and biases between the neurons in various layers. They focused on the ANN with two hidden layers, too. In this study, first the possible effective parameters were collected and then effective parameters were determined using statistical methods (linear regression and correlation coefficient). It was used GA to optimize the ANN parameters such as number of neuron in hidden layer (N.N.H.L), learning rate (L.R), activation functions (A.F), number of epochs for max fails (M.F), validation and testing data percentage (V.D and T.D) as well as trial and error methods to optimize the GA parameters such as population size, the number of generation, crossover and mutation rates and various selection functions such as roulette wheel, tournament, and stochastic uniform.

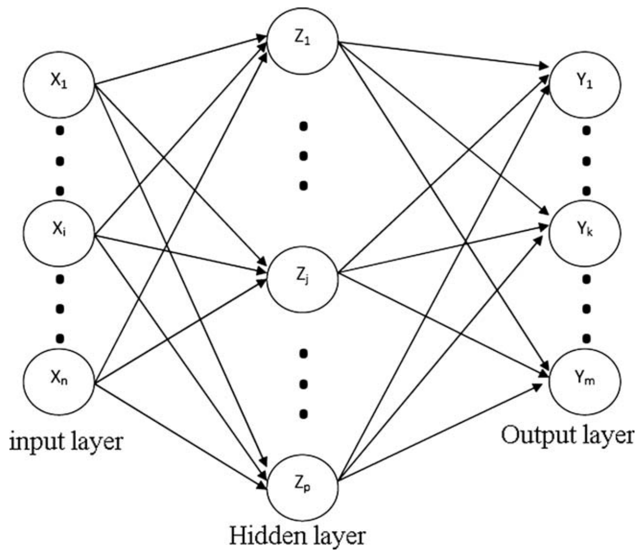

Figure 1 Topology of ANN with one hidden layer.

Neural network model

The ANN model is the information process that can be used for simulating the treatment of nonlinear and complex systems. It has some interesting advantages more than the other modeling methods. ANN model does not need simplifying assumptions and can be used with noisy data or few numbers of experimental points and can calculate their response very rapidly. The basic element in the ANN is called neuron. These elements can be divided to three different layers; input, middle or hidden and the output layer. The input layer receives and distributes the input signals. In the hidden layers, the relation between the input and output layers is created, and the output layer gives the output value. The number of neurons in the input and output layers depends on the number of problem parameters, and there is no order to exactly determine N.N.H.L.[20] Figure 1 shows the ANN with one hidden layer. The output signal of each neuron is calculated based on the sum of the weights of all the connected signals from the previous layer plus a bias and then the A.F generates an output according to follow[21]:

$$z_{in-j} = \sum_{i=1}^{n} w_{ij} x_i + v_{oj} \quad (1)$$

$$z_j = f(z_{in-j}) \quad (2)$$

Where w_{ij} is the associated weight between the i^{th} and j^{th} neurons, x_i is the output signal from the

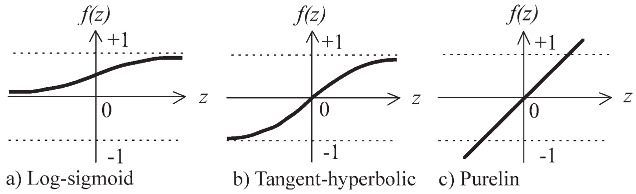

Figure 2 Activation functions.

previous layer neuron, v_{oj} is the bias weight on the j^{th} neuron and $f(z_{in\text{-}j})$ is the F.A on the j^{th} layer. Three customary types of A.F are tangent hyperbolic, Logarithm sigmoid and purelin[22] which are shown in Figure 2 schematically.

$$f(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}} \tag{3}$$

$$f(z) = \frac{1}{1 + e^{-z}} \tag{4}$$

$$f(z) = z \tag{5}$$

The available data is divided to three groups; training, validation and testing sets. The second group is useful when the network begins to over fit, so the error on the validation set typically begins to rise, in this time, the training is stopped for the number of epochs for max fails and the weights and biases at the minimum of the validation error are returned. The last group is used to evaluate the obtained ANN during the testing stage. Another ANN parameter is the learning rate.[22]

Genetic algorithm

Many different optimizing methods have been presented until now but one of the effective and popular search methods to find the optimum option is genetic algorithm (GA) and its adoptions. This method has several advantages; GA searches by means of a set of points not only one point. It follows the eventual principles not definite. Its response is not dependent on the start point and does not need to solve intricate equations. Consequently, it can find the true global optimum option with more probability.[23] In this method, the stronger solutions survive and the weaker solutions are omitted. This algorithm converts each possible solution to a chromosome and then, using some operations, looks for the global optimum solution.[24,25] Of course, there are other methods for optimization as well, such as Particle Swarm Optimization (PSO). But in this study, GA was applied because of its intuitiveness, ease of implementation, the ability to effectively solve highly nonlinear and mixed integer optimization problems.[26,27]

