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ORIGINAL ARTICLE

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Parameter optimization in melt spinning by neural networks and genetic algorithms

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Abstract An approach for determining parameter values in melt spinning processes to yield optimal qualities of denier and tenacity in as-spun fibers is presented. The approach requires a fewer number of experiments than conventional methods. An orthogonal array in the Taguchi method determines the minimum number of experiment trials to be conducted. Whether the experimental data are adopted to train a neural network is justified by an analysis of variance(ANOVA) and confirmed by experiments. A neural network relating 11 process parameters and two quality characteristics is constructed. The genetic algorithm is aimed at finding parameter values in a continuous solution space to optimize a performance measure on denier and tenacity qualities, based on the neural network. The performance measure is evaluated by the technique for order preference by similarity to ideal solution (TOPSIS). To expand the solution space, three different sets of level values for the orthogonal array are chosen from the ranges where the melt spinning will properly work. The results demonstrate that the proposed approach gives the smaller denier and the larger tenacity of polypropylene(PP) as-spun fibers than the Taguchi method.

Keywords Denier · Genetic algorithm · Melt spinning · Neural networks · Taguchi method · Tenacity

1 Introduction

In melt spinning, the qualities of denier and tenacity in as-spun fibers play a critical role in final product quality. The denier and tenacity are mainly influenced by process parameters, such as the speed of an extruder screw, spinning temperature and take-up speed. In practice, the values of the process parameters are determined by engineer experience or trial and error to achieve good quality as-spun fibers. As a consequence, it is easy to suffer from subjective and inaccurate drawbacks, and excessive much time and effort is required. As a solution, this paper develops a decision-making system for parameter values in melt spinning to arrive at the optimal denier and tenacity of as-spun fibers.

Many papers have investigated process parameters that affect qualities of as-spun fibers in melt spinning. Wilczynski et al. [1] analyzed mixing degrees, throughput rates, temperature fluctuations, and viscoelastic properties by changing the screw speed and barrel temperature in an extruder-die section. Gupta et al. [2] described influence of the speed of a metering pump on throughput rates. Dutta et al. [3] used various materials, throughput rates, spinning temperatures, quench air speeds, quench air temperatures, and take-up speeds to yield different properties of as-spun fibers. Ziabicki [4] suggested that the process parameters acting on properties of as-spun fibers include the chemical compositions, molecular structures and physical behaviors of materials; spinning temperatures, dimensions and number of spinneret orifices; and throughput rates, take-up speeds, quench air temperatures, and lengths of spinning paths. Based on the above literature, this study focuses on 11 process parameters, such as speeds in an extruder screw, metering pump, quench air and take-up, temperatures in an extruder barrel, die, metering pump, spinning and quench air, etc., to evaluate the denier and tenacity of as-spun fibers in our melt spinning setup.

A Taguchi experimental design is often used to seek the values of process parameters that optimize a product quality in a much smaller number of experiments, and has been successfully applied in submerged arc welding [5], plasma enhanced chemical vapor deposition [6], rotational molding [7], coat hanger manifolds [8], and injection molding [9, 10]. However, the Taguchi method simply finds optimal values in a discrete solution space constrained by levels of parameters [11], and usually deals with a single quality characteristic. The genetic algorithm, together with a neural network, can be used to find optimal values in a continuous solution space. Hence, the parameter values are optimal in a more extensive solution space than the Taguchi method. In order to resolve multiple qualities problems, the technique for order preference by similarity to ideal solution (TOPSIS) gives a performance measure on the qualities to be op-

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timized. For example, Sette [12] employed a neural network and genetic algorithm for 2160 samples to optimize the yarn tenacity and elongation; and Su [11] used the Taguchi method to determine training samples for constructing a neural network, and then applied the genetic algorithm to optimize a single quality of injection molding.

To yield good qualities of denier and tenacity in polypropylene (PP) as-spun fibers, this paper investigates the choice of 11 parameter values in melt spinning, using the smallest number of experiments. The process parameters include temperatures in three extruder barrel sections, a die, a metering pump, and a spinneret, speeds of a extruder screw and a metering pump, cooled air temperature and speed, and take-up speed. We used a L_{12} orthogonal array in the Taguchi method to determine the minimum number of experiment trials when optimizing a quality characteristic. To find optimal parameter values in a continuous solution space, we constructed a neural network relating 11 process parameters and two quality characteristics, which is trained by the experimental data in the Taguchi method, and applied the genetic algorithm to optimize performance measures on denier and tenacity. The solution space is constrained by the level values in the Taguchi method. Thus, in order to expand the solution space, three different sets of level values are chosen from the ranges where melt spinning will properly work. By means of the analysis of variance (ANOVA) and confirmation experiments, whether or not the experimental data for each set of level values can be used to train the neural network is justified. The performance measure of denier and tenacity is evaluated by the TOPSIS. The results show that compared to the Taguchi method, the proposed approach can yield the smallest denier and the largest tenacity in PP as-spun fibers.

