Bi-Directional Optimization of the Melting Spinning Process with an Immune-Enhanced Neural Network

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***Abstract*—A bi-directional optimizing approach for the melting spinning process based on an immune-enhanced neural network is proposed. The proposed bi-directional model can not only reveal the internal nonlinear relationship between the process configuration and the quality indices of the fibers as final product, but also provide a tool for engineers to develop new fiber products with expected quality specifications. A neural network is taken as the basis for the bi-directional model, and an immune component is introduced to enlarge the searching scope of the solution field so that the neural network has a larger possibility to find the appropriate and reasonable solution, and the error of prediction can therefore be eliminated. The proposed intelligent model can also help to determine what kind of process configuration should be made in order to produce satisfactory fiber products. To make the proposed model practical to the manufacturing, a software platform is developed. Simulation results show that the proposed model can eliminate the approximation error raised by the neural network-based optimizing model, which is due to the extension of focusing scope by the artificial immune mechanism. Meanwhile, the proposed model with the corresponding software can conduct optimization in two directions, namely, the process optimization and category development, and the corresponding results outperform those with an ordinary neural network-based intelligent model. It is also proved that the proposed model has the potential to act as a valuable tool from which the engineers and decision makers of the spinning process could benefit.**

***Index Terms*—neural network, artificial immune system, bi-directional optimization, spinning process**

I. Introduction

THE textile manufacturing processes are a typical example of the most complicated production lines in industrial systems. These systems require a perfect combination of machinery, precise producing configurations, highly effective control and monitoring mechanisms. Successful discovery of such a combination is an extremely challenging mission for the textile manufacturing since it involves varieties of transformations physically and chemically which is also the main difference between it and other pure mechanical processing lines. Another feature brought by these characteristics is the highly nonlinear behaviors of the involved manufacturing process. A minor variation occurred in one section of the whole line, i.e. the fluctuation of set value, the erosion of mechanical equipment, or even a minor control mistake made by human operators, could cause large diversities for the final product. Unfortunately, such minor variations cannot be avoided in practice. So the attempt to grasp the nonlinear behaviors of the manufacturing process and then learn about their influence towards the final product has become a critical task for the system designer, the field engineer and the operator.

As to the textile production, an important direction for learning the nonlinear behaviors of the system is trying to find out the relationship between production configurations in different sections and the quality indices of the final product, e.g. the staple or filament. The main representative of the configuration is the parameter selection of the sections which is also the easiest point that people can think of to find the relationship with the product quality. The technicians are always keeping on looking for better explanations and the corresponding analyzing methods to unveil the connections between process parameters and the final quality indices for the large-scale textile manufacturing from varieties of aspects. Gou and McHugh took the temperature and composition effects into consideration to for staple or filament, are classical instances of complex acquire their respective effects towards the viscosity, glass transformation and zero-shear modulus during the drying spinning process [1]. Lee et al. proposed a reduced-order model (ROM) to approximate the practical nonlinear model of the optic fiber drawing process, and such model can then be used to analyze the parameters that may greatly influence the quality of the final fiber and how to establish effective control for them [2]. For the finishing process, different types of parameters such as process temperature and time, water inlet temperature and liquor ratio, and this is what Cay et al. have made contributions to [3]. Tan et al. developed a one-dimensional slender-jet theoretical model with both upper connected Maxwell and Pan-Thien and Tanner constitutive equations to investigate the

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relationship between the viscoelasticity and processing parameters on the properties of melt blown fibers [4]. As to the origin of the industrial fibers, Duval et al. checked the sampling sections from different parts of the plant which could be used to spin fibers in order to find the connection between the strength of such original materials and their manufactured products [5]. All of them are good examples showing the great effort that the researchers are taking to find out the detailed relationship between the process and the product. Like the two sides of a coin, however, this issue has its two aspects and most of the current achievements only focus one side, namely, that how to get products from process, but leave the other side that how to design a process for a known product aside. The lab scientists may think the former much useful for conducting analytical works, but what the field workers and engineers focus more is the magic on creating new fibers, namely, how to build production to realize their goals.

The rapid development of artificial intelligence (AI) has provided the textile industry with a powerful tool for analyzing its process and products. Due to the comparatively slow executing speed, most of the AI-based approaches are still taken to build offline systems for estimation and prediction of the reasonability of manufacturing and overall quality of the final products, but the effort to bring them to practical online monitoring and control never stops [6-10]. Another trend is that more and more researchers have turned their attention from application of a single AI approach to combination of several ones, e.g. the artificial neural network (ANN), fuzzy system (FS) and genetic algorithm (GA), and usually such an approach can be proved more effective for the highly nonlinear systems, such as the textile production. For the ANN with its variants, Kadi et al. introduced it into the performance estimation of the fiber-reinforced composites [11]. Arafeh et al. combined the fuzzy mechanism with neural network to form an intelligent approach for the material processing [12]. Yu et al. proposed a fuzzy neural network (FNN) that simplified the network structure and feature selection of the classical ANN. This approach can then be applied with a reasonable rule set to conduct the fabric selection among different fabric specimen [13]. Liu et al. introduced another approach, the firing-strength transform matrix to the adaptive neuro-fuzzy inference system (ANFIS) and then took it as a predicator for the trim-beam numbers in the textile manufacturing [14]. As to the upper level of problem solving, namely, the methodology, Deng et al. proposed a series of intelligent decision support tools consisting of different AI methods (or concepts and frameworks) among which different methods take charge of different tasks in a whole plan, and a case of multifunctional textile material design is then taken to verify the effectiveness of such a guiding plan [15]. Yang et al. proposed a hybrid method using back-propagation neural network (BPNN), genetic algorithm (GA) and simulated annealing algorithm to determine the optimal mixing ratio of different components in special types of fibers [16]. Yang et al. proposed an improved GA to subtract unnecessary elements from a large feature set so that the classification for foreign fibers can be realized more efficiently and effectively [17]. There are also some other aspects of the AI, e.g. the artificial immune mechanism, have great potential to be applied to the optimization of the manufacturing process of fiber [18] or used to broaden the application scope of special textiles [19], but the present achievements are still limited.