In the first step, the initial population of chromosomes is initialized. In the second step, the designed neural network was used as a fitness function. In the second step, the fitness value is calculated for each individual in the population, and in third step, individuals are reproduced to form a new population and performing GA operators on the population. These steps are repeated until some condition is satisfied.[28]

Population is the specified number of chromosomes randomly selected from the possible solutions. The fitness function is an appliance to measure the value of a solution. Selection function is a tool to determine which individual remains for the next population and which one should be omitted. This can be done in several ways like roulette wheel, tournament or stochastic uniform. Roulette wheel is a common method to select and base the roulette wheel so the selection chance for chromosome which has higher fitness is more. Tournament selects each parent by choosing the specified players randomly and then choosing the best individual out of that set to be a parent. This game repeats until the next population is completely created. Stochastic uniform selection is like roulette wheel but lays out a line in which each parent corresponds to a section of the line of length proportional to its scaled value. Crossover combines two individuals (parents) to form a crossover child for the next generation which is called offspring. Crossover prepares the diversity of population and can extract new solution from the current solutions. Mutation utilizes random changes to only one individual parent to form new children in the current population. But, not to lose the right path of search, it is needed to preserve the best solutions in each generation. So, the chromosome with the highest fitness is copied into the next generation and is called elitism chromosome.[29]

EXPERIMENTS

The experimental data were prepared in the production line of Poly Acryl Iran Inc. In this line, due to the technical and industrial point, just several parameters can be controlled. From previous and laboratorial works, it was found that the following parameters are more effective on the final properties of fibers; amount of formic acid in the polymer (FA in ppm), water in the solution coming into the extruder (water in %), acrylic polymer in the solution coming into the extruder (solid in %), acrylic polymer basicity (ppm), acrylic polymer viscosity (P), remaining solution before arrival into the extruder (time state in hour), sodium sulfide in the solution (salt in ppm), the temperature in the head of the extruder (E in °C) and the temperature in the surround of the extruder (F in °C).

TABLE I
Designed Chromosome Including Information About Topology and Structure of ANN

V.D	T.D	M.F	L.R	$N.N.H.L_1$	$N.N.H.L_2$	$N.N.H.L_3$	$N.N.H.L_4$	$N.N.H.L_5$	$N.N.H.L_6$	$A.F_1$	$A.F_2$	$A.F_3$	$A.F_4$	$A.F_5$	$A.F_6$	$A.F_7$

The production under study was the manufactured fibers before arriving at the finishing section and the color index of fibers was considered as the quality index, which is a value without the unit and measured by Data-Color apparatus. Every day the parameters and color index were measured. At last, 93 records were prepared from three months of steady product of fiber 5 dtex.

METHODOLOGY

The ANN was trained with the error back propagation algorithm. For faster convergence of ANN and the over fitting error preserve, the training function was chosen Trainlm, based on the Levenberg-Marquardt optimization theory. First, the effective parameters on the color index were determined among all possible parameters using statistical methods and were used in ANN input layer. Then, predicting the color index by ANN and optimizing the ANN parameters by GA were studied. Before using ANN, all data were normalized by mapping the mean and deviation of each parameter to 0 and, 1 separately. In this study, real value encoding method was used. Of course, there is binary encoding, which is the simplest type of encoding and very customary. Nevertheless, value encoding is more general because genes are based on the real numbers. Table I shows the chromosome in GA model. The maximum and minimum of hidden layers were considered 6 and 1, respectively. After choosing elitism, the number of parents for crossover was controlled by crossover rate which is between 0 and 1 and the remaining chromosomes were used for mutation.

The chromosome must include V.D, T.D, L.R, N.N.H.L, and A.F for each layer. The V.D, T.D, M.F and L.R were limited between 0 to %20, 0 to %20, 0 to 5 and 0.01 to 1, respectively. Fifth to tenth genes specified the N.N.H.L. Because the length of chromosome cannot be variable, so the longest chromosome was considered; it means that the chromosome was fixed on the ANN by six hidden layers. $N.N.H.L_i$ is the neuron number in i^{th} hidden layer and its value is between 0 and 30. When $N.N.H.L_i$ equals 0, the i^{th} layer is omitted. In this way, GA can control the number of hidden layers. The remaining genes specified the A.F in hidden layers, respectively. The values in these genes were limited between 0 to 3 and to choose the activation function Table II was applied.

