TENSION CONTROL SYSTEM DESIGN OF A FILAMENT WINDING STRUCTURE BASED ON FUZZY NEURAL NETWORK

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Abstract:

Filament winding products are widely used due to their quality, high strength and a series of advantages in the industrial areas. The process involves winding filaments under varying amounts of tension over a male mould or mandrel. The tension control product has become the most important object in the process. This study describes the tension force control of filament winding with fuzzy neural network controller design and its application to fiber reinforced plastics. The controller produces the error of the closed loop control system response and the actual system output for the desired tension system, instead of ordinary PID adjustment mechanism. Dynamic performance analysis of a traditional PID controller and fuzzy neural network controller is performed in detail using simulation and experiments. The results show that the system can not only exhibit desired dynamic performance but can also adapt to the wide range of speed and tension force changes by a proper servo motor and winding operation. This study provides the primary theoretical guide for the configuration design, optimization and control research of the FNN applications to industrial winding process.

1 Introduction

Filament winding is an important production molding process in fiber reinforced plastics (FRP) products [1]. The products have high strength, good corrosion resistance, low cost, good quality and long life, which are widely used in aerospace, petrochemical, construction and environmental protection, transportation, electricity and other fields. It is an important fabrication technique for manufacturing composite materials, usually in the form of cylindrical structures. The process involves winding filaments under varying amounts of tension over a male mould or mandrel. The mandrel rotates while a carriage moves horizontally, laying down fibers in the desired pattern. The most common filaments are carbon or glass fibers coated with synthetic resin while they are wound. Once the mandrel has been completely covered to the desired thickness, the mandrel is placed in an oven to solidify the resin. After the resin has cured, the mandrel is removed, leaving the hollow final product [2, 3]. In the filament winding process, the primary purpose of applying tension is to control

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the content of resin and to make the fibers arrange regularly on the core. The control of glass fiber tension is a key factor affecting the quality of products [4]. The size of tension, the uniformity of tension between each fiber bundle, and the winding tension of the fibers between layers of uniformity has a great impact on the product quality [5-8]. The study shows that, appropriate and stable tension can enhance the ability to withstand the internal pressure member and to improve its fatigue resistance; however, by contrast it makes the winding stricture of the fibers lose 20 % to 30 % strength. So, filament winding tension is a very important process control parameter in a fiberglass winding process. This study proposes a fuzzy neural network based control system design scheme for filament winding tension control applications to overcome some shortcomings of the ordinary PID tension control used in the system. Also a comparison between the conventional PID controller and a Mamdani type fuzzy inference based control system is designed. Simulated and experiment system responses of the designed prototype are analyzed.

2 Materials and Methods

There are many ways of making composite productions with filament windings and the tension control is an important aspect [9-14]. Even though each technique is different, they all have the following goals [15]:

1) Arranging fibers in the desired orientation and stacking sequence – It ensures the appropriate fiber orientation. This specifies the amount of fiber in each layer of the composite, so it governs the strength and stiffness of the composite.
2) Ensuring adequate wetting of fibers – Adequate wetting of the fiber is important to allow the right amount of resin in between the fibers so as to have an appropriate fiber/resin ratio. This is also crucial to the strength and stiffness of the composite.
3) Curing of resin – Curing enables the bonding of each layer of the composite to each other, thus unifying the product.
4) Minimization of the amount of voids – One of the most important factors in composite manufacturing is the removal of voids or air gaps between two successive layers of fiber. The voids reduce the stress bearing capacity of the fiber.

FRP involves two distinct processes, the first is the process whereby the fibrous material is manufactured and formed, and the second is the process whereby fibrous materials are bonded with the matrix during the molding process. FRP is usually used in designs that require a measure of strength or modulus of elasticity, whereas those non-reinforced plastics and other material choices are either mechanically or economically ill suited. This means that the primary design consideration for using FRP is to ensure that the material is used economically and in a manner that takes advantage of its specific structural enhancements.