In this paper, a set of optimization problems for both the manufacturing processes of staple and filament are raised and generalized, through which we try to find a reasonable way to solve by applying a hybrid intelligent approach. This approach is established on the neural network and the artificial immune system (AIS). The neural network is used for building a black-box model for the bi-directional relationship between production parameters and final quality indices of the textile product, and the AIS is further introduced to make the approximation of the neural network model more precisely. Based on the practical production data, a software platform for the realization of the proposed model is established, and the bi-directional simulation and assessment can therefore be conducted on it. Computerized simulation shows that the bi-directional simulation and optimization can be achieved by the proposed model, and estimations on the quality indices and suggestions for the improvement of production parameters can also be acquired. With the help of the software platform, the proposed model can further be applied to the practical textile manufacturing process.

The main contribution of this paper is listed as follows. Firstly, the optimization of the melting spinning process is generalized as a parameter-based bi-directional problem which is then modeled by applying the proposed immune-enhanced neural network model. Meanwhile, a software platform embedded with the proposed model is developed and verified by using the practical production data in the textile production. Such platform with the proposed model can be applied to the manufacturing processes with similar procedures as the melting spinning process, which can ultimately be regarded as a guidance for the product improvement in the industry field.

The remaining parts of this paper are organized as follows. Section II makes a brief introduction for the melting spinning process of textile, which includes both the staple and the filament productions. Section III provides the basic idea of the bi-directional optimization of the manufacturing process, and the necessity of applying AI approaches to solve this problem. The detailed design of the proposed immune-enhanced neural network model is provided in Section IV. Section V provides the simulation and corresponding results with analysis, followed by the establishment of the software platform. The whole paper is concluded in Section VI.

II. The Melting Spinning Process and its Bi-Directional Optimization

A. The Basic Structure of the Melting Spinning Process

A general melting spinning system for filament can be depicted as in Fig. 1. It mainly consists of a melting

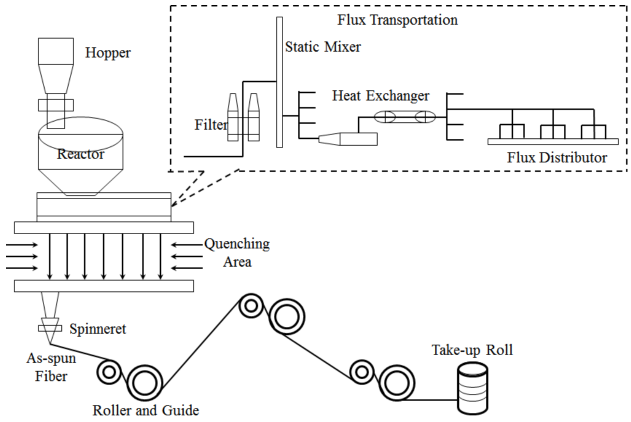


Fig. 1. Melt spinning procedure.

transportation system and a spinning system. The main task of the melting transportation system is to convert the raw materials for spinning to liquid with a predefined viscosity and temperature. The liquid can then be shaped with ease, and the detailed spinning procedure can be accomplished by the following spinning system [20, 21]. At the very beginning of the process, the raw materials for spinning, no matter what its original form is, are firstly molten down to solution, and then transported to a group of spinnerets through branched tube systems. The dense spinning solution is then intruded through the holes on bottom of the spinnerets and enters the blowing area. In the blowing area, the air blowing from different directions helps to solidify the solution streams so that the so called "as-spun" fibers can be formed. The "as-spun" fibers can be stretched according to a designated stretching ratio in the following procedures. Different types of filaments ask for different combinations of equipment and special raw materials, but the basic processing procedures are similar. As requested by various specifications of the final products, more procedures may be added to the whole production line. The melting spinning technology for the staple is similar to that for the filament to a large extent, and the main difference is that a cutting procedure is added in so its final product would be short fibers, compared to the long fiber of filament.

B. Key Parameters and Quality Indices of the Melting Spinning Process

The determination of the parameters for spinning is one of the most critical parts on optimizing the manufacturing process [22, 23]. Since the whole production line is a combination of several complex sections, some features can be summarized during the selection of these parameters. 1) There are numerous variables to be determined in a single processing section, and these variables should be coordinated harmoniously so that such a single section can work properly. 2) Different sections have different parameters. This indicates the whole production is under a specific condition based on a reasonable combination of each section. So the parameters for all the sections should be taken into consideration together to build such a foundation. 3) The working status of the spinning line may vary with time, which results in redetermination of process configuration. On most occasions, the changes for better parameters are inevitable. Moreover, the challenge brought by the great nonlinear nature is that the shift of parameter value cannot be judged by purely applying a constant trend or fixed schemes, e.g. the rising of heating temperature will cause either lower spinning speed afterwards or higher, which may not be explained by a simple mathematical model. So all the factors in the whole spinning process (including the key parameters) should be put together to make a thorough analysis, and a correctly modified plan against the change of working status can be generated. Plus, the intensity of changes is also a great factor against the processing fluctuation. Inappropriate modification of parameters may lead worse results rather than pulling the production back to normal.

All the features about the parameters in the production as above imply a challenging task to determine the most critical ones and how to tune them when changes occur.

C. The General Paradigm of the Optimization for Spinning Process

The melting spinning process is a large complex system with numerous variables coupling with each other. Its complex mechanism raises the difficulty level of conducting an accurate model to demonstrate its detailed dynamic behaviors, which consequently brings more challenges to the process analysis and optimization. When approaching a practical problem with multiple key points, people always tend to apply the "divide and conquer" strategy, and so do they with the optimization of the textile spinning system. Fig. 2 illustrates a workflow diagram of a complete process for modeling the textile spinning production with its application. The whole process starts from a disassembly of the spinning line, and then the key factors that play critical roles can be extracted for further inspection. With the aid of computation techniques, one or more models can be selected as candidates for modeling the spinning process. The model that fits for the actual process is generated out of the framework (base models) and the data source (key factors). After that, a series of experiments should be elaborately

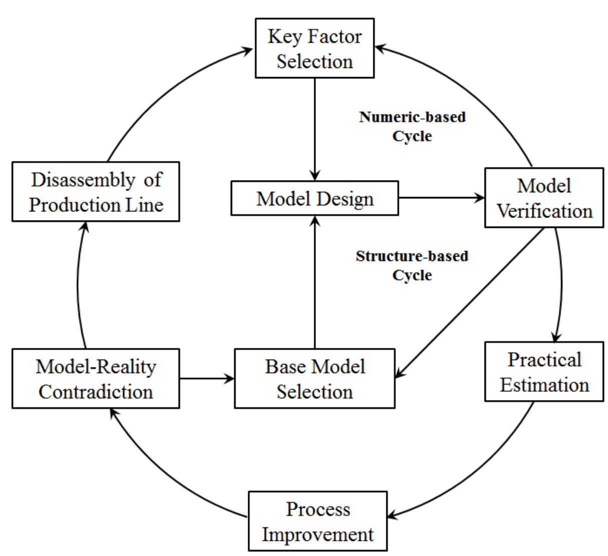


Fig. 2. General workflow of the spinning process optimization.