TABLE II
Coding the Activation Functions

$0 \leq$ tangent hyperbolic < 1	$1 \leq$ Log-sigmoid < 2	$2 \leq$ Pure line < 3

$A.F_i$ is the activation function of i^{th} layer. The fitness function in present work equals the inverse of mean square error (mse) between ANN prediction and the testing group by coefficient -1. Following equations show the fitness function.

$$\text{mse} = \frac{1}{n} \times \sum_{i=1}^{n} (y_i - t_i)^2 \qquad (6)$$

$$\text{ff} = \frac{-1}{\text{mse}} \qquad (7)$$

If the fitness function is lower, its chromosome creates better topology of ANN and has greater chances to survive. GA is looking for the highest fitness function or best topology of ANN. Figure 3 shows the structure of GA model.

RESULTS AND DISCUSSION

One of the methods to determine the parameter effectiveness on an object is through the linear regression. Thus, it was used to study which parameters are effective on the color index and vice versa. All mentioned parameters were separately considered with the color index in linear regression because simultaneous evaluation of all parameters on the color index is very difficult.

Regression test require normally distributed variables and the Kolmogorov-Smirnov and Shapiro-Wilk tests can be used to test that a variable is normally distributed. So they were studied for ensuring the regression in 0.95 level of confidence interval on the regression standardized residuals.

The correlation coefficient Kendall's Tau-b and Spearman's-Rho are a measure of association between two variables and do not need normal distributed data, so they were calculated between all

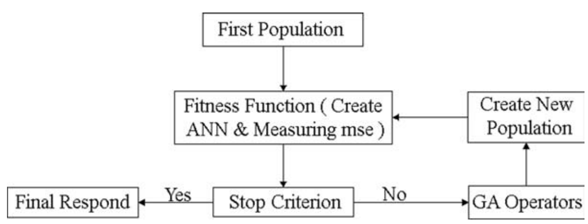

Figure 3 Plan of GA structure to optimize ANN.

TABLE III
Statistical Results (Line Slope in Linear Regression and Correlation Coefficients) to Determine Effective Parameters on C.I

Parameter	Regression coefficient (line slope)	Spearman's Rho	Kendall's Tau-b
FA	0.097	0.080	0.121
Water	0.553	0.313	0.441
Solid	−0.057	−0.072	−0.104
Basicity	0.355	0.211	0.311
Viscosity	0.05	0.014	0.031
Time state	0.45	0.275	0.393
Salt	−3.12	−0.189	−0.28

parameters and color index. If the obtained coefficient closes to -1 or 1, it means the correlation between two parameters is high, and when the coefficient is 0 or close to it, it means two parameters are independent. Table III shows the obtained results by statistical methods.

But, the kind of data is different about E and F. There are 8 and 7 levels of E and F, respectively, thus one way ANOVA was used to evaluate their influence instead of regression and it was observed that both E and F are effective on the color index. Tables IV and V show the ANOVA results. Regression coefficient, Kendall and spearman of viscosity are 0.05, 0.014, and 0.031, respectively, that are very close to 0. Also, the solid and FA coefficients are very close to 0.

From the obtained results, it can be found that the F.A, solid and viscosity have not any significant effect on the color index. But other parameters approximately have a good regression model and their correlation tests show that color index depends on them. Therefore, water, basicity, time state, salt, E and F were given in input layer of ANN and color index in the output layer. S+ software was used to calculate the statistical methods.

GA has some parameters, by controlling of which, it is possible to control GA and they must be determined before GA execution. There is no order to determine them like ANN layers. The stopping criteria of GA should be specified by several criteria like predetermined generation or execution time. In this study, GA stops when fitness function is lower than 0.001 or generation reaches the specified value. To study ANN and GA, Matlab7 software was used. GA was run many times for each reported case because it is a stochastic algorithm. The utilized system had these characteristics; processor (CPU): 64 × 2 dual core 3600 + 2GHz, RAM: 512MG and Hard Disk: 160GB and each running time was about 3.5 h. In optimizing GA parameters, each parameter was studied separately when the other parameters were considered constant; population size = 50, generation = 50, elitism number = 1, crossover rate = 0.5, mutation rate = 0.5, selection function was stochastic uniform.

TABLE IV
ANOVA- Color is Dependent Variable and E Temperature is Independent Variable

	Sum of Squares	df	Mean Square	F	Sig.
Between groups	15.273	9	1.909	4.652	0.000
Within groups	34.469	84	0.410		
Total	49.741	93			

TABLE V
ANOVA- Color is Dependent Variable and F Temperature is Independent Variable

	Sum of Squares	df	Mean Square	F	Sig.
Between groups	12.033	7	2.006	4.574	0.000
Within groups	37.708	86	0.438		
Total	49.741	93			

First, the initial population size was optimized; if it is greater, then the search space will be greater. So GA can search among more solutions, but, on the other hand, the number of calculations increases and takes more time for execution GA. Figure 4 shows the minimum and maximum fitness function values in each generation. So, the best and worst fitness values are the minimum and maximum in vertical lines, respectively, and the connected points show the mean fitness value in each generation. When mean and the best fitness function values are closing each other, it means all chromosomes or solutions are becoming similar to others or becoming one solution. The best fitness value improves until about generation 7 and after that it is approximately constant, but the mean value has different behaviors in each population size. Convergence occurs between mean and the best values in the last generations and the mean value is close to the best value, especially in generation 46, when population size is 30. But, when population size is more than 30 (50, 70, and 90), the mean is a little close to the best value and this occurs until 20th generation and then there is no more convergence and the mean is paralleled with the best value. Particularly when the population size is 90, mean has the most distance from the best value. Therefore, optimum population size is 30.

