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Textile Production Process Parameters Inversion Based on Genetic Algorithm

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Abstract: Aiming at the characteristics of complex production process design which mainly based on experience, and has no single scheme, the appraisal target diversification, this paper through neural network and genetic algorithm establishment production process inversion model, consider yarn CV value as the qualitative index for production process of main process parameters inversion, adjust its dynamic production process' sensitive parameters according to the inversion results which to make the product quality standards and improve the process efficiency. Finally a instance is given to demonstrate the feasibility and validity of the method, the method plays an important role in guiding the textile production process quality control, meanwhile also has the good model function to the enterprise new product fast decision-making of process development design.

Keywords: Process design, Parameter inversion, Quality control, Genetic algorithms

1. Introduction

Textile production is a complex multi-stage process, in order to effectively and reasonably for machining quality prediction and control, many experts and scholars uses intelligent algorithms to build models and achieved good results[1-4]. Production quality prediction is obtains the machining quality of the products by raw material and equipment process parameters in advance to ensure product quality and shorten the production cycle. Relative to the predicted, the so-called inverse problem, is to consider the quality of processed products, for selected raw materials and main technological parameters have a preliminary selection and design to enhance process development of targeted, reducing production cost.

Forward modeling of textile production process can be expressed as a nonlinear function of the model parameters, thus the inversion can also be classified as non-linear optimization problems. Thorough search is the most simple and direct method among all nonlinear inversion methods [5], The advantage of this method is that as long as there are to meet the conditions of the solution, then we will be able to search the solutions, but in fact in the calculation in order to achieve the complete search is not possible, the work of computer cannot be completed, therefore it is necessary to find an effective algorithm for inversion. In recent years, GA algorithm, BP artificial neural network algorithm for global optimization has become a research hotspot in the field of domestic and foreign inversion [6-9]. The literature of [10] with direct approximation method, combining remote sensing and cotton model, established the remote sensing - cotton inversion model, with the initial data and parameters to the inversion model of cotton required, experimental verification of the model is feasible. The literature of [11] by genetic algorithm (GA) of the artificial neural network (ANN) prediction and inversion model weights and threshold optimization, set up fine wool textile virtual machining system, to achieve the regulation of quality prediction and control of process parameters, the dynamic process in the production process. The literature through the establishment of a finite element model of genetic neural network instead of rock-fill dam calculation program to improve the inversion calculation efficiency, at the same time using genetic optimization algorithm global search function to find the optimal parameters of genetic neural network simulation of the smallest group of error between the values and the measured values, and is realized by using MATLAB inversion analysis of rock-fill parameters of genetic algorithm and genetic neural network, based on the inversion results show that, the algorithm can improve the accuracy and efficiency of the inverse analysis.

The traditional parameter inversion algorithm convergence and stability isn't ideal, the inversion precision is low, and the computation speed is slow and so on are often appear frequently in the practical application. This paper uses the genetic algorithm optimization the weight and threshold value of BP neural network to establish a genetic neural network model, according the CV value to inversion the initial process input parameters of the model. The results show that, with the use of genetic algorithm and genetic neural network, has the obvious superiority in solving the inverse problem of textile process parameters, so the prediction of stability and convergence speed model and inverse model are maintained at a high level, provide the regulation of textile technology parameters and reliable theoretical basis.

2. Textile processing parameters inversion problem description

For the textile production, performance parameters, such as: oil, raw wool fiber length, fiber fineness and top resurgence, spinning drafting, process parameters, and the process such as: draft in ring spinning, spinning coils of wire diameter and spinning speed and so on, are the key factors that influence the process of the processing efficiency and product quality. The output of target parameters in the process of once identified, in which one or several variable input parameters under the condition of different combinations of input parameters, obtained by inverse model, then according to the condition of machining efficiency, the production costs and so on optional combination screening, finally to obtain the optimal combination of input parameters, so as to realize the process more reasonable design, so it is of great significance to effectively inversion for some important parameters. The inversion process parameters in this paper to solve the problem is: the known part of the input parameters, output parameters of target, through the construction of inversion model, inverse the same output to meet a large number of optional input parameter combinations, and lay the foundation for the further adjustment of optimum process parameters

3. Design of inversion algorithm

3.1 The basic steps of inversion algorithm

(1) Firstly, based on the oil content of partially known yarn, wool tops, sample moisture regain of fiber linear density (average line density), line density discrete (discrete coefficient), fiber length (hauteur LH), fiber quality unevenness, roving twist factor, draft in ring spinning, spinning wire circle diameter, spinning speed and other conditions of use the structure of neural network algorithm, an initial spinning CV prediction model.