designed so that the performance of the selected model can be quantized for comparison. It may also be necessary to roll back to the previous steps for picking up better model basis or influential factors. The verification of models is followed by the practical value estimation whose responsibility is to put the model and results with the actual fiber product data together, and some advice may appear to make the process optimized during this procedure. The optimization may include addition/remove/modification of the existing devices, or better valuation for process configurations. This may probably lead to a distraction between the proposed model in theory and the process itself. In this case, another round of model designing and test will start. During the whole process, the output (or results) of one procedure can be used as the input (or source) of its subsequent procedure(s).

For the candidate models of the spinning process, a rigid mathematical deduction is usually accompanied by numerous equations with plenty of parameters and assumptions as conclusion. However, these achievements always ask for more care if the working status of the spinning procedure changes even a little [24, 25]. A reasonable alternative to solve such problem is to build a black-box-like model that only the input and output of the target system are concerned while the internal details can be ignored, or more precisely, be modeled by the black-box itself. Usually, researchers take the process parameters and the quality indices as the input and the output of the model, respectively. By applying some nonlinear methods, the quality of the final textile product related to the selected parameters can be calculated [26, 28]. But such model still has limitations. First of all, the data of the manufacturing process required for building and verifying the model may not be acquired sufficiently, because the parameters of a fixed manufacturing process for a specific textile product are mostly stable (or just fluctuates within a tiny scope). It cannot provide a large range for fully analyzing the behavior of the whole process. Meanwhile, a simple input-output model is only responsible for acquiring the predicted properties of textile products, which can therefore be regarded as a static analysis. It does not have the ability to tell the on-site operators how the process parameters should be tuned to improve the product quality, while this may be more significant for the practical textile manufacturing. As a result, a reverse optimizing procedure from indices of final products to the process configuration is required.

D. The Bi-Directional Intelligent Optimization

The basic idea of building a bi-directional optimization model rather than a common one as above is derived from the actual needs of textile manufacturing itself. It may be useful and sufficient for scientists and researchers in laboratories to implement a forward model that shows the relation from process to products. But what the industrial experts, analysts and operators in the spinning workshop need is a tool that helps them find the possible sources of problems that deteriorate the quality and how to eliminate them. Unlike the lab version model, such requirement just asks for a backward one to make the problems above solved. This is also the main motivation for looking for a bi-directional spinning model and related methodology. Based on the situation of the textile industry, an effective model that qualifies for practical application in the textile production should meet the requirements as below,

(1) The relation between the process configuration (e.g. the parameters) and the quality indices of final product should be simulated so that the possible changes of product quality are foreseeable. This is actually the main task that the contemporary models should finish.

(2) The quality indices of the final textile product should have the ability to be taken as a source to get process configurations with the proposed model. By this means, the on-site operators can take advantage of such model to develop new types of textile productions with desired qualities The actual production line can then be reconfigured with the deducted set of parameters. The possible waste that may come with unsupervised change of process configuration can also be prevented.

These two points as above actually reveals a pair of modeling processes consisting of a forward path and a reverse path, which is shown in Fig. 3. In the forward path, the process parameters are taken as input to gain the corresponding quality indices of the final product through a nonlinear model (which may be covered by a black-box type mechanism). In the reverse path, on the other hand, these parameters are regarded as the destination that can be calculated by another model with the quality indices as its source. Both the models can be those with strong nonlinear characteristics to match the features of production, and self-learning capability to generalize knowledge from varieties of in-process data. In the textile industry, the forward approach here can be called “process optimization” for it can help to discover the relation between the changes of production configuration and the subsequent product variations. The reverse approach can be called “category development” for its ability to propose a reasonable set of parameters that lead the textile quality to a known desired level. This would be of special significance for some textile factories and engineers because the idea how to produce something with expected performance is their kernel consideration, which may be more meaningful than just grasping the relationship between production and product.

III. The Design of the Immune-Enhanced Neural Network for the Melting Spinning Process

A. The neural network for the spinning process

As a useful tool, varieties types of neural networks (NNs) with their derivations have been applied to system analysis and optimization [29, 30]. An appropriate selection of a NN model depends on the characteristics of the target system and the type of data set involved (this may be the most critical point for the selection). The spinning process is a classical system with a huge number of process data collected in a sequential but discrete sampling time series. So the corresponding NN for modeling this process should have a good master on discrete

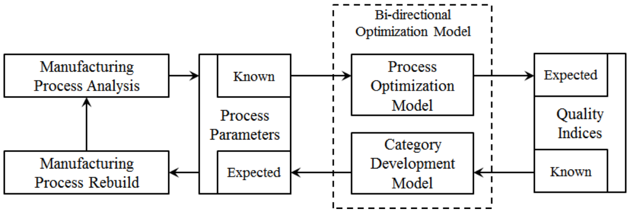


Fig. 3. Schematic of the bi-directional optimizing process.

data. The radial basis function (RBF) NN is featured by its ability on approximating discrete system [31], which is therefore picked here to play as the foundation of the optimization model. The basic structure of the RBFNN for the melting spinning process is shown in Fig. 4. The process data are received by an input layer, and then transformed by a hidden layer with tunable connecting weights and kernel functions. The output layer is responsible for generating results for the whole RBFNN. For the analysis and optimization of the spinning process, two types of data can be taken as the input data, namely, the parameters of different sections and the final quality indices of fibers. Their detailed roles depend on which direction of the analysis should be made. For the process optimization (the forward path), the parameters of sections on the production line are selected as the input data, and the desired output is the predicted quality indices. For the category development, the expected quality indices should be treated as the data source for optimization. The in-process parameters can be calculated by the corresponding model, hoping that such parameters can lead to a satisfactory production of fibers. The basic structure of the RBFNN can be shared by both the procedures above, but the specific configuration of the models may vary according to different requirements.