Next parameter is the number of generations. It was considered in four different values; 30, 50, 70, and 90. Like the population size, for large values of generation number, growth of the execution time is remarkable. Figure 5 indicates the effect of generation on GA results. The best results were obtained in generation number 30 and 50. When the number of generation is 70 or 90, there is no improvement in

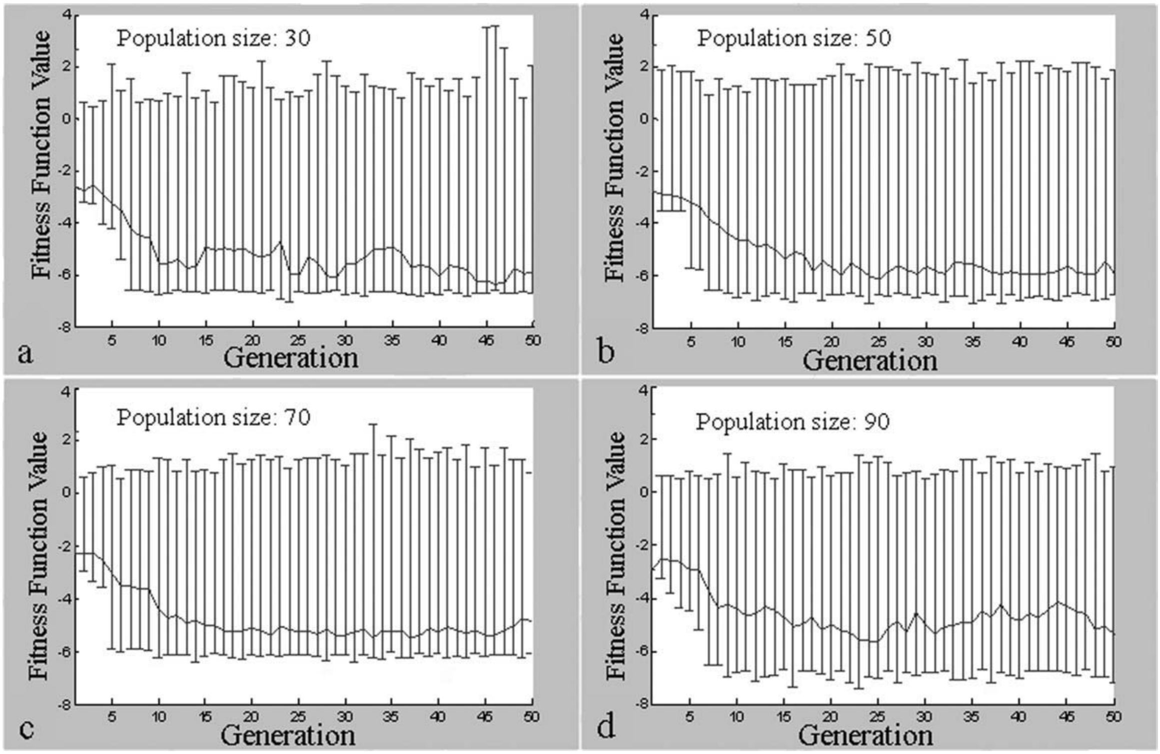

Figure 4 Influence of population size on the GA - Generation = 50, Elitism number = 1, Crossover-rate = 0.5, Mutation-rate = 0.5, Selection function is stochastic uniform.

the results. Thus, considering the time execution and convergence between the mean and best values, 30 can be selected for the optimum number of generation.

Figure 6 presents the obtained results for various crossover or mutation rates. If crossover rate is 1 or 0, there is no mutation or crossover, respectively, so the complete effect of them can be seen.