(2) Forward calculation of initial value of spinning CV, obtains the calculation data, calculating the observed data and calculated data of the root mean square error of whether it meets the requirements of accuracy, if met iteration termination, otherwise continue the iteration until meeting the precision requirements.

(3) In order to inverse iteration, based on the current model by genetic algorithm inversion model.

(4) With the CV value of observation data and calculated data of difference as the objective function, inverse based on new model required parameters.

(5) For all eligible inversion data, function to calculate the evaluation function value, to choose the best parameters inversion.

3.2 BP neural network prediction

The parameters of the forward model adopts 3 layers of BP neural network, its structure is schematically shown in Figure 1, a network with m neurons in input layer, hidden layer neurons in hidden layer containing n, the transfer function is f_1, the output layer containing k neurons, the output layer transfer function for f_2.

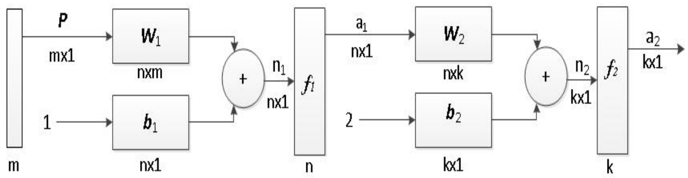

Figure 1 structure of 3 layers BP neural network

Mapping of 3 layers BP neural network can accomplish arbitrary n-dimensional to m dimension, hidden layer node number selection of empirical formula for S

$$s = \sqrt{(0.43mn + 0.12n^2 + 2.54m + 0.77n + 0.35)} + 0.51 \qquad (3\text{-}1)$$

In the formula: m is the number of input neurons and n is the number of output neurons.

3.3 GA optimization neural network weights and threshold3

(1) Population initialization

The method of individual encoding is decimal encoding. Each individual represents a real number string, including the input-the hidden neuron weights, the input - the hidden neuron threshold, the implication – the output neuron weights and the implication – the output neuron threshold.

The initial encode of weights and thresholds:

$[w\_111, \cdots w\_11m, \cdots w\_1i1, \cdots w\_1im, w\_1n1, \cdots w\_1nm, b\_11, \cdots b\_1n, w\_211, \cdots w\_21n, \cdots w\_2j1, \cdots w\_2jn, w\_2k1, \cdots w\_2kn, b\_21, \cdots b\_2k]$ w_1ij is the input of mxn dimension – elements in the hidden neuron weights matrix W_1, b_1i is the input of nx1 dimension-elements in the hidden neuron threshold matrix B_1, w_2ij is the implication of nxk dimension – elements in the output neuron weighting matrix 【W】_2, b_2i is the implication of kx1 dimension-elements in the output neuron threshold matrix B_2.

(2) Fitness function

For the specified training sets and test sets, Design the fitness function and take the average absolute relative deviation (AARD) of the actual output and the expected output r as a function fitness.

$$f = \left(\sum_{i=1}^{N} |y_i - o_i|\right)/N \tag{3-2}$$

(3) Selection

Adopt the principle of proportional distribution of fitness, that is, the possibility of future generations legacy is proportional to the probability of individual fitness value. For example, there are N individuals forming the populations. If the fitness of Individual i is f(i), the selected probability of i were:

$$p_i = \frac{f(i)}{\sum_{i=1}^{N} f(i)} \tag{3-3}$$

Depending on the value of p_i, use the roulette method to complete the selection operation.

(4) Crossover

Using a linear combination way to complete the crossover operation, the specific operation is as follows:

Suppose that make arithmetic crossover between the corresponding Gene x_i^k and Gene y_j^k, new individual genes will generate as the following formula:

$$x_i^k = (1-\mu)\cdot x_i^k + \mu \cdot y_j^k \tag{3-4}$$

$$y_j^k = (1-\mu)\cdot y_j^k + \mu \cdot x_i^k \tag{3-5}$$

μ is a random number among(0,1). The above formulas show that the use of arithmetic crossover operator can guarantee two produced individuals to search between two parnts' area.