3 Analysis of Filament Winding Tension Control System

Typically, a filament winding tension control system consists of three parts: the deconvolution section, the measurement section, the control section and auxiliary transmission apparatus, which are shown in Fig. 1.

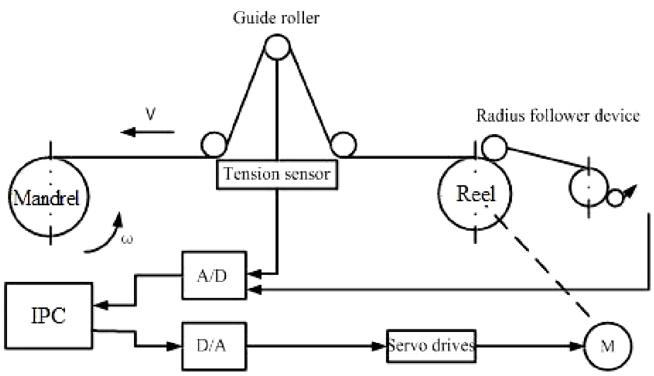


Figure 1. Fiber tension control system diagram.

3.1 Deconvolution Section

The deconvolution process refers to the method of winding a material into a roll which releases the fiber by rotating under the winding material tension [6]. In fiberglass winding process, the glass fiber is driven to produce movement by the rotation of the mandrel. Between the rolls and the mandrel, there may be plurality guides of rolling guides for controlling winding fibers and making them move smoothly.

3.2 The Measurement Section

Tension control system uses a closed-loop control mode in order to get real-time detection tension feedback signal. The strain gauge pressure sensor is adopted, which has a fast response, high accuracy and characteristics of small displacement.

The center of the servo motor shaft and the reel center are in co-axial connection and fixed. The mandrel driven by the spindle motor rotates, and the yarn produces uncoiling movement.

At this point, the servo motor produces the opposite direction to the yarn outlet electromagnetic torque, inevitably producing a tension to overcome the resistance moment.

In the normal operation of the winding machine, the servo motor is in the reverse state operation, the yarn tension is proportional to the output torque of the motor. When the yarn group radius decreases, the required tension will be reduced so as to ensure constant yarn tension. If yarn group radius decreases, the motor output torque must also be decreased. Radius follower devices are capable of real-time feedback to the radius change of the yarn group. The one end of the radius follower arm is on the deconvolution yarn, and the other end is connected to the rotary potentiometer through a gear mechanism. Thus the radius of the yarn package change is converted into a voltage variation and taken into the industrial personal computer via A/D converter modules.

3.3 Control Section

The control section includes controllers and actuators. The controller of tension control system is composed of controlling machine, analog/digital (A/D) and digital/analog (D/A). The device is implemented to generate the resistance torque in the deconvolution roll. Implementation of the device should have the dynamic characteristics of fast response, good static characteristics and high reliability. The AC servo motor is the tension actuator in this system.

4 Fuzzy Neural Network Control Algorithm for Filament Winding Tension

The mathematical model of the servo motor has nonlinear characteristics. At the beginning of the winding, it runs in reverse to the mandrel and the fiber speed is varied. Therefore, the fiber tension often needs to go through several adjustments. During uniform operation stage of winding tension, there will be a random velocity changes for some reason, such as dipping unevenness. In the winding process, with an increase of winding layers, the diameter of the mandrel will also be increased. This will cause load inertia changes, consequently the system dynamic equations will change and affect the tension. On the other hand, due to changing of the radius of the yarn group, the moment of inertia of roll and the outlet velocity of fiber are changing, which brings about the changes in tension. When the yarn winding process is in a loose condition, in other words, when the tension is reduced to a certain value, the system requires a rapid servo motor reversal in order to achieve the backward-movement of the yarn.