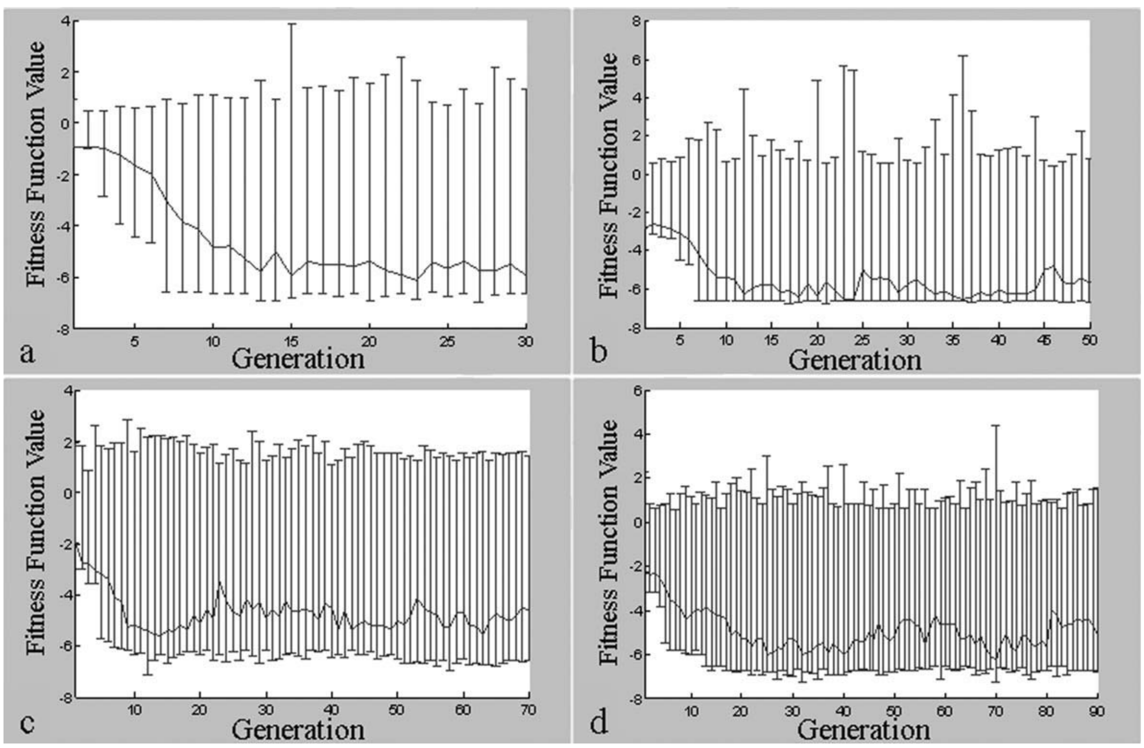

Figure 5 Influence of number of generation on the GA - Population Size = 30, Elitism number = 1, Crossover-rate = 0.5, Mutation-rate = 0.5, Selection function is stochastic uniform.