2 Methodology

2.1 Taguchi design of experiments [13]

A conventional experiment design, such as full factorial design, usually requires a large number of experiments to be conducted when there are many process parameters to be studied. Thus, the method is time-consuming and expensive. To overcome this drawback, the Taguchi method uses an appropriate orthogonal array to perform experimental design with a significant reduction in the number of experiments. The orthogonal array determines the minimum number of parameter-level combinations in experiments, which are a small fraction of that obtained in a full factorial design. The orthogonal array has levels arranged in columns and rows, representing the process parameters and individual trials, respectively. Each experiment trial is carried out based on parameter-levels in each row. Since two quality characteristics of denier and tenacity are investigated in this study, the experimental data of denier are transformed into signal-to-noise(S/N) ratios by the smaller-the-better characteristic:

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1}$$

and the experimental data of tenacity are by the larger-the-better characteristic:

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \tag{2}$$

where $y_i, i = 1, \ldots, n$, are experimental data and n is the number of tests. The larger S/N ratio corresponds to the better quality characteristic. The means of S/N ratios at the same level for each process parameter are tabulated in the response table. From the response table, the optimal level of the process parameter is the level with the highest S/N ratio.

Furthermore, an ANOVA is performed to determine process parameters which significantly affect the quality characteristic. In the F-test, we must calculate the sum of squares due to a factor, the sum of squares due to error, and the associated degrees of freedom. The F-test reveals that in the case of the F-ratio of a factor, a ratio of the variance due to a factor to the variance of the pooled error is greater than F_α means that a change of the factor has a significant effect on the quality characteristic at a confidence of 1-α. The value of F_α, based on the degrees of freedom of the factors and the pooled error, can be referred to as an F-distribution table. When the sum of squares due to error is equal to zero, we pool the factors with the smaller sums of squares into the error, and regard them as insignificant factors on the quality characteristic without the need of computing their F-ratios. The final step is to predict and experimentally verify the quality characteristic using optimal parameter-levels through confirmation experiments. A confirmation experiment ensures reproducibility of experimental results and prevents fault processes or inadequate experiment design from deteriorating final results. The predicted S/N ratio, $\hat{\eta}$, of the quality characteristic is calculated by [5]:

$$\hat{\eta} = \eta_m + \sum_{i=1}^{q} \left(\bar{\eta}_i - \eta_m\right) \tag{3}$$

where $\bar{\eta}_i$ is the mean S/N ratio at the optimal level, η_m is the mean of total S/N ratios, and q is the number of process parameters that significantly affect the quality characteristic. If the predicted and experimental S/N ratios are close to each other, it reveals that the experimental data possess good reproducibility and can become training samples of a neural network.

2.2 Back-Propagation neural network

A typical three-layer neural network has one input layer, one hidden layer, and one output layer. Each layer has various numbers of nodes. First of all, the data to the input layer are normalized between 0 and 1. The input data are then calculated forward to produce outputs of the hidden and output layers. The qth node in the hidden or output layer receives a net input, shown by:

$$net_q = \sum_i w_{iq} z_i - \theta_q \tag{4}$$

and produces an output $y_q = 1/(1+e^{-net_q})$, where w_{iq} is a connection weight between the ith node and qth node in the input-to-hidden or hidden-to-output layer, z_i is the output of the ith node in the preceding layer, and θ_q is the threshold of the qth node in the hidden or output layer. The initial weights and thresholds are randomly given. The errors between actual outputs and target outputs are propagated back through the network to update the weights and thresholds in a way of decreasing the sum of squared errors among total training samples and outputs by a gradient descent method. The recursive forms of the weight and threshold changes are given by:

$$\Delta w_{iq}^{(k+1)} = \eta \delta_q z_i + \alpha \Delta w_{iq}^{(k)} \tag{5}$$

$$\Delta \theta_q^{(k+1)} = -\eta \delta_q + \alpha \Delta \theta_q^{(k)} \tag{6}$$

where δ_q is the error signal of the qth node in the hidden or output layer [14], η is a learning rate, α is a momentum factor, and the superscript of $\Delta w_{iq}^{(k)}$ denotes the kth iteration.