B. The immune-enhanced optimization

The RBFNN based optimization model could bring an approximation to the spinning process, but its accuracy may not be satisfied. The input data collected from the fiber production can be treated as independent points in a continuous data space, but there are no apparent clues indicating how the other points, e.g. other production configurations are located in such a space. This feature will make the RBFNN model achieve wrong

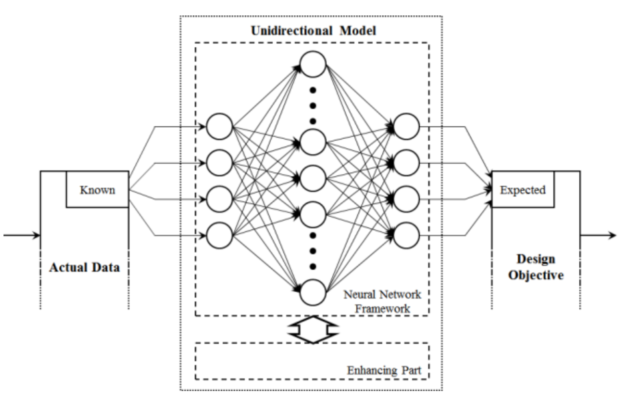


Fig. 4. RBFNN -based optimizing model for the melting spinning process.

results. Moreover, the data set for building the optimization model is limited in practice, but the test data set (or more practically, the real production data) is unlimited theoretically and the trend of the data cannot be well predicted. Such a contradiction between the idealized model and the reality may further deteriorate the accuracy of the proposed model in the long run. To solve these problems, the artificial immune mechanism is introduced to strengthen the robustness of the RBFNN framework by tuning the weights and parameters of the kernel functions of the nodes in the RBFNN. The algorithm can be demonstrated as in Fig. 5 a). For the optimization of the spinning process, each part of the algorithm should have its own specific meaning. A detailed procedure for optimizing the spinning process with the artificial immune mechanism can be given by the steps as follows,

Definition of antigen, antibody, and memory cells. The antigen (Ag) in an artificial immune system can be the mathematical statement of the problem to be solved, and the antibody (Ab) is therefore its possible solution. Multiple antibodies form a solution set Abs with the generation evolving. The affinity of Ab against Ag is defined as its ability on eliminating the antigen, namely, resolving the target problem which can be written as

$$Aff_{Ab_x \sim Ag} = \frac{F(Ab_x)}{\sum_{y \in Abs} F(Ab_y)}, \tag{1}$$

where $Aff_{Ab_x \sim Ag}$ denotes the affinity of x-th antibody against the antigen, $F(Ab_i)$ denotes the fitness value of the i-th antibody which can be acquired by substituting the antibody to its detailed target problem to get the corresponding solution. The affinity between different Abs is defined as

$$Aff_{Ab \sim Ab}(x) = \frac{\min_{y \in (Abs - \{x\})} (\|x - y\|)}{\max_{y,z \in Abs} (\|y - z\|) + 1}, \tag{2}$$

where $Aff_{Ab \sim Ab}(x)$ is the affinity of the x-th antibody and all the other antibodies in a certain antibody set Abs, $\|x - y\|$ is the distance between the x-th antibody and the y-th antibody (the detailed measurement may vary based on different requirements). The superior antibodies with higher affinities against the antigen or other antibodies can be picked up and stored in another set M which is called the memory cell set, and the antibodies in M are called memory cells Mc.

As to the spinning process, two types of data in the spinning process can be taken to play the role of antibody or antigen, and the detailed assignment is decided by the direction where the optimization will be conducted as shown in Fig. 3. For the process optimization, the quality indices of fiber products should be taken as antigen, and the configuration of the neural network model should be the antibody (note that a whole set of configuration including all the weights and bias is a single antibody). For the category development, the process parameters that may lead to certain quality indices of final products are taken as antigen, and the antibody is still the network configuration. Note that here the antibodies do not function on the antigen directly but play as a component of the neural network which is the real source of possible solutions to eliminate the antigen.

Creation of Abs and M. At the beginning of the optimization, some antibodies are generated randomly in the solution scope and then formed an original M. The original antibody set Abs is left empty. A threshold T_m is generated by calculating the mean Ag-affinity of all the memory cells in M. For the spinning process, since there is no memory cell existed at the beginning of the optimization, a randomly generated set of antibodies is provided to form the original M, and the contents of each memory cell is a set of parameters of the neural network that will be tuned. As to the antibody set Abs, it is left blank and waiting for the antibody insertion from M.

Clonal selection. For each Mc, calculate its Ag-affinity and compare the result with a predefined threshold T_s. If the Ag-affinity of a Mc excesses T_s, clone it at a certain probability and then put the new ones into the Abs. The probability for clonal selection is defined as

$$Clonal(x) = \text{int}[m_{rclonal} \bullet Aff_{Ab\sim Ag}(x) \bullet Aff_{Ab\sim Ab}(x)], \quad (3)$$

where $Clonal(x)$ is the probability of the x-th antibody for cloning and $m_{rclonal}$ is a reference clonal coefficient which is usually greater than one. For each Mc in the memory cell set of the spinning process-specified approach, namely, a candidate set of neural network parameters, a temporary neural network framework is built to verify its performance. The memory cells with a higher Ag-affinity over T_S will be picked out and added to the Abs. In general, there are a series of parameter-index pairs that have been collected from the actual production and can be used for verification. Meanwhile, a potential qualified neural network should be capable to simulate the behavior of the real system on most occasions. So the Ag-affinity of the memory cell should be generated based on tests with all the data.

Maturation of Mc with high affinity. For the Mc that is selected to join the Abs, make a mutation with a certain probability on its contents (e.g., by changing several parameters in the whole set on a random basis whose probability is predefined by field experience) and put the mutated individuals into the current Abs. The mutation probability is defined as

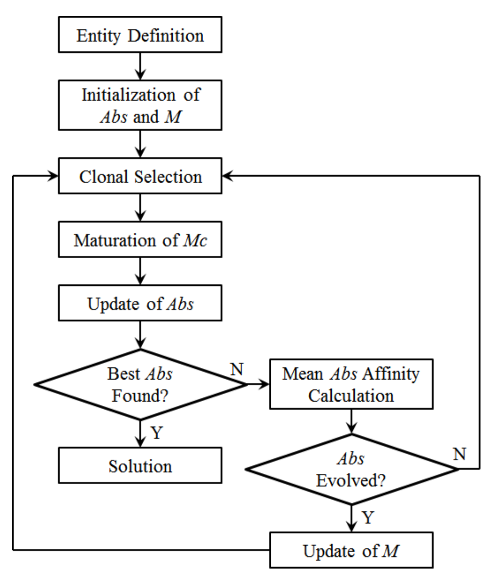
$$P_{mut}(x) = \frac{1}{Aff_{Ab\sim Ab(x)} + 1}, \quad (4)$$

where $P_{mut}(x)$ denotes the probability for mutation. Eq. (4) indicates that the antibody with a higher Ab-affinity will acquire more chances for mutation so that all the antibodies can spread in the solution scope as widely as possible.