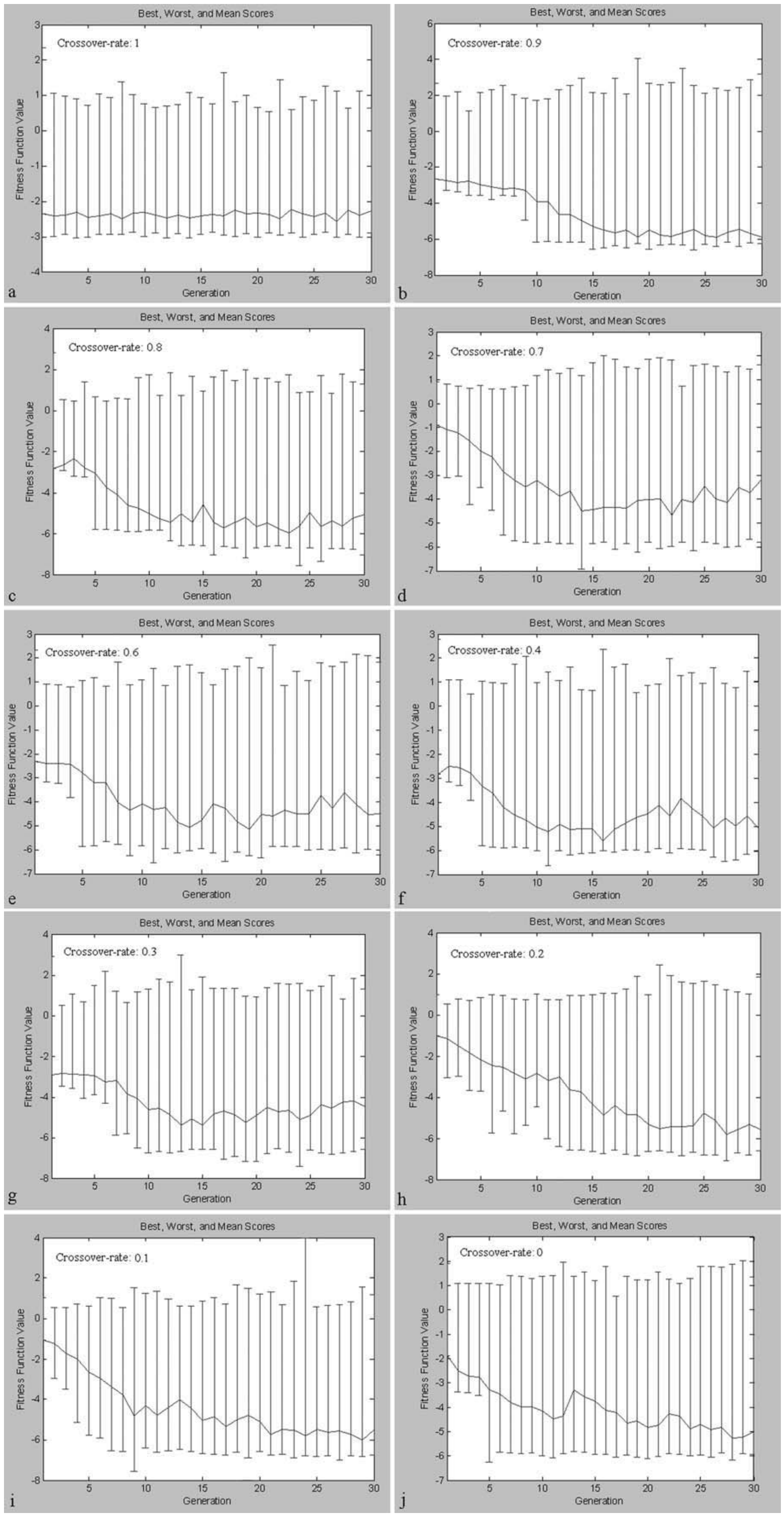

Figure 6 Influence of crossover or mutation rates on the GA - Population Size = 30, Generation = 30, Elitism number = 1, Selection function is stochastic uniform, Crossover-rate = *i*, Mutation-rate = 1-*i*, *i* = 0.1,0.2,. . .1. When the crossover rate is 0.5 the result is like Figure 5.a.

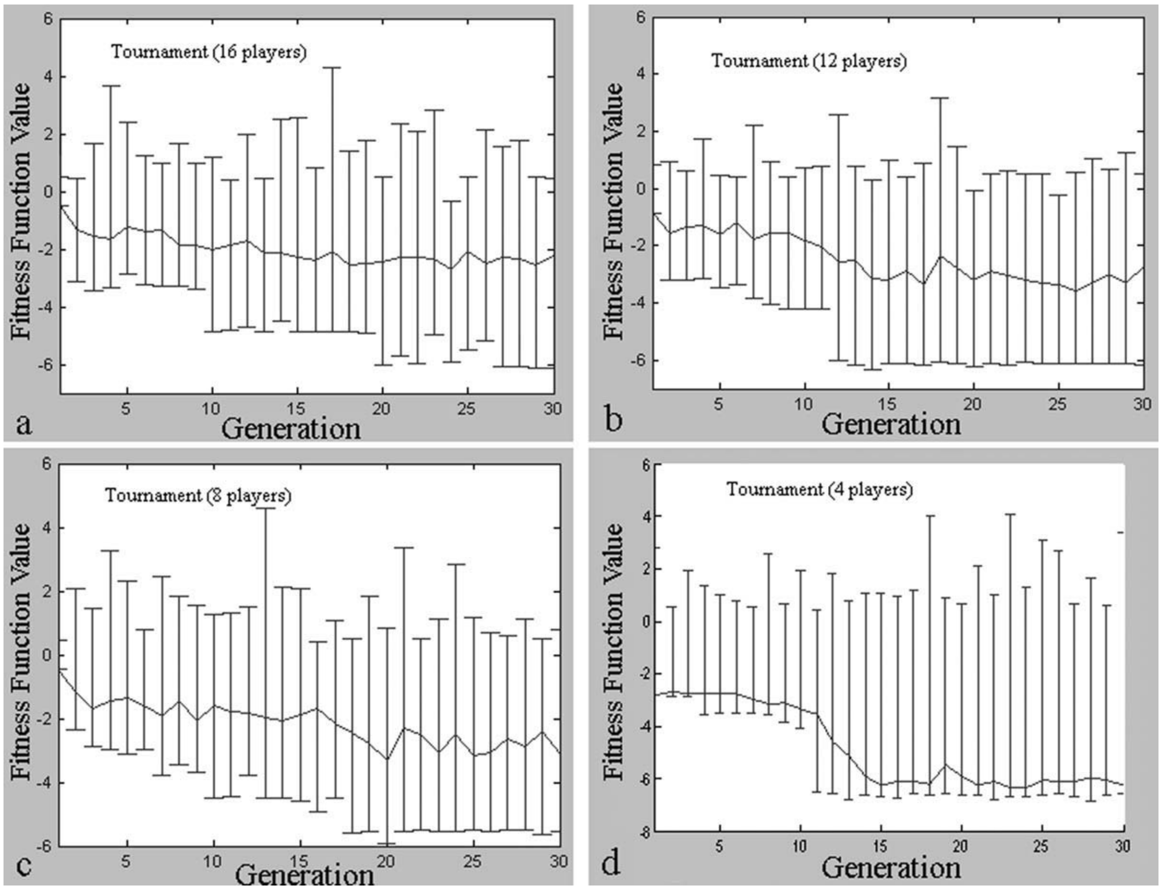

Figure 7 Influence of tournament size on the GA - Generation = 30, Elitism number = 1, Crossover-rate = 0.9, Mutation-rate = 0.1.