2.3 Genetic algorithms [15]

The genetic algorithm is aimed at finding parameter values that maximize an objective function $J(q_1, q_2)$, while each parameter, x_i, $i = 1, 2, \ldots, 11$, is in the domain $[a_i, b_i]$, where J, defined by the TOPSIS, is a measure on the relative closeness of the alternative to the ideal solution. The denier and tenacity qualities, q_1 and q_2, are expressed by S/N ratios in evaluating J. q_i, $i = 1, 2$, and x_i, $i = 1, 2, \ldots, 11$, are related by a neural network. The largest value of J means the shortest distance of the alternative to the ideal solution.

The genetic algorithm starts with a set of random solutions in a population. Each individual in the population is a chromosome. A chromosome is a binary string, including binary representations of all parameter values. The search of an optimal solution to the problem is conducted over a space in a binary representation. We input parameter values of each chromosome to the network and output S/N ratios of denier and tenacity, q_{i1} and q_{i2}, $i = 1, \ldots, n$, to form a matrix, $Q = [q_{ij}]_{n\times 2}$, where n is a population size. The weighted normalized matrix, $V = [v_{ij}]_{n\times 2}$, is given as [6]:

$$v_{ij} = w_j q_{ij} \Bigg/ \sqrt{\sum_{i=1}^{n} q_{ij}^2} \tag{7}$$

where w_1 and w_2 are weights on denier and tenacity qualities, and $w_1 + w_2 = 1$. The separation measures of each chromosome from the ideal solution, S_i^+, and from the negative-ideal solution, S_i^-, are given by:

$$S_i^+ = \sqrt{\sum_{j=1}^{2} (v_{ij} - V_j^+)^2}\,, \quad S_i^- = \sqrt{\sum_{j=1}^{2} (v_{ij} - V_j^-)^2} \tag{8}$$

where $V_j^+ = \max v_{ij}$ and $V_j^- = \min v_{ij}$, $j = 1, 2$, are the ideal and negative-ideal solutions, respectively. The fitness value, which is the value of an objective function, is defined as:

$$J = \frac{S_i^-}{S_i^+ + S_i^-} \tag{9}$$

The chromosome with the largest relative closeness is the best choice.

The genetic operations, namely reproduction, crossover and mutation, create the next generation. A roulette wheel approach is adopted in the reproduction operation. It selects a single chromosome for a new population with respect to the probability distribution based on fitness values. The crossover and mutation rates, which determine the number of chromosomes to mate and the number of genes to mutate, respectively, are both between 0 and 1. The mutation occurs with a small probability. In the crossover operation, several pairs of chromosomes are randomly selected, and it generates the offspring by swapping the genes from the cut-point to the end of the chromosome for each pair. The mutation operation flips one of the bits of the chromosome string at a randomly selected location. The evolution of the population terminates after a preset number of generations.

3 Experiment and results

Our melt spinning setup is of laboratory scale and includes an extruder with screw diameter of 25 mm, a metering pump, a spinning pack, and a take-up device, which is schematically shown in Fig. 1. The spinneret has 20 holes, and each capillary hole is of diameter 0.5 mm and L/D ratio of 2. The outflow rate of a metering pump is 0.6 ml/s. The take-up device is located 250 cm down from the spinneret. We used a polypropylene (PP) material with a melt flow index of 25 g/10 min, a density of 0.9 g/cm^3, and an average molecular weight of 228 000 g/mol. The PP is melted in an extruder and discharged into a metering pump and spinning pack. Molten PP is extruded through a spinneret into a cooled air

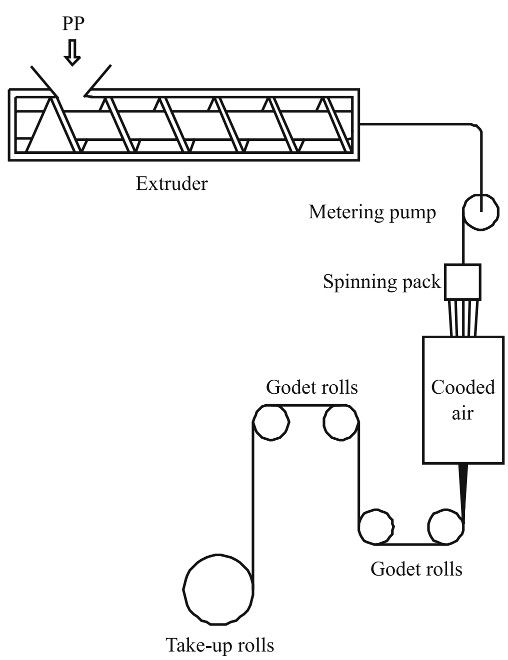

Fig. 1. Schematic representation of the melt spinning setup

stream. The solidified PP as-spun fiber is then wound on take-up rolls.

