Optimizing Multiple Qualities in As-Spun Polypropylene Yarn by Neural Networks and Genetic Algorithms

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ABSTRACT: This investigation considers a quantitative procedure for determining the values of critical process parameters in melt spinning to optimize the qualities of denier, tenacity, breaking elongation, and denier variance in as-spun polypropylene yarn. An orthogonal array in the Taguchi method defines the minimum set of parameter-level combinations that are experimentally tested. The significant process parameters, namely the third extruder barrel temperature, spinning temperature, metering pump speed, and take-up velocity, are identified on the basis of the analysis of variance and *F* test. After a confirmation experiment is conducted to ensure the reproducibility of the experimental results, the back-propagation neural network establishes a continuous system linking 10 process parameters and four qualities. The technique for order preference by similarity to an ideal solution can be used to obtain a performance measure for assessing multiple qualities. The genetic algorithm attempts to find parameter values for optimizing the quality performance, including the denier, tenacity, breaking elongation, and denier variance. Finally, the experimental results demonstrate that the smallest denier, largest tenacity, smallest breaking elongation, and second smallest denier variance of as-spun polypropylene yarn can be achieved with the proposed approach in melt spinning. © 2006 Wiley Periodicals, Inc. J Appl Polym Sci 100: 2532–2541, 2006

Key words: networks; poly(propylene) (PP)

INTRODUCTION

The qualities of as-spun yarn, including the denier, tenacity, breaking elongation, and denier variance, are influenced primarily by the process parameters in melt spinning.[1] These qualities determine the successive textile operations and the properties of the end products, such as the hand, stability, and fatigue.[2] Quantitative relationships between the qualities and process parameters enable the control and optimization of product quality, improve new product development, and process trouble shooting. The explicit relationships cannot directly be formulated and usually neglect numerous process parameters and narrow the valid range. Additionally, engineers typically use trial and error and personal experience to determine the values of process parameters for the optimum qualities. Most of those techniques require considerable time and effort to learn and can cause subjective and inaccurate issues. Therefore, this study adopts the Taguchi method, neural networks, the technique for order preference by similarity to an ideal solution (TOPSIS), and the genetic algorithm to construct a parameter optimization system that simultaneously evaluates the four qualities of as-spun polypropylene (PP) yarn, as shown in Figure 1. The proposed approach provides a performance measure for denier, tenacity, breaking elongation and denier variance and can seek the values of 10 process parameters for performance optimization.

Quantitative correlations between factors, including elongational flow, molecular orientation, rheological properties, and crystallization, govern the melt-spinning process, and mathematical simulation has been performed to forecast the mechanical properties and structure of as-spun yarn.[3] Covas et al.[4] selected the screw rotation speed and three barrel temperature profiles on the basis of the genetic algorithm to evaluate the extrusion output, length of the screw required for melting, melt temperature, and power consumption in single-screw extrusion. Wilczynski[5] analyzed the mixing degrees, throughput rates, temperature fluctuations, and viscoelastic properties by changing the screw speed and barrel temperatures in an extruder-die section. Gupta et al.[6] used the take-up speed and throughput rate to boost productivity and discussed the fiber structure and properties of as-spun yarn for polyester, nylon, and PP. They described the influence of the speed of a metering pump on the throughput rates. Hence, the throughput rate is changed by the temperatures of the extruder, die, metering pump, and spinneret as well as the speeds of

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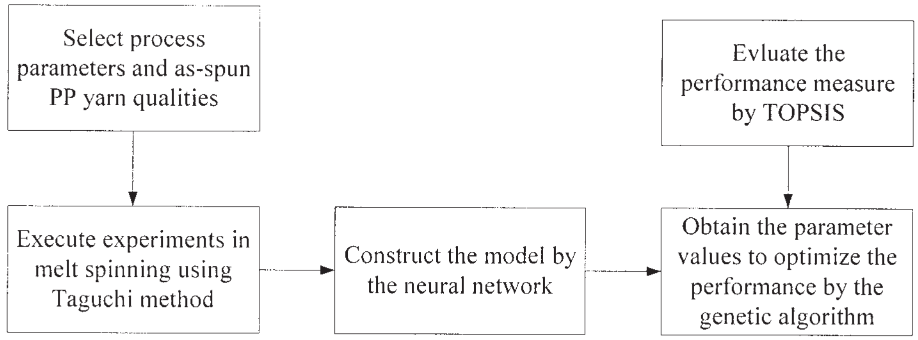

Figure 1 Flow chart of the parameter optimization system in melt spinning.

the metering pump and screw extrusion in melt spinning. Ziabicki[7] reported that primary process parameters used to influence qualities involve the properties of materials, spinning temperatures, dimensions and number of spinneret orifices, throughput rate, spinning path length, take-up velocity, cooling conditions, and so on. The cooling conditions involve the speed and temperature of cooling air. Moreover, the extrusion temperature, melt intrinsic viscosity, feed rate, and take-up velocity influence polyester fiber orientation.[1] Dutta and Nadkarni[8] used various materials, throughput rates, spinning temperatures, quench air speeds, quench air temperatures, and take-up velocities to yield different properties of as-spun yarns. Moreover, the formation speed is the formation condition of as-spun yarn in practical melt spinning. In this study, therefore, we selected 10 process parameters, including the speed and temperature of a metering pump, three section extruder barrel temperatures, the die temperature, the spinning temperature, the formation speed, the take-up speed, and the cooling air speed, because these parameters were adjustable in our melt-spinning setup. The screw speed was related to the metering pump speed, so the pressure with the pump was about 70 kgf/cm^2.