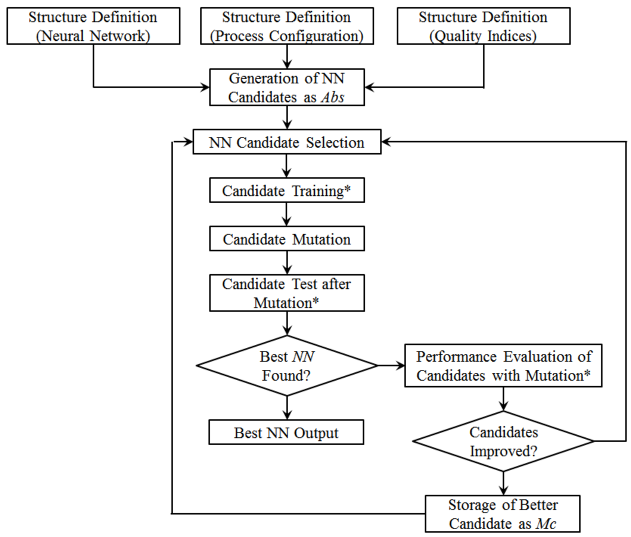
Update the Abs. The Ag-affinity of each antibody in the current Abs should be tested, and those with lower affinities are removed. Meanwhile, check if there is any antibody whose Ag-affinity has been high enough to match the antigen, namely, whether the solution with a certain precision has been found. The value of such a threshold depends on the specific parameters of a certain network. A large threshold will call the algorithm for much time to get to the optimum solution, and a small one may keep the algorithm stuck in an infinite loop. If a solution is found, end the optimization and exit, or the following steps will proceed. For the memory cell that consists of network configuration, the mutation is implemented by introducing a tiny fluctuation to the parameters it represents, which would result in different results on the network based on it. The memory cells both with and without mutation are added to the Abs, and then all the antibodies in the Abs are substituted to the network structure to verify its present performance represented by Ag-affinity. Those with inferior performance will be removed from the current Abs. Meanwhile, the best antibody will also be checked to determine whether the optimal solution, namely, a neural network that satisfactorily matches the actual spinning system has been found, and in that case the optimization will terminate.

Cycling. Calculate the mean affinity in the current Abs, and then compare it with the predefined threshold. If the mean affinity is lower than the threshold which means the mutation makes no quality improvement to the current antibodies, turn back to *Clonal selection* step.

Update the memory cells. Compared the Ag-affinity of the antibodies in the Abs with those in the current M, and insert the individuals antibodies with a higher affinity than the current



a) Artificial immune mechanism



b) Spinning-specified implementation

Fig. 5. Flow charts for the artificial immune mechanism and its spinning-specified implementation.

memory cells into M to become new memory cells. Adjust the threshold for the memory cells for the new M, and remove those Mc whose affinity is under the new threshold from M so that the mean affinity of the M can be increased generation after generation.

All the spinning process-specified procedures can be depicted as shown in Fig. 5 b).

IV. Application and Results

A. *Experiment design*

An industrial fiber production line (1.56dtex cotton-type polyester staple fiber, semi-open outer quenching applied) in one of the leading Chinese textile manufacturer is taken as the optimizing target by applying the proposed immune-NN based bi-directional optimization approach. It is a classical polymer manufacturing process whose various requirements for the fiber products should be met by tuning the in-process parameters. A large amount of real-time data has been accumulated by technicians for further analysis, which is beneficial for applying the intelligent optimizing methods.

(1) Data collection

A RBFNN-based optimizing mechanism generally requires a series of input and output data for training and testing, and these data should cover a wide range of values so that the trained model with the related RBFNN approximates the practical plant as precisely as possible. But such requirement cannot always be satisfied in the analysis of the spinning system. As a practical industrial process with large quantities of products, the manufacturing configuration should always be kept stable, or at least generally unchanged for a long time. So the room for adjusting the parameters and the corresponding quality indices is limited. To eliminate the disadvantage of such characteristic of the spinning system, more running data must be acquired to guarantee the optimizing model can cover a larger solution scope, which could consequently improve the accuracy of the model. In the following experiments, 200 groups of input and output data from the practical spinning process are collected for building the optimizing model. Each group consists of process parameters and the corresponding production quality indices. Note that the roles of these two parts of data depend on what kind of optimization needs to be made. For the process optimization, the process parameters are taken as the input, and the quality indices of fibers are taken as the output. For the category development, however, their roles should be swapped. The detailed information about the data collected is listed in Table I, e.g. the categories and the approximate ranges of the data. Before the formal experiments, all the data are randomly arranged and then taken to train the proposed model, and a pure NN model for comparison is also trained with the same data set. The reason for the random arrangement of data before training is to guarantee the trained model with better adaptation. Consequently, the model itself does not need to make an extra extrapolation which may decrease the accuracy.

(2) Process design

The basic configuration of the production line including the process and devices for conducting the experiments is listed in Table II. Here four process parameters, namely, the spinning velocity (SV), the spinning temperature (ST), the quenching velocity (QV), and the quenching temperature (QT) are taken as the major factors of the spinning process, and the performance indices, namely the elongation corresponding to 1.5 times the yielding stress (EYS1.5) and its coefficient of variance (EYSCV), breaking tenacity (DT), and the ability of elongation (DE), are represented by four major considerations. The basic production configuration, e.g. the fineness and the post-drawing ratio is kept unchanged, and the device parameters are also stable due to the practical foundation of such simulation. The whole procedure consists of three parts as below.