Depending on adjustable settings of the melt spinning setup, 11 process parameters to be investigated are temperatures in three extruder barrel sections (Factors A, B, and C), a die (Factor D), a metering pump (Factor E), a spinneret (Factor F), speeds of a extruder screw (Factor G), a metering pump (Factor H), cooled air temperature (Factor I), speed (Factor J), and take-up speed (Factor K). Factors A, B, C, D, E, F, and I are temperatures in °C. Factors G, H, and K are speeds in rpm. Factor J is the speed from scale one to scale seven. In order to reduce the number of experiments, we use a L_{12} orthogonal array, which can handle 11 two-level process parameters (as shown in Table 1) in the Taguchi method to plan experiments. In the L_{12} orthogonal array, only twelve trials are required to study entire discrete solution space. Each trial prepares five samples of PP as-spun fibers and their values of denier and tenacity are measured. To expand the solution space, we conducted three experiments with different sets of level values assigned to each process parameter, as given in Table 2. The level values are chosen for the ranges where the setup will properly work.

To measure the denier of PP as-spun fibers, we prepared three bundles of fibers, each having twenty 10-m long fibers, and weighed them with a sensitive electronic balance. The denier is estimated by the averaged weight of a PP as-spun fiber. The tenacity is measured by an Orientec Tensilon tester (RTA-1T) at an extension rate of 25 mm/min using a 25-mm long PP as-spun fiber.

To analyze experimental results, the values of denier and tenacity for each trial are first transformed into S/N ratios by Eq. 1 and by Eq. 2, respectively. For each of the three experiments, the means of SN ratios at the same level for each process parameter are computed to give the response table. The parameter and level with the largest response value in the response table yields the optimal parameter-levels for a quality characteristic. To demonstrate, for the denier quality in Table 3, the optimal parameter-levels are A2, B2, C2, D1, E2, F2, G1, H1, I2, J2, and K2 for experiment 1. A2 represents factor A, temperature in the first extruder barrel section, at level 2, B2 represents factor B, temperature in the second extruder barrel section, at level 2, etc. In Tables 3, 4, and 5, as a result, the optimal parameter-levels for each experiment and quality characteristic corresponds to the response values with "∗" marked in the subscript.

In the ANOVA, F-ratios for the factors are obtained in Table 6, and no values in the F-ratio column, marked by "—-", correspond to the factors with the smaller sums of squares. The F-test reveals that in experiment 1, for example, factors G and K significantly affect the denier quality at the 95% confidence level because their F-ratios are greater than $F_{0.05}$. The values of $F_{0.05}$

Table 1. L_{12} orthogonal array

Trial number	A	B	C	D	E	F	G	H	I	J	K
1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	1	2	2	2	2	2	2
3	1	1	2	2	2	1	1	1	2	2	2
4	1	2	1	2	2	1	2	2	1	1	2
5	1	2	2	1	2	2	1	2	1	2	1
6	1	2	2	2	1	2	2	1	2	1	1
7	2	1	2	2	1	1	2	2	1	2	1
8	2	1	2	1	2	2	2	1	1	1	2
9	2	1	1	2	2	2	1	2	2	1	1
10	2	2	2	1	1	1	1	2	2	1	2
11	2	2	1	2	1	2	1	1	1	2	2
12	2	2	1	1	2	1	2	1	2	2	1

Table 2. Two-level values of factors

Factor	Experiment 1		Experiment 2		Experiment 3	
	Level 1	Level 2	Level 1	Level 2	Level 1	Level 2
A	170	180	165	175	170	175
B	190	200	185	195	190	195
C	225	235	220	230	225	230
D	250	260	245	255	250	255
E	235	245	230	240	235	240
F	215	240	220	230	220	230
G	25	35	20	30	25	30
H	40	50	35	45	40	45
I	20	30	25	35	25	30
J	4	7	1	5	3	6
K	1000	3000	1700	2400	1700	2400