Taguchi tabulated 18 orthogonal arrays (OAs) that define the minimum set of parameter-level combinations tested in an experiment. The Taguchi method uses the signal-to-noise (SN) ratio, response table, and analysis of variance (ANOVA) for product quality optimization and has been successfully applied in numerous different manufacturing systems. The cylindrical lapping process is performed with an L_8 OA in experiments, and the effective variables and interaction effects are identified with the ANOVA.[9] Lau and Chang[10] employed the analysis of the mean and ANOVA to select the most important factors for wafer bumping with stencil printing and then used the L_4 OA for determining the other material and process factors. Moreover, Jaisingh et al.[11] used the SHEET-S program for designing bell-shaped components of various sizes based on an L_9 OA, with control factors including the strain-hardening exponent, plastic strain ratio, friction coefficient, and five blank holder forces in deep drawing processes. However, a confirmation experiment is extremely important to verify the reproducibility of the experiment, and it can be satisfactorily applied in the turning operations[12] and face-milling process.[13,14]

Generally, the Taguchi method suffers some practical limitations.[15] The feasible solution space is constrained by parameter-level values. The Taguchi method is only for the optimization of a single quality characteristic and cannot handle interactions among parameters. Thus, approaches to overcome these drawbacks must be sought. Davim and Reis[16] demonstrated that the relationships between the cutting conditions and cutting characteristics of turning metal matrix composites can be obtained through multiple linear regression with an L_{27} OA and ANOVA. Accordingly, a new method combines the Taguchi method with neural networks for a continuous system that is capable of efficiently showing the relationships between qualities and process parameters.[17,18] The genetic algorithm can simultaneously evaluate numerous peaks to seek the globally optimum value of each variable. Su and Chiang[19] used the back-propagation neural network (BPNN) and genetic algorithm to optimize the integrated circuit (IC) wire bonding processes, and the result is better than the Taguchi method according to the process capabilities. Su et al.[15] integrated this approach with the Taguchi method for optimizing a single injection-molding quality and effectively handled the interactions among the parameters. Yu et al.[20] applied the integrated approach to optimize extrusion blow-molding processes, and the fitness function was used by fuzzy rules to enhance search efficiency in genetic algorithms. Hsu et al.[21] presented a novel approach using the neural network, exponential desirability function, and genetic algorithm that is better than the traditional Taguchi method for optimizing multiple optical performance in the broadband tap coupler.

Principally, the specifications of as-spun yarn qualities are denier and tenacity. PP yarns are produced in a variety of types with different deniers and tenacities designed to suit various market requirements. Denier is the weight, fineness, and appearance of final products. Tenacity is a measure of how strong the yarn is. Moreover, breaking elongation is generally the measured percentage of deformation in the direction of the load and controls the processability of subsequent textile processes. The stability in manufacturing affects the denier variance, which indicates the uniformity of as-spun PP yarns. In this study, we consider 10 process parameters to generate as-spun PP yarn with good qualities of denier, tenacity, breaking elongation, and denier variance. Thus, we attempt to optimize a quality performance of denier, tenacity, breaking elongation, and denier variance. The optimization of the quality performance indicates that the four qualities are good simultaneously. Therefore, a multi-input, multi-output system is a good choice to achieve the goal. In such a way, the consequence that some qualities are good and the other qualities do not meet our needs, which is often the case if a single quality is to be optimized, can be avoided.

This study uses TOPSIS[22] to create a performance measure for the qualities of denier, tenacity, breaking elongation, and denier variance, and the genetic algorithm examines the values of process parameters to optimize the measure on the basis of the neural network relating 10 process parameters and four qualities. The optimized performance measure gives the smallest denier, largest tenacity, smallest breaking elongation, and second smallest denier variance for ensuring the optimum product, and these are compared with those determined by the Taguchi method.

EXPERIMENTAL

Taguchi design of the experiments[23,24]

The Taguchi method systemically adopts a special OA design to study the entire parameter space with a small number of experiments. The OA is a matrix arranged in columns and rows. Each column represents a process parameter as a control factor. Meanwhile, each row denotes a parameter-level combination as the state of a control factor. Each experimental trial is carried out on the basis of its parameter-level combination in each row. Because the denier, breaking elongation, and denier variance qualities of as-spun yarn are conducted for minimization, the smaller-the-better characteristic can be used for the quality analysis:

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

For the tenacity quality, the larger-the-better characteristic can be used for maximization:

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

where n is the number of repetition data in each trial and y_i is the ith measured quality. Larger SN ratios indicate better quality characteristics.

The means of SN ratios at the same level for all the process parameters are computed to give the response table. The optimum parameter-level combination is then selected on the basis of the highest response value in the response table. Moreover, the predicted SN ratio ($\hat{\eta}$) at the optimum parameter-level combination can be calculated as follows:

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

where $\bar{\boldsymbol{\eta}}_i$ is the mean response, η_m represents the mean of the total SN ratios, and p is the number of significant factors identified via ANOVA and F tests.