Figure 6(a) presents a set of GA when crossover rate is 1. It can be observed that the mean fitness function has small values in each generation, moreover the mean is parallel with the best fitness value from the first until the last generation. Therefore, mutation is necessary; otherwise, GA cannot work very well. There is no acceptable convergence when crossover rate is between 0.3-0.4 or 0.6-0.8, on the other hand, the mean fitness has a descending course from the first generation to the end and can close to the best fitness but not reach it in 0-0.2 and 0.5 of crossover rates. But, the most convergence is observed in crossover rate 0.9, and the mean fitness can reach almost the best value. Moreover, the best

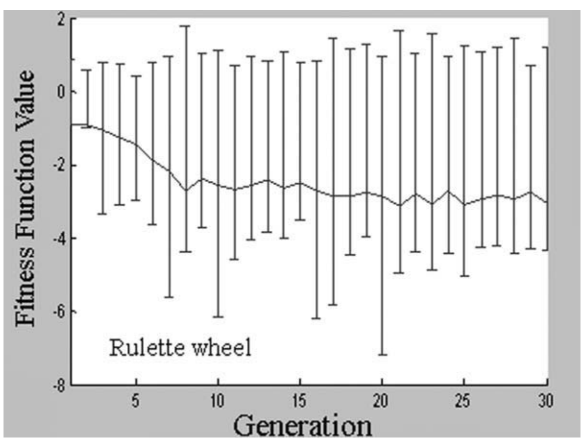

Figure 8 Influence of selection function roulette wheel on the GA - Generation = 30, Elitism number = 1, Crossover-rate = 0.9, Mutation-rate = 0.1.

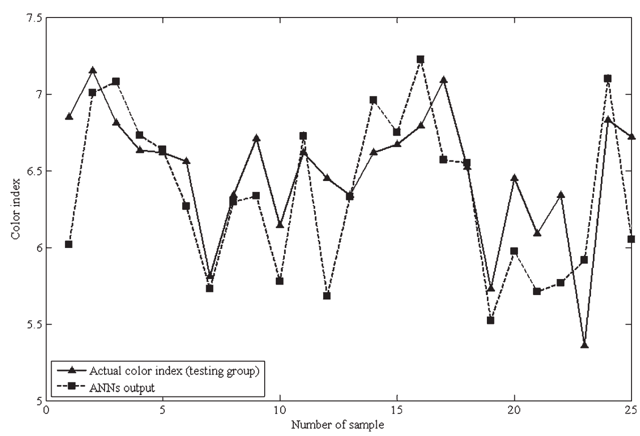

Figure 9 The ANNs outputs and testing group data (mse = 0.1571).

TABLE VI
Best Obtained Individual of GA by mse = 0.157

V.D	T.D	M.F	L.R	$N.N.H.L_1$	$N.N.H.L_2$	$N.N.H.L_3$	$N.N.H.L_4$	$N.N.H.L_5$	$N.N.H.L_6$	$A.F_1$	$A.F_2$	$A.F_3$	$A.F_4$	$A.F_5$	$A.F_6$	$A.F_7$
%0	%25	1	0.19	1	0	0	0.26	0	2.42	0	1.53	0.22	0	0	0	0

value is large (minimum mse). So, the best value of crossover rate or mutation is considered 0.9 or 0.1, respectively.

Another parameter is the type of selection. So far, stochastic uniform selection was used in GA, but in this study, two different kinds of selection were tested, too: roulette and tournament selections. Several tournament sizes were studied to compete (4, 8, 12, and 16) and the obtained results are shown in Figure 7. As can be seen, considering convergence between the best and mean value, the tournament with 4 players had the best result and the mean value has inconsiderable distance from the best value, which shows small mse.

Figure 8 exhibits the effect of roulette wheel selection functions on GA. It was observed that the best fitness value is variable in all generations and its mean is about -4 which has a lower accuracy than other selection methods. Although the worst fitness value in tournament is more variable than stochastic uniform selection, using each of them has produced similar results.

Eventually, the best chromosome or output in the end of GA running with the obtained optimum setting (population size = 30, generation = 30, elitism number = 1, crossover rate = 0.9, mutation rate = 0.1, selection function: stochastic uniform), or in other words, the optimum structure of ANN is shown in Table VI.

According to the Table VI, an ANN can predict the color index with high accuracy (mse = 0.157) when the ANN has two hidden layers; the first and second hidden layers had 1 and 2 neurons and V.D, T.D, M.F and L.R were 0%, 25%, 1 and 0.19, respectively. Figure 9 shows the ANN outputs and testing group for best design ANN.