Preliminary verification. An optimizing model with a pure NN as its core is introduced, and one of the important quality indices of the spinning process, the EYS1.5 is taken to verify the ability of approximation of such model. 150 groups of actual data (sorted by spinning speed ascending) are taken for training the model and the remaining 50 groups act as the test set. The aim for doing a preliminary experiment is to reveal the possible drawback of an optimizing approach with conventional AI methods that have been widely applied to the spinning process,

TABLE I
PROCESS CONFIGURATION AND COLLECTED DATA

Item	Unit	Range
Spinning Velocity (SV)	$m \times \min^{-1}$	1000~1197
Spinning Temperature (ST)	$^{\circ}C$	280~299
Quenching Velocity (QV)	$m \times \min^{-1}$	100~139
Quenching Temperature (QT)	$^{\circ}C$	20~24
EYS	1	196.29~237.78
EYSCV	1	5.46~10.04
DT	1	5.82~6.81
DE	1	20.94~24.05

and therefore the necessity for modification can be easily concluded.

Process optimization. The process optimization is conducted by applying the process parameters as known knowledge and the quality indices of the fiber products as the expected results. The proposed intelligent model and the pure NN-based model are taken for experiment, and their respective results can be compared with the actual quality indices collected from the real production. The objective of this part is to explore the dynamics of the process parameters and their corresponding influence, e.g. a minor modification on the final quality of the fiber products. Practically, such experiment can also help to verify the ability of the proposed model on generating products with a series of specifically tuned producing environments so that the time-consuming and high-cost online test can be avoided. The parameters of the models applied are listed in Table III.

Category development. Opposite to the process optimization part, the category development turns the input and the output around, namely, acquiring the process configuration through known fiber quality indices. The approaches applied here are the same as those in the process optimization. The implementation in such a reverse direction is similar to the process optimization simulation technically, but may have greater significance for the industrial manufacturers. The aim for conducting this part is to determine whether the proposed model has the ability to provide reasonable configuration under the guidance of the final products. With the proposed intelligent mechanism, it is easy to design and make fiber products with desired qualities, and the cost for testing different combinations of manufacturing parameters can be cut off in a great amount. The process and device parameters for this experiment are the same as those for the process optimization instance.

All the experiments above take actions through a Microsoft .NET framework-based software specifically designed for connecting and optimizing the spinning manufacturing process. Both the optimizing approaches including the proposed intelligent method and the NN model are coded. This software provides the possibility that the proposed AI-based approach can be applied to the practical manufacturing without support of the laboratory (or even computerized) environment. As a result, the proposed algorithm can be implemented by an experienced programmer (who builds the codes of the algorithm) along with a control engineer (who connects the software with the field devices to get running data, meanwhile managing to send instructions downward to establish optimization). So the expectation that the academic achievements involved can be served as a powerful tool for the on-site engineers in the spinning factories can be realized, which is the very goal for this work.

TABLE II
BASIC CONFIGURATION OF THE SPINNING PROCESS AND DEVICES

Category	Item	Value
Product Category	Fineness/ $dtex$	1.56
	Post-drawing Ratio	3.6523
Spinning Parameters	Spinning Velocity/ $m \times \min^{-1}$	Variable
	Spinning Temperature/ $^\circ C$	Variable
	Characteristic Viscosity/ $dl \times g^{-1}$	0.63
	Quenching Velocity/ $m \times \min^{-1}$	Variable
	Quenching Temperature/ $^\circ C$	Variable
Device Parameters	Non-quenching Gap Height/ cm	6
	Number of Spinneret Orifice	3064
	Diameter of Spinneret Orifice/ cm	0.0022
	Pump Mass Throughput/ $g \times (\min \times hole)^{-1}$	0.0097
Performance Indices	EYS1.5	Variable
	EYSCV	Variable
	DT	Variable
	DE	Variable

TABLE III
PARAMETERS OF THE MODELS APPLIED

Item	Value
Number of Input Neurons	4
Number of Output Neurons	4
Number of Hidden Neurons	6
Size of Memory Cell Set (M)	5
Size of Antibody Set (Abs)	20
T_S	0.25
$m_{rclonal}$	10
Maximum Cycling Time	50

B. Results and analysis

(1) Preliminary verification

Fig. 6 shows the response of the EYS1.5 (shown as “EYS” in figures for short) for a model based on the RBFNN, in which the EYS1.5 is given in ascending order. The RBFNN-based model is firstly trained with the training set of 150 groups of the original data, and then tested with both the training set and the test set (50 groups). It can be observed that the RBFNN-based model approximates the actual value of EYS1.5 satisfactorily for the first 150 groups of original data (the training set). But the absolute error starts to increase when it comes to the test set. Noted that although there’re 150 groups of data which cover three fourth of the curve being taken for training, their corresponding errors of them still exist. For the test dataset (covers the last one fourth part of the curve), the error between the model generated value and the actual value of the EYS1.5 increases gradually. By comparing the actual value and the calculated one, the proportion between them can be acquired as a tiny decimal, which indicates this model should be compensated by multiplying a small coefficient to its original result to get a better performance. But such a procedure is not theoretically proved so that it cannot be introduced to the current model as a reasonable correction. The preliminary experiment shows that the RBFNN-based optimizing model may not be capable to stimulate the spinning system for acceptable performance, especially for the uncovered data, which therefore asks for further modification.

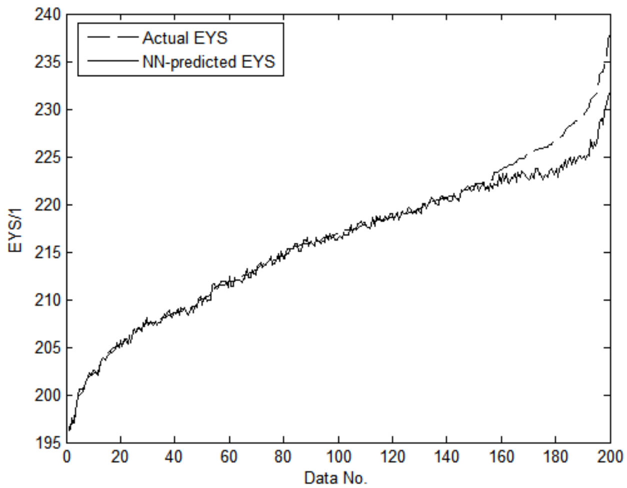


Fig. 6. Response of the EYS1.5 against variation of spinning velocity using the RBFNN.

(2) Process optimization

The process parameters as input of the optimization are listed in Table IV, in which the row marked with “Base” means it’s the basic configuration for experiment. One out of four major parameters is selected to make changes while keeping others stable and its value is tuned for four times. So the whole experiment process can be separated to four smaller independent experiments and the responses of the product indices are provided as shown in Fig. 7 a)-d), respectively. It can be observed that the EYS1.5 rises with the increment of spinning velocity, spinning temperature or quenching velocity, but drops as the quenching temperature becomes higher. For the EYSCV and DT, a higher spinning velocity leads to a lower index, and the results for tuning the spinning temperature, quenching velocity and quenching temperature are similar. For the DE, the trend is just opposite to that of the DT.