Finally, a confirmation experiment is performed to verify the reproducibility of the experiment on the basis of the confidence interval $[-\beta, \beta]$. β is computed as follows:

$$\beta = \sqrt{F_{\alpha,1,v_2} V_e \left[\frac{1 + \sum_{i=1}^{p} dof_i}{N_d} + \frac{1}{r}\right]} \tag{4}$$

where $F_{\alpha,1,v_2}$ represents the F ratio, α denotes the risk, v_2 is the number of degrees of freedom associated with the pooled error variance (V_e) of the experiment, N_d is the trial number of OA, dof_i is the degree of freedom associated with significant factors, and r is the sample size for the confirmation experiment ($r \neq 0$). Once the error between the predicted and experimental SN ratios is within the confidence interval, the experiment is demonstrated to be reproducible. By then, the experimental data are adopted as training samples for a neural network.

BPNN[25]

BPNN is the most popular and widely used way to describe complex relationships between the inputs and outputs. A typical BPNN comprises an input layer, one or more hidden layers, and an output layer. The training data are collected for developing a BPNN model. Additionally, the data sets display a wide distribution and must be pretreated by normalization.

The input layer uses the input data to produce its own outputs and passes these outputs to the next layer. Each node in the hidden and output layer calculates an activation value by summing the weighted inputs. The sum is then used by a sigmoid function to give the output value of each node. Forward calculation is performed for the next layer until the output layer of the network is reached. The outputs generated by the network then are compared to the target values. The error is propagated back through a gradient-descent learning algorithm to update the weights and thresholds. The adjustments of the weights ($\Delta w_{ij}^{(k)}$) and thresholds ($\Delta\theta_i^{(k)}$) at iteration k are given as

$$\Delta w_{ij}^{(k)} = \eta\delta_i z_j + \alpha\Delta w_{ij}^{(k-1)} \tag{5}$$

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

where η is a learning rate, δ_i represents the error signal of the ith node in the hidden or output layer, z_j denotes the output of the jth node in the preceding layer, and α is a momentum factor. The iteration continues until the calculated outputs reach the required precision in relation to the target outputs. Finally, the following root-mean-square error (RMSE) can be used to measure the mean difference between the predicted and target outputs for the training patterns:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N_d}\sum_{j=1}^{N_q}(SN_{ij} - Y_{ij})^2}{N_d N_q}} \tag{7}$$

where N_q is the number of output nodes representing the denier, tenacity, breaking elongation, and denier variance qualities, so $N_q = 4$. SN_{ij} and Y_{ij} represent the target and predicted outputs of the jth node for the ith trial data, respectively.

Genetic algorithms[26]

The genetic algorithm attempts to find the optimum values of process parameters on the basis of the feasible solution space. This study presents the feasible solutions, known as the population, with numerous chromosomes. A chromosome is a binary bit string that represents a sequence of all parameter values, and the individual site is called a gene. The total chromosome length is determined on the basis of the required precision of each parameter. Notably, the initial population of the feasible solutions is randomly generated within the process parameter domains. This study inputs the parameter values of each chromosome to the network and outputs SN ratios of the denier, tenacity, breaking elongation, and denier variance (Y_{i1}, Y_{i2}, Y_{i3}, and Y_{i4}, $i = 1,2, \ldots, n$, respectively). The TOPSIS procedure involves six steps for estimating a performance measure based on minimizing the distance from the ideal solution and maximizing the distance from the negative-ideal solution:[22]

1. The normalized matrix, $R = [r_{ij}]_{n\times N_q}$, where n is a population size, is calculated:

$$r_{ij} = \frac{Y_{ij}}{\sqrt{\sum_{i=1}^{n} Y_{ij}^2}} \tag{8}$$

2. The weighted normalized matrix, $V = [v_{ij}]_{n\times N_q}$, is calculated:

$$v_{ij} = w_j r_{ij} \tag{9}$$

where w_j denotes the weight of the jth quality and $\sum_{j=1}^{N_q} w_j = 1$.

3. The ideal (A^+) and negative-ideal (A^-) solutions are determined by

$$A^+ = \{(\max v_{ij} | j = 1,2,\cdots,N_q) | i = 1,2,\cdots,n\} = \{V_1^+, V_2^+, \cdots, V_j^+, \cdots, V_{N_q}^+\} \tag{10}$$

$$A^- = \{(\min v_{ij} | j = 1,2,\cdots,N_q) | i = 1,2,\cdots,n\} = \{V_1^-, V_2^-, \cdots, V_j^-, \cdots, V_{N_q}^-\} \tag{11}$$

where V_j^+ and V_j^- represent the ideal and negative-ideal solutions, respectively.