This method can be used when the number of processing data is not much or extensive knowledge about the process is not available. Right now, this method is used as software in the Poly Acryl Iran Inc and can prevent from the manufacturing of undesired fibers.

CONCLUSIONS

This study introduces a new, simple and effective approach to optimize the quality of acrylic dry spinning, the complex and nonlinear system, based on the ANN and GA. First, the effective parameters were determined using statistical methods like linear regression, correlation coefficient and ANOVA. The ANN was used to design a model to predict the color index of the produced fibers and GA was applied to optimize the ANN topology and structural parameters. Information about the ANN such as V.D, T.D, L.R, M.F and A.F for each layer was coded into the chromosome using real value encoding. The designed ANN was trained based on the back propagation algorithm. For fitness function, first mse was calculated between ANNs output and the testing group data and then mse was inversed and multiplied by coefficient-1.

Many different values for GA parameters were tested to obtain the best result from GA such as population size, number of generation, crossover and mutation rates and various selection functions such as roulette wheel, tournament, and stochastic uniform. The obtained results showed that an ANN with two hidden layers has the highest accuracy when the first and second hidden layers had 1 and 2 neurons and V.D, T.D, M.F and L.R were 1, 2, 0 and 25%, 1 and 0.19, respectively.

References

1. Tian, Y.; Zhang, J.; Morris, J. Chem Eng Proc 2002, 41, 531.
2. Bajaj, P.; Sreekumar, T. V.; Sen K. J Appl Polym Sci 2002, 86, 773.
3. Masson, J. C. Acrylic Fiber Technology and Application; Marcel Dekker: NewYork, 1995.
4. Ziabacki, A. Fundamentals of Fibre Formation; Wiley: NewYork, 1976.
5. Giudici, R.; Nascimento, C. A. O.; Beiler, I. C.; Scherbakoff, N. J Appl Polym Sci 1998, 67, 1573.
6. DiRaddo, R. W.; Garcia-Rejon, A. Polym Eng Sci 1992, 32, 1401.
7. Seo, Y. J Appl Polym Sci 1990, 41, 25.
8. Tanoue, S.; Iemoto Y. Polym Eng Sci 1999, 39, 2172.
9. Rao, R. S.; Shambaugh R. L. Ind Eng Chem Res 1993, 32, 1300.
10. Chen, T.; Wang, X.; Huang, X. Text Res J 2005, 77, 76.
11. Sun, Q.; Zhang, D.; Chen, B.; Wadsworth, L.C. J Appl Polym Sci 1996, 62, 1605.
12. Chen, T.; Wang, X.; Huang, X. J Appl Polym Sci 2006, 101, 4275.
13. DiRaddo, R. W.; Garcia-Rejon, A. Polym Eng Sci 1993, 33, 653.
14. DiRaddo, R. W.; Garcia-Rejon, A. Adv Polym Technol 1993, 12, 3.
15. Huang, H. X.; Liao, C. M. Polym Test 2002, 21, 745.
16. Huang, H. X.; Liao, C. M. Polym Test 2003, 22, 509.
17. Huang, H. X.; Lu, S. J Appl Polym Sci 2005, 96, 2230.

18. Sette, S.; Bullart, L.; Van Langenhove, L. Control Eng Practice 1998, 6, 523.
19. Curteanu, S.; Leon, F. Int J Quantum Chem 2008, 108, 617.
20. Krose, B.; Smagt, P. An Introduction to Neural Networks, 8th ed.; The University of Amsterdam: Amesterdam, Netherland, 1996.
21. Fausett, L. Fundamental of Neural Networks, Prentice Hall International: New Jerssey, 1994.
22. Babu, B. V.; Angira, R. Comp Chem Eng 2006, 30, 989.
23. Demuth, H.; Beale, M.; Hagan, M. Matlab Neural Network Toolbox User's Guide Boca Raton 2007.
24. Chamber, L. Practical Handbook of Genetic Algorithms; CRC Press: Boca Raton, FL, USA, 1995.
25. Goldberg, D. E. Genetic Algorithms in Search, Optimization, and Machine Learning; Addison-Wesley Publishing: Boston, MA, USA, 1989.
26. Hassan, R.; Cohanim, B.; Weck, D. W. Am Inst Aeronautics Astronautics 2004, 1, 1–13.
27. Uysal, O.; Bulkan, S. Int J Computat Intelligence Res 2008, 4, 159.
28. Eberhart, R.; Simpson, P.; Dobbins, R.; Computational Intelligence PC Tools; Waite Group Press: San Diego, CA, USA, 1996.
29. Genetic Algorithm and Direct Search Toolbox User's Guide, The MathWorks, Inc 2007.