Fiber tension control system can quickly reach a constant tension point in the initial winding process. That is a good dynamic performance. And the system can ensure the actual value of the tension within the allowable error range of the radius changes of the yarn package and the speed core. That means it should have a better steady state performance. Currently the tension controller often uses a traditional PID algorithm [15-17]. The principle of PID is simple. It is easy to implement, but its parameter tuning requires experience with poor ability to adapt when the parameters change. In this study, the tension control system with fuzzy neural network control algorithm can achieve higher control precision.

4.1 The structure of fuzzy neural network control system in fiber tension

From the analysis above, a filament winding tension control system is a complex multi-variable coupling of time-varying systems. Thus, the designed tension control fuzzy neural network system consists of two types of neural network: one is neural network predictor for the servo motor output prediction, which predicts the servo motor control voltage the network. This allows the controller perceive trends of output state and make appropriate adjustments in advance. The other is fuzzy neural network for the servo motor, as shown in Fig. 2. The current status is a neural network input model to calculate the tension of the fibers output of next step of time, and to get the difference E_t by subtracting the expected tension values, and calculating the rate of change E_c. E_t, E_c and R_t (yarn group radius) for the fuzzy network controller input can be obtained by calculating the servo motor control output by using the fuzzy inference operation, and then by putting it to the predictor model tensioning system to obtain the tension output value T_t.

To identify a training model of servo motor, the neural network predictor is designed to run on parallel system with the controlled object, using the tension system input and output signals. A fuzzy neural network controller is connected to the controlled object in series to form a closed loop negative feedback control loop. A BP algorithm is used to adjust and train the parameters of the neural network controller to the desired performance of least-square estimation of the difference between the input and output values. In this way, the optimal objective function and the control rule membership function weights will be obtained. This system structure does not need a precise mathematical model controlled object. Nor are its control rules and membership functions dependent on experts' experience. It can be obtained by using neural networks. The error objective function J is defined as:

$$J = \frac{1}{n}\sum_{k=1}^{n}\sum_{c=1}^{l}[D_l - y_l]^2 = \frac{1}{n}\sum_{k=1}^{n}\sum_{c=1}^{l}[d(k) - y(k)]^2 \quad (1)$$

where D_l and $d(k)$ are desired outputs, y_l and $y(k)$ the output of network calculating, n is the number of sampling points per batch, l is the number of the amount charged.

D_t is a set point of the system; T_t is the actual output value of the system; E_t is the deviation of set point and actual output value; E_c is the rate of change of deviation of set point and the actual output value; R_t is the voltage value of the potentiometer which corresponds to the detected radius of the yarn group; $\hat{T}_t$ is the output of neural network prediction; E_2 is the error of prediction output and the actual output value; U is output control quantity of the controller.

4.2 Design of servo motor fuzzy neural network controller

A fuzzy neural network controller structure for the implementation of components is shown in Fig. 3. Using neural network memory fuzzy control rules, rules of thumb will be transformed into an abstract neural network of the samples [18, 19].

The controller uses these experiences in the way of associative memory. This study uses one-way propagation multilayer feed forward networks. It has a simple structure, ease of implementation, and has the capabilities of adaptive self-learning and self-organizing. The network consists of five layers: input layer, fuzzy layer, rule layer, normalized layer and output layer.

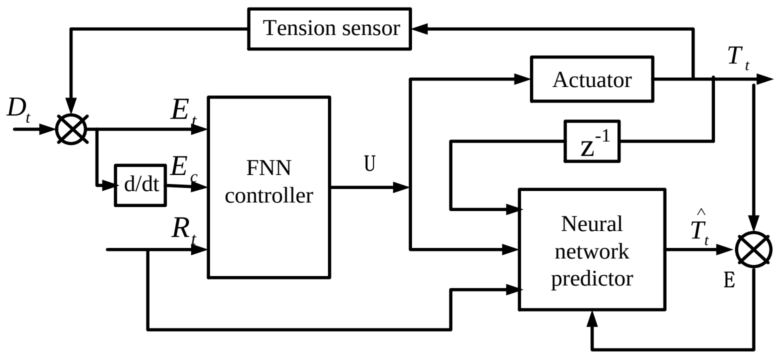


Figure 2. The structure of fuzzy neural network system in fiber tension control.