4. The separation measures of each chromosome from the ideal solutions (S_i^+) and from the negative-ideal solutions (S_i^-) are obtained by

$$S_i^+ = \sqrt{\sum_{j=1}^{N_q}(v_{ij} - V_j^+)^2} \quad \text{and} \quad S_i^- = \sqrt{\sum_{j=1}^{N_q}(v_{ij} - V_j^-)^2} \tag{12}$$

5. The fitness function can be used to measure the relative closeness of the alternative to the ideal solution and is defined as

$$J = \frac{S_i^-}{S_i^+ + S_i^-} \tag{13}$$

6. The alternative with the largest relative closeness is selected as the optimum choice.

The genetic operations, including the reproduction, crossover, and mutation, create the new generations, which are called offspring. Several pairs of chromosomes are randomly determined on the basis of the crossover rate from the mating pool and simultaneously generate a random cut point within the chromosome length. Each selected pair swaps relative genes between the cut point and the end of the chromosomes to complete the crossover operation. The number of mutated genes is determined by the mutation rate. The mutation operation flips one of the bits of the chromosome string at a randomly selected location. The offspring process continues until a desirable solution is obtained or a predetermined generation size is reached. The maximum value of J indicates the shortest distance between the alternative and ideal solutions, enabling the optimum chromosome to be obtained.

TABLE I
L_{50} Orthogonal Array

No.	Factor											
			A	B	C	D	E	F	G	H	I	J
1	1	1	1	1	1	1	1	1	1	1	1	1
2	1	1	2	2	2	2	2	2	2	2	2	2
3	1	1	3	3	3	3	3	3	3	3	3	3
4	1	1	4	4	4	4	4	4	4	4	4	4
5	1	1	5	5	5	5	5	5	5	5	5	5
6	1	2	1	2	3	4	5	1	2	3	4	5
7	1	2	2	3	4	5	1	2	3	4	5	1
8	1	2	3	4	5	1	2	3	4	5	1	2
9	1	2	4	5	1	2	3	4	5	1	2	3
10	1	2	5	1	2	3	4	5	1	2	3	4
11	1	3	1	3	5	2	4	4	1	3	5	2
12	1	3	2	4	1	3	5	5	2	4	1	3
13	1	3	3	5	2	4	1	1	3	5	2	4
14	1	3	4	1	3	5	2	2	4	1	3	5
15	1	3	5	2	4	1	3	3	5	2	4	1
16	1	4	1	4	2	5	3	5	3	1	4	2
17	1	4	2	5	3	1	4	1	4	2	5	3
18	1	4	3	1	4	2	5	2	5	3	1	4
19	1	4	4	2	5	3	1	3	1	4	2	5
20	1	4	5	3	1	4	2	4	2	5	3	1
21	1	5	1	5	4	3	2	4	3	2	1	5
22	1	5	2	1	5	4	3	5	4	3	2	1
23	1	5	3	2	1	5	4	1	5	4	3	2
24	1	5	4	3	2	1	5	2	1	5	4	3
25	1	5	5	4	3	2	1	3	2	1	5	4
26	2	1	1	1	4	5	4	3	2	5	2	3
27	2	1	2	2	5	1	5	4	3	1	3	4
28	2	1	3	3	1	2	1	5	4	2	4	5
29	2	1	4	4	2	3	2	1	5	3	5	1
30	2	1	5	5	3	4	3	2	1	4	1	2
31	2	2	1	2	1	3	3	2	4	5	5	4
32	2	2	2	3	2	4	4	3	5	1	1	5
33	2	2	3	4	3	5	5	4	1	2	2	1
34	2	2	4	5	4	1	1	5	2	3	3	2
35	2	2	5	1	5	2	2	1	3	4	4	3
36	2	3	1	3	3	1	2	5	5	4	2	4
37	2	3	2	4	4	2	3	1	1	5	3	5
38	2	3	3	5	5	3	4	2	2	1	4	1
39	2	3	4	1	1	4	5	3	3	2	5	2
40	2	3	5	2	2	5	1	4	4	3	1	3
41	2	4	1	4	5	4	1	2	5	2	3	3
42	2	4	2	5	1	5	2	3	1	3	4	4
43	2	4	3	1	2	1	3	4	2	4	5	5
44	2	4	4	2	3	2	4	5	3	5	1	1
45	2	4	5	3	4	3	5	1	4	1	2	2
46	2	5	1	5	2	2	5	3	4	4	3	1
47	2	5	2	1	3	3	1	4	5	5	4	2
48	2	5	3	2	4	4	2	5	1	1	5	3
49	2	5	4	3	5	5	3	1	2	2	1	4
50	2	5	5	4	1	1	4	2	3	3	2	5

TABLE II
Level Values of the Process Parameters

Level	Factor									
	A	B	C	D	E	F	G	H	I	J
1	1	210	220	230	240	240	230	15	25	1000
2	3	215	225	235	245	245	235	25	50	1250
3	5	220	230	240	250	250	240	35	75	1500
4	7	225	235	245	255	255	245	45	100	1750
5	9	230	240	250	260	260	250	55	125	2000

RESULTS AND DISCUSSION

This study used a melt-spinning setup (Shinko Machinery Co., Osaka, Japan) to manufacture the as-spun PP yarn. 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 was used for the experiments. The PP chips did not need to dry before the spinning operations and were fed into an extruder via a hopper. The extruder was a single-screw type with a diameter of 25 mm. PP was melted in the extruder and discharged into a metering pump, which metered the flow of the molten polymer to the spinning pack. The outflow rate of the metering pump was 0.6 mL/rev. The spinneret was a metal plate containing 20 holes, each with a capillary diameter of 0.5 mm and an aspect ratio of 4. The molten polymer was extruded via a spinneret into a quenching air stream blowing