Table 3. Response table for experiment 1

Factor	Denier		Tenacity	
	Level 1	Level 2	Level 1	Level 2
A	−25.19	−24.34*	4.76	5.42*
B	−25.12	−24.41*	4.86	5.32*
C	−25.01	−24.52*	4.97	5.21*
D	−24.64*	−24.88	4.72	5.46*
E	−25.25	−24.27*	4.68	5.50*
F	−25.04	−24.49*	5.22*	4.96
G	−23.98*	−25.54	5.27*	4.91
H	−24.36*	−25.17	5.30*	4.88
I	−25.22	−24.30*	4.86	5.32*
J	−24.87	−24.65*	5.19*	4.99
K	−29.07	−20.46*	1.47	8.71*

Table 4. Response table for experiment 2

Factor	Denier		Tenacity	
	Level 1	Level 2	Level 1	Level 2
A	−22.37*	−22.60	5.01*	3.92
B	−22.71	−22.27*	4.04	4.88*
C	−22.56	−22.42*	4.49*	4.43
D	−22.35*	−22.63	4.89*	4.03
E	−22.56	−22.41*	4.64*	4.28
F	−22.63	−22.34*	4.48*	4.45
G	−21.51*	−23.47	5.20*	3.72
H	−21.99*	−22.99	4.53*	4.40
I	−22.57	−22.41*	4.63*	4.29
J	−22.51	−22.46*	4.05	4.88*
K	−24.08	−20.90*	3.50	5.42*

Table 5. Response table for experiment 3

Factor	Denier		Tenacity	
	Level 1	Level 2	Level 1	Level 2
A	−23.29	−23.16*	5.14*	4.68
B	−23.56	−22.88*	4.86	4.96*
C	−23.48	−22.97*	4.32	5.50*
D	−23.18*	−23.27	4.71	5.10*
E	−23.09*	−23.35	5.27*	4.54
F	−23.25	−23.19*	4.74	5.08*
G	−22.74*	−23.71	5.10*	4.71
H	−22.73*	−23.72	5.32*	4.50
I	−23.28	−23.17*	4.35	5.47*
J	−23.10*	−23.35	4.92*	4.89
K	−24.41	−22.04*	3.74	6.07*

Table 6. F-ratios in the ANOVA

Factor / $F_{0.05}$	Experiment 1		Experiment 2		Experiment 3	
	Denier	Tenacity	Denier	Tenacity	Denier	Tenacity
A	13.55	7.61	3.15	165.99*	16.92*	—
B	9.40	3.70	11.60*	97.52*	7.87	13.03
C	4.52	—	—	—	—	20.69*
D	—	9.70	4.50	104.58*	13.95*	1.92
E	18.16	11.78*	—	17.82*	—	—
F	5.65	—	5.02	—	6.03	3.30
G	45.84*	2.23	225.51*	308.05*	125.83*	53.95*
H	12.23	3.12	58.88*	—	29.35*	3.31
I	15.69	3.81	—	16.32*	3.99	16.93
J	—	—	—	95.68*	—	17.28
K	1387.96*	914.31*	600.90*	517.65*	531.28*	482.10*
$F_{0.05}$	18.51	10.31	7.71	10.31	10.31	18.51

are also listed in Table 6. Consequently, for three experiments, Table 6 indicates that factors corresponding to F-ratios with "$*$" in the subscript are significant factors on the denier and tenacity qualities. We then computed the predicted values of denier and tenacity, respectively, at optimal parameter-levels by Eq. 3 and compared them with experimental results through confirmation experiments. The predicted and experimental results, which are tabulated in Table 7, are in good agreement if the error between them is within ±5% of the predicted value [16]. Experiments 1 and 2 are in good agreement. However, experiment 3 with an error in the tenacity quality of greater than 5%, is not in good reproducibility and hence, we should not adopt its experimental data as training samples for a neural network.

The neural network is used to construct a model which relates 11 process parameters and two quality characteristics in S/N ratios. The input layer, which represents 11 process parameters, has 11 nodes. The output layer has two nodes, namely the output quality values of denier and tenacity. Nine nodes are chosen in the hidden layer. A total of twenty-four data, 12 data from experiment 1 and 12 data from experiment 2, are used to train the neural network. The learning rate $\eta = 1.0$ and the momentum factor $\alpha = 0.75$ are chosen. The initial weights in the input-to-hidden and hidden-to-output layers are randomly given between –0.3 and 0.3. The weights and thresholds update until the root mean squared error (RMSE) reaches 10^{-6} in 20 000 epoches.