As to the performance of optimization, both the models have the ability to follow the fluctuation of the process parameters as input, and the difference lies that in the proposed algorithm has smaller absolute errors. The introduction of the AIS broads the searching scope of the optimizing model so that the model can “see” those solutions that may have been excluded during the training process of the original NN (the configuration of the network has actually been fixed once the training process finishes, so the result for a specific input is known without ability for possible exploration). In the view of numeric calculation and the inherent feature of the NN, the errors of both the models can be acceptable. Note that a minor fluctuation of the process parameter, however, may result in substantial changes in quality indices, so a comparative small error should still be an advantage.

TABLE IV
PROCESS PARAMETERS AS INPUT OF THE PROCESS OPTIMIZATION

Fineness / $dtex$	**SV** / $m \times \min^{-1}$	**ST** / $^{\circ}C$	**QV** / $m \times \min^{-1}$	**QT** / $^{\circ}C$	**Notes**
	1100	289	23.5	125	Base
	1110	293	24.5	130	
1.56	1120	297	25.5	135	
	1130	301	26.5	140	
	1140	305	27.5	145	

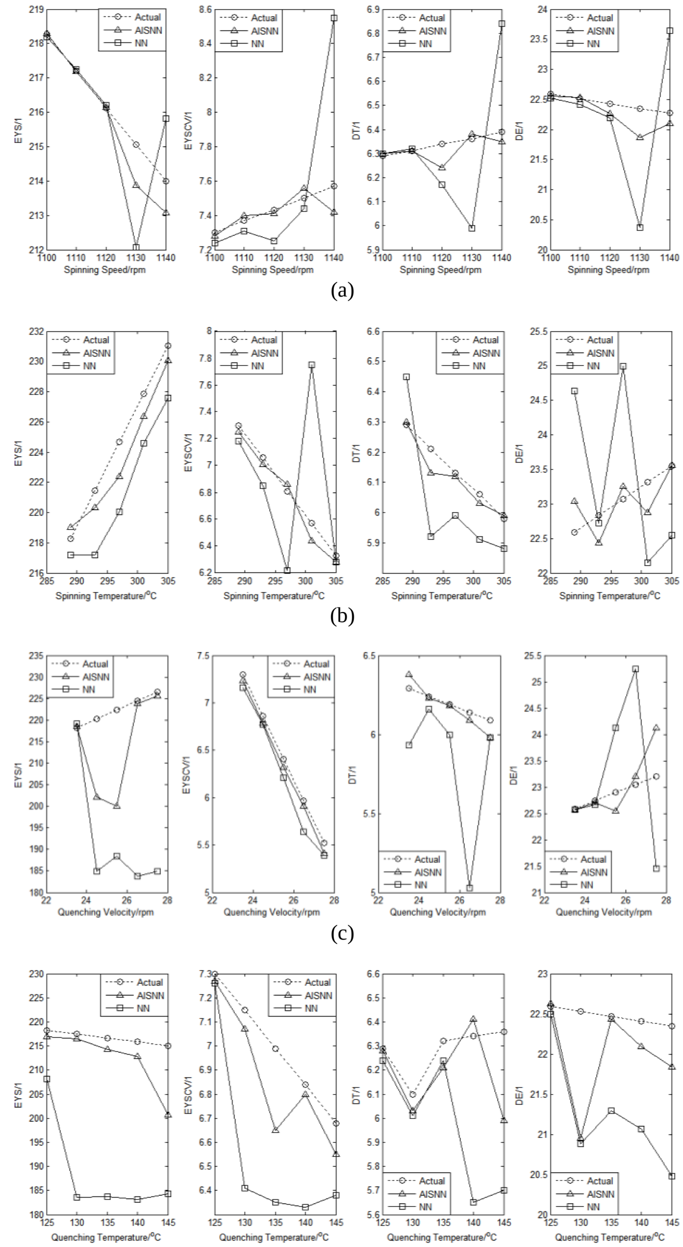


Fig. 7. Responses of quality indices against variations of different process parameters.

(3) Category development

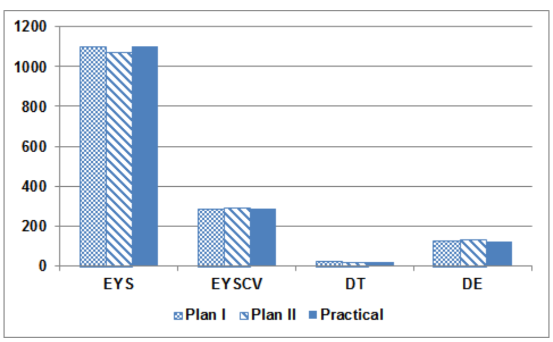
In the category development experiment, five sets of quality indices are selected as the input of the reverse models, compared to those for the production development. These quality indices are collected from the practical manufacturing process, covering the whole scope that the quality may possibly fluctuate and the required process configuration for each set is known. Their detailed values of these sets are listed in Table V, and the row marked with “Base” indicates this set is also used for training of the NNs included in the models. By applying the

TABLE V
QUALITY INDICES AS INPUT OF THE CATEGORY DEVELOPMENT

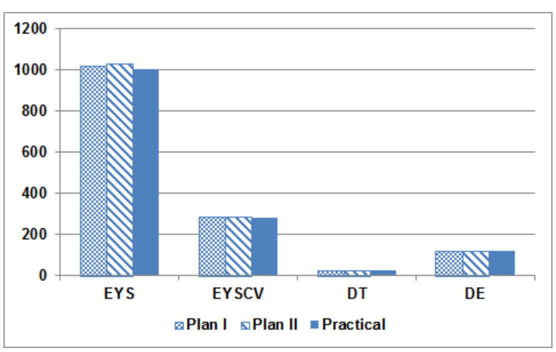
Fineness / *dtex*	**EYS**	**EYSCV**	**DT**	**DE**	**Notes**
	218.27	7.3	6.29	22.59	Base
	224.41	7.42	6.14	23.05	Group 1
1.56	211.52	7.6	6.45	22.08	Group 2
	206.04	8.23	6.58	21.67	Group 3
	220.67	8.79	6.23	22.77	Group 4

proposed intelligent optimizing model, the possible process configuration that contains four parameters can be generated, which can be regarded as a plan for manufacturing. Considering different combination of processing parameters may lead to similar quality indices, here not one but two plans generated from the AIS procedure are recorded to verify the performance of the proposed model (they are also the two best antibodies at the end of the optimization). Fig. 8 provides the plans generated by the proposed model and the actual production configuration (The Plan I for the base set is almost identical to the actual configuration, for the base set is one of the training sets).