TABLE III
Response Table for Denier

Factor	Level 1	Level 2	Level 3	Level 4	Level 5
A	−40.84[a]	−40.94	−40.94	−40.89	−40.84[a]
B	−40.78[a]	−40.97	−40.97	−40.83	−40.91
C	−40.91	−40.90	−40.95	−40.80[a]	−40.90
D	−40.96	−40.89	−40.95	−40.91	−40.75[a]
E	−40.95	−40.96	−40.89	−40.77[a]	−40.88
F	−40.88	−40.90	−40.78*	−40.95	−40.95
G	−40.97	−40.82[a]	−40.92	−40.89	−40.86
H	−34.77[a]	−38.90	−41.69	−43.73	−45.37
I	−40.94	−40.83[a]	−40.92	−40.91	−40.86
J	−44.02	−42.14	−40.50	−39.40	−38.40[a]

[a] Highest response value, which was used to determine optimum parameter-level settings.

TABLE IV
Response Table for Tenacity

Factor	Level 1	Level 2	Level 3	Level 4	Level 5
A	6.82	6.44	6.84	6.92[a]	6.89
B	7.03[a]	6.61	6.66	6.73	6.86
C	6.97[a]	6.92	6.76	6.87	6.39
D	6.63	6.59	6.65	7.06[a]	6.97
E	6.64	6.76	6.82	6.96[a]	6.73
F	6.86	6.66	6.94[a]	6.70	6.75
G	6.54	7.02[a]	6.91	6.63	6.81
H	9.44[a]	7.37	6.09	5.62	5.38
I	6.87[a]	6.86	6.65	6.71	6.81
J	3.89	5.72	7.21	7.99	9.11[a]

[a] Highest response value, which was used to determine optimum parameter-level settings.

TABLE VI
Response Table for Denier Variance

Factor	Level 1	Level 2	Level 3	Level 4	Level 5
A	−15.37	−11.40	−9.87[a]	−11.59	−10.99
B	−10.10[a]	−14.84	−11.03	−11.91	−11.35
C	−12.72	−10.31[a]	−11.92	−11.46	−12.82
D	−12.03	−12.56	−15.22	−11.02	−8.41[a]
E	−10.86	−11.01	−14.59	−12.47	−10.29[a]
F	−10.74[a]	−11.24	−13.23	−12.21	−11.81
G	−14.51	−13.93	−7.79[a]	−11.82	−11.18
H	−8.14[a]	−10.68	−12.11	−13.80	−14.51
I	−11.65	−13.95	−11.68	−9.25[a]	−12.70
J	−8.68[a]	−12.38	−14.06	−11.15	−12.96

[a] Highest response value, which was used to determine optimum parameter-level settings.

across the spin line. The take-up device was located 250 cm below the spinneret. The solidified filament was then wound on a take-up roll at a speed significantly faster than the extrusion velocity.

The process parameters included the cooling air speed (factor A), three section extruder barrel temperatures (factors B–D), the die temperature (factor E), the metering pump temperature (factor F), the spinning temperature (factor G), the metering pump speed (factor H), the formation speed (factor I), and the take-up velocity (factor J). Factor A was the speed from scale one to scale nine. Furthermore, factors B–G denoted the temperatures (°C). Factors H and I were the speeds (rpm). Factor J was the velocity (m/min). Because a 5-level factor has four degrees of freedom, 10 5-level factors require 40 degrees of freedom. Generally, the experimenter should seek the smallest OA with at least 40 degrees of freedom. This study used an L_{50} OA with 12 columns and 50 rows, as illustrated in Table I. This array had 49 degrees of freedom and could handle a 2-level factor and 11 5-level factors. This array thus represented a good choice for this experiment. Each factor was assigned to a column in Table I, and only 50 experimental trials were required to investigate the entire parameter space. Although the temperature parameters were dependent, they could be set independently in our setup; thus, we regarded them as independent factors and planned them in the L_{50} OA.

In the Taguchi method, the ranges of the process parameters are generally selected so that the as-spun PP yarn can be successfully formed. In the literature, the level values are usually defined by the equidistance within the feasible space to execute experiment design. Thus, we selected the level values on the basis of the equal partition of the ranges. The operation temperature for PP in practical melt spinning generally ranges from 210 to 260°C. Because the temperature parameters are dependent, the neighboring temperatures will interact, and thus their difference should not be large. The different ranges for the temperature parameters were set. The lower limit of the range increased from 210 to 240°C for the extruder to the die section and decreased from 240 to 230°C for the metering pump to the spinneret section. Each temperature parameter had a range of 20°C, and thus we had a span of 5°C between the neighboring levels. The

TABLE V
Response Table for Breaking Elongation

Factor	Level 1	Level 2	Level 3	Level 4	Level 5
A	−49.32	−49.27	−49.30	−48.72[a]	−49.24
B	−49.08	−49.32	−48.81[a]	−49.24	−49.38
C	−49.26	−49.41	−49.02	−49.25	−48.90[a]
D	−49.21	−49.41	−49.07	−49.05[a]	−49.09
E	−49.29	−49.00	−49.51	−48.98[a]	−49.06
F	−49.08	−48.94[a]	−49.00	−49.49	−49.33
G	−49.46	−49.32	−49.26	−49.02	−48.77[a]
H	−45.92[a]	−48.24	−50.04	−50.46	−51.18
I	−49.40	−48.97	−48.81*	−49.21	−49.45
J	−52.27	−50.66	−49.28	−47.86	−45.76[a]

[a] Highest response value, which was used to determine optimum parameter-level settings.