We employed the genetic algorithm to search for optimal parameter values in a continuous solution space. The domains of 11 process parameters, x_i, $i = 1, 2, \ldots, 11$, are appropriately set as [165, 180], [185, 200], [220, 235], [245, 260], [230, 245], [215, 240], [20, 35], [35, 50], [20, 35], [1, 7], and [1000, 3000]. The required precision for each parameter is five places, so the total length of a chromosome is 238 bits. In the TOPSIS, the performance measure in the denier and tenacity has weights of 0.4376 and 0.5624, respectively [6]. In the genetic algorithm, we set the number of generations and the population size to be 1000 and 10, respectively. The crossover and mutation rates are 0.2 and 0.001, respectively. The genetic algorithm is repeatedly executed until the number of generations reaches 1000. As a result, optimal values of process parameters, x_i, $i = 1, 2, \ldots, 11$, are 170.6, 188.1, 235.0, 245.0, 245.0, 215.0, 27.3, 39.7, 24.5, 5.6, 2860.1. Therefore, optimal settings of the melt spinning setup are temperatures in the first extruder barrel section of 171 °C, the second section of 188 °C, the third section of 235 °C, a die of 245 °C,

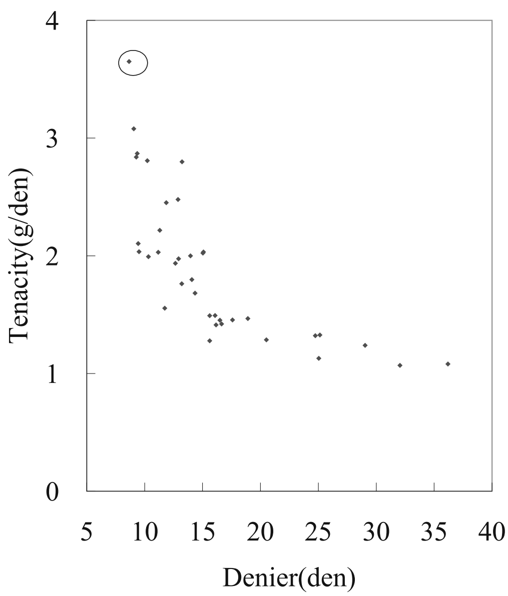

Fig. 2. Denier versus tenacity plane for experimental results

Table 7. Comparison of predicted and experimental denier and tenacity

Experiment number	Denier(S/N ratio)			Tenacity(S/N ratio)		
	Prediction	Experiment	Error(%)	Prediction	Experiment	Error(%)
1	−19.11	−19.68	2.88	9.04	9.12	0.86
2	−19.48	−19.21	1.43	8.05	8.32	3.23
3	−21.04	−20.25	3.88	6.73	7.43	9.42

a metering pump of 245 °C, a spinneret of 215 °C, and cooled air of 24.5 °C. The speed of a extruder screw was 27.3 rpm, a metering pump was 39.7 rpm, cooled air was scale 6, and take-up roll was 2860 rpm. At these settings, the experiment results are 8.43, 8.10, and 8.64 den for the denier and 4.11, 3.97, 3.74, 4.12, and 3.46 g/den for the tenacity, yielding a mean denier of 8.39 den and a mean tenacity of 3.85 g/den. The denier and tenacity of PP as-spun fibers produced at parameter-levels in the Taguchi method and at optimal parameter conditions by the genetic algorithm are plotted in the denier-tenacity plane. Figure 2 shows that parameter conditions decided by the genetic algorithm result in the smallest denier and the largest tenacity, which is indicated by an encircled mark in the denier-tenacity plane.

4 Conclusions

In melt spinning, good qualities of denier and tenacity in as-spun fibers are essential to final quality products. However, the setting of process parameters to achieve good qualities often consumes much time and effort. This paper provides a systematic approach, which is the application of the Taguchi method, neural network, and genetic algorithm, to deal with the choice of parameter values for the optimal denier and tenacity in PP as-spun fibers. The experimental layout in the Taguchi method provides training samples of a neural network. Hence, only a few of experiments are needed to construct the neural network. Since the solution space is constrained by the level values in the orthogonal array, three different sets of level values are used to expand the solution space. The results show that the proposed approach can yield better qualities of denier and tenacity in PP as-spun fibers than the Taguchi method.

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