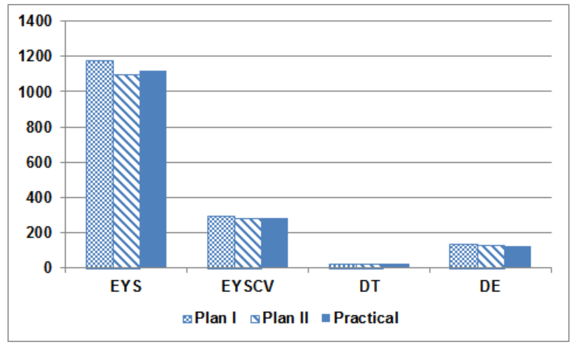
The verification for these plans is a little different from the procedure in the production development simulation. Since a different combination of processing parameters may contribute to similar products, the performance of these plans cannot be summarized only through comparing their contents with the actual configuration but should be put back into the actual manufacturing process to see what kind of product can be produced, and the difference between plans can therefore be verified by comparing their final products. Table VI shows the production quality with the generated plans and the real ones, and the mean errors of the two plans for each index are also provided.



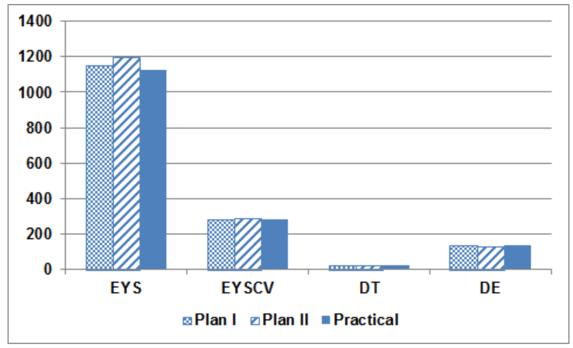
a) Base



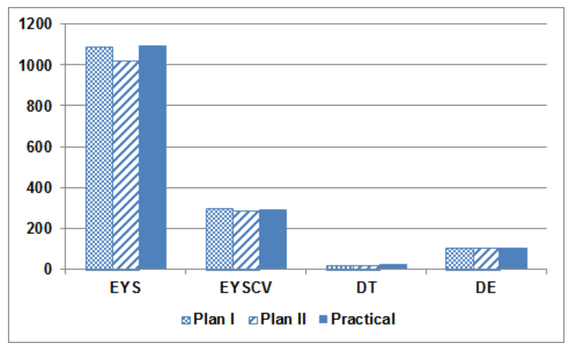
b) Group 1



c) Group 2



d) Group 3



e) Group 4

Fig. 8. Optimal plans generated under different quality requirements.

V. CONCLUSIONS

In this paper, a bi-directional optimizing approach for the melting spinning process based on an immune-enhanced neural network is proposed. The goal of the proposed bi-directional model is not only revealing the internal nonlinear relationship between the process configuration and the quality indices of the fibers, but also providing a tool for engineers to develop new fiber products with expected quality specifications. A neural network is taken as the foundation of the bi-directional model, and an artificial immune component with algorithm is introduced to enlarge the searching scope of the solution field so that the neural network has a larger possibility to find the appropriate and reasonable solution. The proposed intelligent model can also help to determine what kind of process configuration should be made in order to produce satisfactory fiber products. To make the proposed model practical to the manufacturing, a software platform is developed which performs independently without the academic or laboratory

TABLE VI
QUALITY VERIFICATION OF THE GENERATED PLANS AND REAL ONES WITH ERRORS.

	Indices	**Actual Value**	**Plan I**	**Error /%**	**Plan II**	**Error /%**
Base	EYS1.5	218.27	218.27	0	217.31	0.44
	EYSCV	7.3	7.3	0	7.00	4.11
	DT	6.29	6.29	0	6.00	4.61
	DE	22.59	22.59	0	22.99	1.77
Group 1	EYS1.5	224.41	224.35	0.03	223.86	0.25
	EYSCV	7.42	7.28	1.92	7.09	4.45
	DT	6.14	6.14	0	6.15	0.16
	DE	23.05	23.04	0.04	23.01	0.17
Group 2	EYS1.5	211.52	211.14	0.18	212	0.23
	EYSCV	7.6	7.81	2.76	7.33	3.55
	DT	6.45	6.46	0.16	6.44	0.16
	DE	22.08	22.05	0.14	22.12	0.18
Group 3	EYS1.5	206.04	205.71	0.16	205.05	0.48
	EYSCV	8.23	7.98	3.04	8.22	0.12
	DT	6.58	6.59	0.15	6.6	0.30
	DE	21.67	21.65	0.09	21.6	0.32
Group 4	EYS1.5	220.67	222.53	0.84	225.28	2.09
	EYSCV	8.79	8.48	3.53	8.55	2.73
	DT	6.23	6.18	0.80	6.12	1.77
	DE	22.77	22.91	0.61	23.11	1.49

environment. Simulation results show the proposed model can eliminate the approximation error raised by the neural network-based optimizing model, which is due to the extension of focusing scope by the artificial immune mechanism. Meanwhile, the proposed model with the corresponding software can conduct optimization in two directions, namely, the process optimization and category development, and the corresponding results outperform those with an ordinary neural network-based intelligent model. It is also proved that the proposed model has the potential to act as a valuable tool that the engineers and decision makers of the spinning process can turn to for advice, which actually reaches the goal mentioned above.

The future research directions include the deepening development of the optimizing model and the broadening exploration of the application scopes in the spinning manufacturing for different types of fibers. It should be an effective way to combine the inherent dynamic of the spinning process with the AI-based methods to form a more accurate model, hoping to acquire forward-looking results so that the quality of fibers can be much more improved. Similar ideas for developing such kind of model can also be applied to other spinning processes, or even the manufacturing processes with similar characteristics to make the scientists and producers involved know not only the reason for possible changes (“why”) but also the approaches for better changes (“how”), which is also the eventual goal of this work.

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