TABLE VII
***F* Ratios in ANOVA**

Factor	Denier	Tenacity	Breaking elongation	Denier variance
A	—	1.55	0.49	1.71
B	2.02	—	—	1.28
C	—	2.25	—	—
D	2.05	1.91	—	2.41[b]
E	1.72	—	—	—
F	1.35	—	0.41	—
G	—	1.6	0.56	2.81[b]
H	4954.23[a]	114.12[a]	33.46[a]	2.58[b]
I	—	—	0.58	—
J	1401.77[a]	167.95[a]	47.13[a]	1.68
$F_{\alpha,4,25}$	4.18	4.18	4.18	2.18

[a] $p < 0.01$.
[b] $p < 0.1$.

TABLE VIII
Confirmation Experiments

	Denier	Tenacity	Breaking elongation	Denier variance
Experiment	−32.11	12.06	−41.74	6.33
Prediction	−32.28	11.77	−42.52	−0.63
Error	−0.17	−0.29	−0.78	−6.96
Confidence interval	[−0.27, 0.27]	[−0.74, 0.74]	[−1.70, 1.70]	[−9.65, 9.65]

temperature differences between the two neighboring sections for the experiments planned in the L_{50} OA were within 30°C. The speeds of cooling air and formation were constrained by the mechanical limits. In our setup, the speed of cooling air was adjustable from scale 1 to scale 9, and the formation speed had a maximum of 150 rpm. The metering pump speed and take-up speed were selected by trial and error in an attempt to enhance throughput. The level values of the process parameters are listed in Table II.

To measure the denier of as-spun PP yarn, 20 bundles of yarn, each with 20 fibers that were 30 m long, were prepared for each trial and were weighted with a sensitive electronic balance to estimate the weight of a bundle. The denier variance was subjected to 20 denier measurements for estimating the filament uniformity. Ten bundles of yarn 300 mm long were used to obtain the tenacity and breaking elongation with an Orientec Tensilon tester at an extension rate of 150 mm/min.

To analyze the experimental results, the experimental data of four qualities were transformed into SN ratios. The quality characteristics of denier, breaking elongation, and denier variance were defined as the smaller the better [eq. (1)], and the tenacity was defined as the larger the better [eq. (2)]. The number of repetitions was given for which the denier was 20, the tenacity and breaking elongation were 10, and the denier variance was 1. Regardless of the category of quality characteristics, a larger SN ratio corresponded to better quality characteristics. The mean of the SN ratios for the cooling air speed at level 1 was calculated by the averaging of the SN ratios for trials 1, 6, 11, 16, 21, 26, 31, 36, 41, and 46. The mean of the SN ratios for each level of the factors is summarized as a response table and shown in Table III. For the denier quality, the optimum parameter-level setting (A1 or A5, B1, C4, D5, E4, F3, G2, H1, I2, and J5) was selected on the basis of its highest response value, as marked with a superscript a. A5 represents the cooling air speed at level 5, B1 denotes the first extruder barrel temperature at level 1, and so forth. Moreover, this investigation identifies the optimum parameter-level combinations for the tenacity, breaking elongation, and denier variance as listed in Tables IV–VI, respectively.

ANOVA was performed with each factor with the SN ratios and calculated *F* ratios. The contribution of factors with markedly lower variation than that of others was pooled to estimate the total experimental variation. There were 25 degrees of freedom of total variance in L_{50} OA, and the pooled factors are indicated by the symbol — in Table VII. For the denier quality, the results demonstrate that significant factors were identified when the *F* ratio exceeded the *F*-test

TABLE IX
Response Table for Learning Schedule

Item	Level 1	Level 2	Level 3
Nodes of the hidden layer	77.78	100.54	112.99[a]
Learning epoch	93.84	100.73[a]	96.74
Learning rate	94.87	96.75	99.69[a]
Momentum factor	92.74	100.44[a]	98.13

[a] Highest response value, which was used to determine optimum parameter-level settings.