(5) Mutation

The main purpose of mutation operation is to maintain population diversity. Randomly select an individual from the population, and then select a point to mutate. A better individual can be produced by the mutation. Suppose Gene j of Individual i is a_{ij}, the mutation operation of a_{ij} is:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{max}) \cdot f(g), r > 0.5 \\ a_{ij} + (a_{min} - a_{ij}) \cdot f(g), r < 0.5 \end{cases} \quad (3\text{-}6)$$

(a_{min}, a_{max}) is the upper and lower bounds of gene a_{ij}; $f(g) = r_2(1 - {}^{g}/_{G_{max}})^2$, r_2 is a random number, g is the current number of iterations, G_{max} is the maximum number of evolution , r is a random number among [0,1].

3.4 Inversion of GA algorithm

(1) Genetic code

Coding method not only influences chromosomal arrangement, also decided the individual from the search space of genotype to phenotype transformation decoding solution space. For the problem of textile parameters inversion such, real code simply cannot be discrete coding sequence and continuous particle position corresponding up, in order to facilitate the parameter inversion description and genetic operation, this paper proposes to use a binary number with the real combination method to encode the particle.

Particle code consists of two parts, as shown in Figure 2, the left part of the A, B, C, ··· by composition between total n, whose number is equal to the inversion parameters, the numerical representation parameters inversion position. The right part of the Gray mode coding, A, B, C...... Composed of random number 0 or 1, every parameter inversion from the binary encoded eight bit representation, let M= [A, B, C,···], length (M) =8*n.

$$\underbrace{a, b, c, \cdots\cdots}_{n}, \underbrace{A, B, C, \cdots\cdots}_{8*n}$$

Figure 2 particle coding structure

(2) Generate of initial population

The population initialization process, parameters inversion by gene the left part of the actual to decide, such as a=2, b=5, said the need for the inversion of the tops of moisture regain and fiber length, once identified populations a, b values do not change during the iteration process; the right part with different number and parameter inversion different, if the number of inversion parameters is 2, is in a certain range of randomly generated 0, 1 numerical matrix of 1 rows and 16 columns to initialize population

(3) Select

The choice of operation is based on the individual fitness degree based on the evaluation of the individual in population, according to the degree of adaptation from big to small order, use the roulette selection method. Assume that each individual fitness is $f_k(k = 1,2, \cdots l)$, the total population fitness for the $\sum_l^1 f_k$, will be the proportion of $f_k / \sum_l^1 f_k$.as the k individual choice probability. Through the choice of operation makes the individual fitness values are close to the optimal solution.

(4) Crossover and mutation

Crossover and mutation are one way to produce new individuals, variation and cross combination, can avoid selecting and crossover causes some loss of information, guarantee the effectiveness of genetic algorithms.

This paper uses the cross algorithm is as follows: (1) according to the parameter inversion in a number n n a randomly generated 0 or 1 number T_1， T_2， ...... T_n; (2) T_1， T_2， ...... T_n insert binary chromosome coding fragment, every eight insert a Tn, as shown in the figure; (3) determine the value of Tn, if Tn=0, then the gene does not make any changes, if Tn=1, then the paired two individual code string a random set of two intersection points, exchanges partial chromosomes of two individuals in two cross point between the set.

Set 2 parent individuals that require cross-operations X1 and X2, respectively, and their progeny of the cross to y, crossover process is shown in Figure 3:

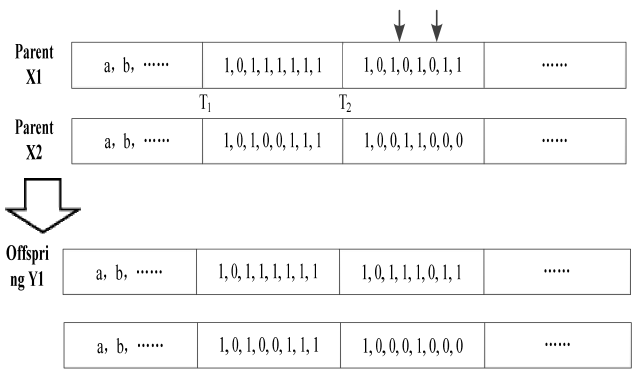

Figure 3 overlapping schematic drawings

The mutation operator with uniform mutation, in order to specify each individual gene encoded string in the seat for the variation points, for each point mutation,

mutation probability range to from the corresponding gene in take a random number to replace the original value, as shown in figure 4.