TABLE X
Experimental Results by Genetic Algorithms

No.	Denier (den/20 f)	Tenacity (g/den)	Breaking elongation
1	41.1	4.18	126.4
2	41.0	4.06	135.8
3	40.1	4.43	134.7
4	40.7	4.28	98.3
5	39.5	4.33	99.0
6	37.5	4.14	112.4
7	39.0	4.18	111.6
8	39.8	4.12	98.1
9	40.7	4.35	107.9
10	40.3	4.30	108.2
11	39.2		
12	40.3		
13	39.8		
14	39.0		
15	39.2		
16	39.6		
17	40.5		
18	39.5		
19	38.9		
20	37.8		
Average	39.7	4.24	113.2
variance	0.95		

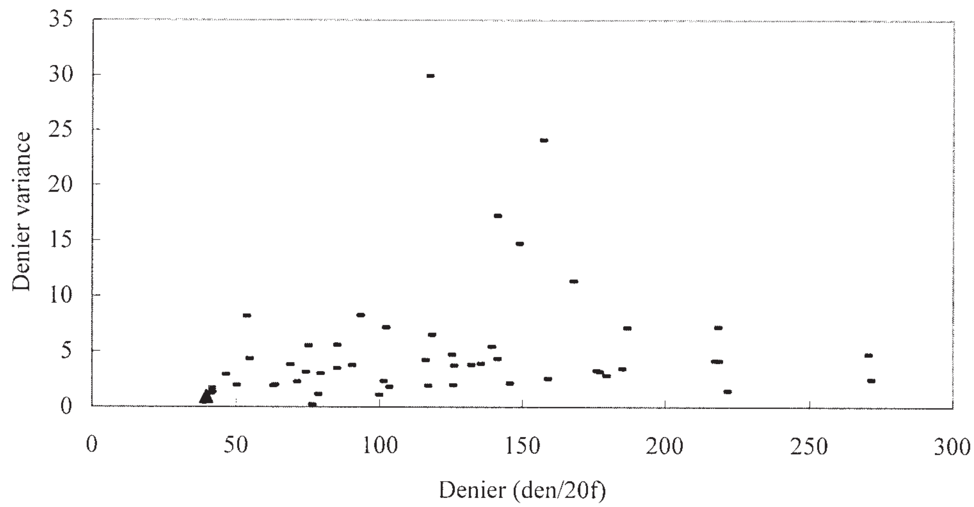

Figure 2 Experimental data of denier and denier variance.

value; thus, factors H and J, marked by a superscript a, were significant at the risk of 0.01. Similarly, the significant factors could be verified, as illustrated in Table VII; the tenacity, breaking elongation, and denier variance were at risks of 0.01, 0.01, and 0.1, respectively.

The confirmation experiment was of crucial importance in the experimental design. The estimated SN ratios of the as-spun yarn qualities with these optimum settings were calculated with eq. (3). When the predictions were compared with reality, good agreement could be ensured if the error was within the confidence interval. To obtain the confidence interval by eq. (4), α was 0.1 for the denier variance and 0.01 for the other qualities, v_2 was 25, $F_{0.01,1,25}$ was 7.77, $F_{0.1,1,25}$ was 2.92, N_d was 50, and r was 20, 10, 10, and 1 for the denier, tenacity, breaking elongation, and denier variance, respectively. Table VIII reveals that the errors between the predicted and experimental results in the denier, tenacity, breaking elongation, and denier variance of the as-spun yarn were within the confidence interval. Consequently, the results displayed good reproducibility of the experimental data, indicating that the interactions of the temperature parameters were not significant. Thus, it was appropriate to plan the temperature parameters in the L_{50} OA.

This investigation used BPNN to describe relationships between 10 process parameters and four quality characteristics of as-spun yarn in melt spinning. BPNN comprised one input layer, one hidden layer,

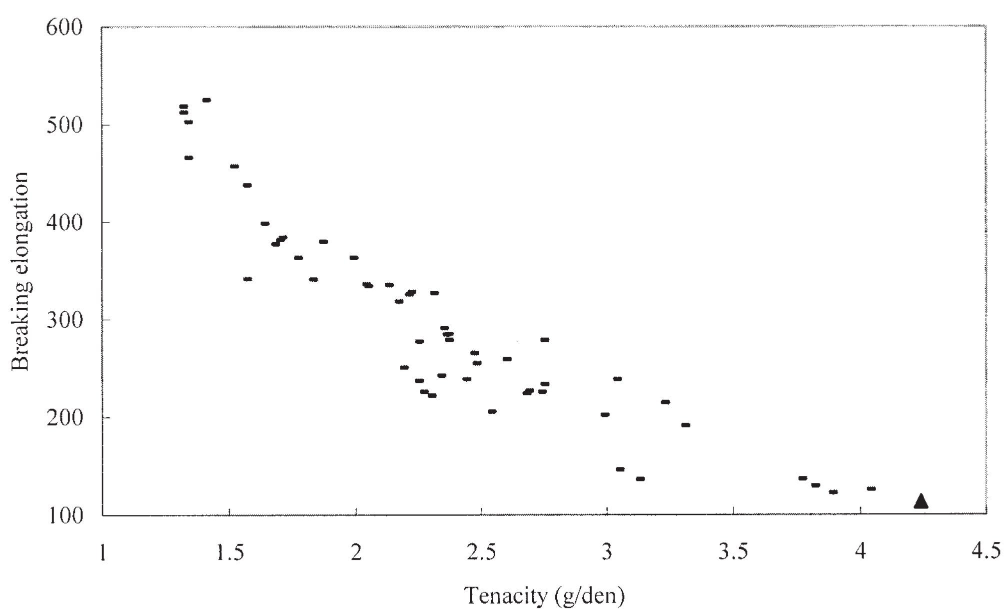

Figure 3 Experimental data of tenacity and breaking elongation.