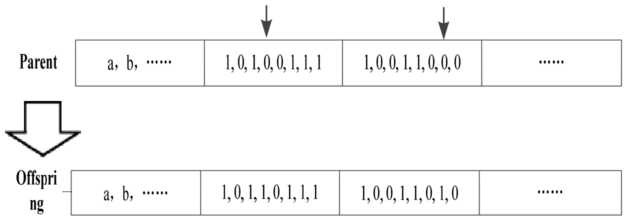

Fig. 4 Schematic diagram of mutation operator

4. Application examples

The spinning process is spinning bottleneck, it restricts the production status quality improving yield and quality, this paper takes a company sand production process top oil content and the spinning parameters inversion as an example to illustrate the realization process of the algorithm. Known to a yarn production data , firstly established a spinning CV prediction model, the input for the top oil content, moisture regain, wool fiber linear density (average line density), line density discrete (discrete coefficient), fiber length (hauteur LH), fiber quality unevenness, roving twist factor draft in ring spinning, spinning frame, steel coil diameter, spinning speed, output for spinning CV value, the former 30 as training set selection in data records, 31 to 35 records as a model test set.

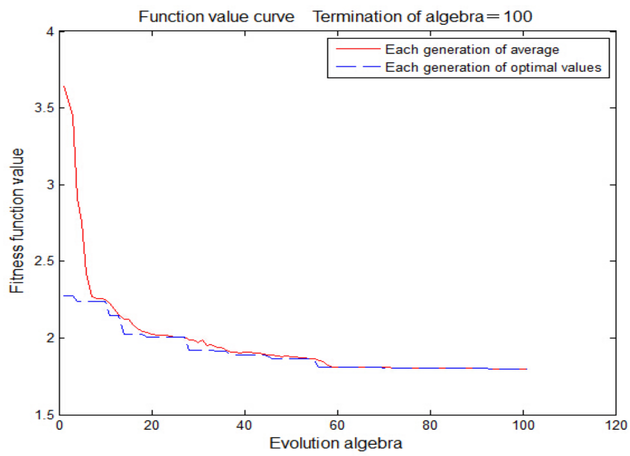

Figure 5 spinning CV value prediction model of iterative evolution diagram

It can be seen from the figure, when the hereditary algebra over 60 generations, the fitness function value (i.e. the average relative error of prediction of test set results) is relatively stable, at about 1.9%, the average fitness values close to the best fitness value, that each individual in the optimal solution around.

The predictive model of neural network training is finished, is given a new set of data, as shown in table thirty-sixth, by the genetic algorithm inversion which top oil and the spinning parameters. Set the genetic algorithm inversion parameters: population size is set to 20, the maximum number of iterations is 100, the probability of crossover mutation probability is 0.8, 0.05. The genetic algorithm inversion iteration results as shown in Figure 6, it can be seen from the figure is less than ten times iterative algorithm has convergence, the five parameter inversion results of optimal output as shown in table 1.

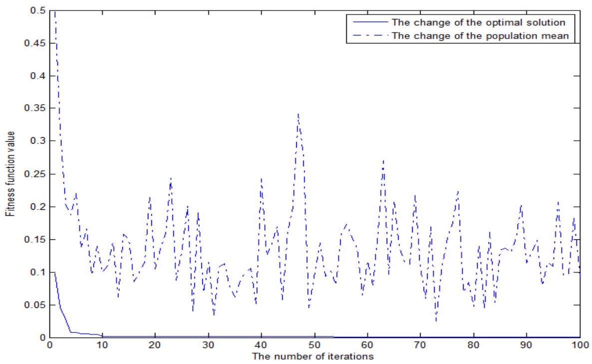

Figure 6 genetic algorithm neural network inversion iteration results

Table 1 parameters inversion results

	1	2	3	4	5	The true value	The average error
oil content of tops	1.29	1.28	1.32	1.21	1.24	1.2	5.67%
yarn draft ratio	20.24	20.31	20.23	20.26	20.33	19.0	6.70%

5. Conclusion

In view of the textile process part parameters is not easy to get on the process have an important impact on the situation, the algorithm of BP neural network to establish the forward model, the initial threshold weights of the network is optimized by genetic algorithm, so the network prediction precision is improved greatly. On this basis, to solve the inversion parameters by improved genetic algorithm, and examples to verify the feasibility of the algorithm and the effectiveness of the company, improve the technological development of targeted, reduce the cost of production has certain reference function.

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