TABLE XI
Comparison of Quality Characteristics Based on Optimum Conditions by the Taguchi Method and Genetic Algorithm

	Denier (den/20 f)	Tenacity (g/den)	Breaking elongation	Denier variance
Optimum denier	40.3	3.81	129.2	1.25
Optimum tenacity	40.7	4.03	125.5	1.34
Optimum breaking elongation	40.6	3.88	122.2	1.71
Optimum denier variance	75.3	2.43	238.7	0.23[a]
Genetic algorithm	39.7[a]	4.24[a]	113.2[a]	0.93

[a] Optimum quality characteristic.

and one output layer. The nodes of the input layer and output layer represented 10 parameters and four qualities, respectively. The experimental data from the L_{50} OA were training samples. This method applied trial and error to select the number of nodes in the hidden layer, learning epoch, learning rate, and momentum factor. The more efficient method was to use the Taguchi method for the learning schedule.[27,28] Because four 3-level factors required 8 degrees of freedom, an L_9 OA with four columns and nine rows was a good choice. The level values, which were the numbers of nodes (7, 11, and 14) in the hidden layer, learning epochs (5000, 10,000, and 15,000), and learning rates and momentum factors (0.2, 0.5 and 0.8), were selected. The convergence criterion of network training was generally the RMSE [e.g., eq. (7)], and the quality characteristic of the RMSE could be used with the smaller-the-better characteristic to discuss network training accuracy. Each parameter-level combination for an L_9 OA was implemented five times. To analyze the simulation results, the values of the RMSE were transformed into SN ratios with eq. (1). The means of the SN ratios at the same level for the factors were calculated to yield the response table in Table IX. Finally, 11 nodes in the hidden layer, 10,000 learning epochs, the learning rate $\eta = 0.8$, and the momentum factor $\alpha = 0.5$ were selected on the basis of the largest response values.

This investigation used the genetic algorithm to seek the optimum parameter values. The domains of the 10 process parameters were [1, 9], [210, 230], [220, 240], [230, 250], [240, 260], [240, 260], [230, 250], [15, 55], [25, 125], and [1000, 2000], respectively. The required precision for each process parameter was five places, so the total chromosome length was 238 bits. The operational conditions including the generation sizes of 1000 and population sizes of 10 were considered. The genetic algorithm began with an initial population representing 10 solution sets. The chromosome was a binary type organized via a sequence of 10 parameters. The proposed approach input the parameter values of each chromosome into the network and output the SN ratios of four qualities. The fitness value was calculated with eq. (13) to estimate a performance measure for four qualities, with the weight of 0.25 on each quality. In the reproduction procedure, a single chromosome was selected by the roulette wheel approach for a new population. The selection process was repeatedly executed until the number of chromosomes reached 10. We selected the crossover rate of 0.2, and thus two pairs of chromosomes were randomly replaced in the mating pool in the crossover procedure. In the mutation procedure, the number of mutated genes was determined by the mutation rate of 0.001, and hence each generation included two mutation genes. To randomly select two integer numbers within the permissible region of 2380 bits, the mutated genes were changed by the selected locations. The offspring process continued until the generation of 1000 was reached.

The genetic algorithm program was executed over 10 times to determine the optimum chromosome. The optimum settings for the melt-spinning setup included cooled air of scale 1.0, three section extruder barrel temperatures of 210.0, 220.0, and 250.0°C, a die temperature of 251.7°C, a metering temperature of 259.5°C, a spinning temperature of 250.0°C, a metering pump speed of 15.0 rpm, a formation speed of 50.2 rpm, and a take-up velocity of 1995.9 m/min. The practical qualities are listed in Table X on the basis of the optimum process parameters, which included denier of 39.7 den/20 f, tenacity of 4.24 g/den, breaking elongation of 113.2, and denier variance of 0.95. Finally, the whole experimental results are compared in Figures 2 and 3, and the results of the genetic algorithm are marked with triangles. The optimum quality characteristics by the Taguchi method and our proposed approach are compared in Table XI. Thus, the smallest denier, largest tenacity, smallest breaking elongation, and second smallest denier variance of as-spun PP yarn were obtained with the proposed approach in melt spinning. Although the optimum denier variance by the Taguchi method yielded the smallest variance, the other three qualities were much worse than the experimental results by the genetic algorithm.

CONCLUSIONS

This article presents a systematic approach, which is the application of the Taguchi method, neural network, TOPSIS, and genetic algorithm, to set optimum parameter values in melt spinning, rather than using engineering experience. Good reproducibility of product qualities by a smaller number of experiments was achieved on the basis of the Taguchi method. Combining the Taguchi method with the neural network easily solved the interactions among the parameters. To yield good multiple qualities in as-spun PP yarn, the performance measure of the denier, tenacity, breaking elongation, and denier variance, was assessed with TOPSIS. This study applied the genetic algorithm to optimize the performance measure and then obtained the parameter combination. Finally, the experimental results demonstrated that the genetic algorithm could obtain the smallest denier, largest tenacity, smallest breaking elongation, and second smallest denier variance.

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