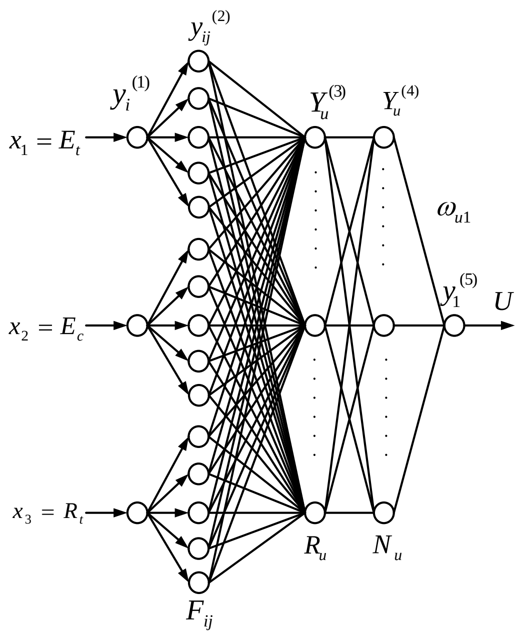


Figure 3. The structure of fuzzy neural network controller.

Fuzzy neural network inputs are composed of deviation with tension, the tension deviation rate and yarn group radius. Outputs are servo motor control voltage.

▪ Layer 1: input layer

There are three nodes in the layer. Inputs are deviation consisting of the amount of charge named E_t, deviation change rate made up of the amount of charge named E_c and the yarn group radius named R_t. The connection weight of layer 1 to layer 2 is 1 and can be expressed as:

$$X = [E_t, E_c, R_t] \tag{2}$$

$$Y_i^{(1)} = x_i, \quad i = 1,2,3 \tag{3}$$

X_i is a K_i quantified by the amount of the digital universe.

▪ Layer 2: fuzzy layer

Calculate the inputs that belong to the membership of fuzzy set in each linguistic variable. Each node represents a membership function of a linguistic value [20]. Three input variables of fiber tension control system are taken into 5 monograph domains which are {NS, NB, ZO, PS, PB}. Therefore, there are 15 fuzzy layer nodes. This study makes differentiable Gaussian function be the membership function. The weight value is 1 and it can be expressed as:

$$Y_{ij}^{(2)} = \exp[-\frac{(Y_i^{(1)} - c_{ij})^2}{\sigma_{ij}^{\ 2}}], \quad i = 1,2,3, \quad j = 1,2,3,4,5 \tag{4}$$

where, $Y_{ij}^{(2)}$ is the j-th membership function of x_i, c_{ij} is the j-th value of the Gaussian membership function of x_i, σ_{ij} is the j-width of the Gaussian membership function of x_i.

▪ Layer 3: rule layer

This layer can complete fuzzy logic inference work. Each node represents a fuzzy rule antecedent. By calculating the degree of activation of each rule, the weight connected with next layer is the output value of each rule. The number of layer nodes reflects the number of fuzzy rules. The tension control system has three inputs and each has five linguistic values. Space partitioning is based on fuzzy rules and there are 125 fuzzy rules. Node can fuzzy “and” operate, and the weight of 1 may be expressed as:

$$\begin{aligned} &Y_u^{(3)} = Y_{ip}^{(2)} \cdot Y_{iq}^{(2)} \\ &p = q = 1,2,3,4,5, \quad u = 1,2,\ldots,125 \end{aligned} \tag{5}$$

▪ Layer 4: normalized layer

By normalized calculation of each fuzzy rule, the oscillation in learning process caused by the excessiveness of each correction can be avoided. This layer of nodes with the same number of fuzzy rules, each node in the blur “or” operation with the same output condition synthesis rules can be expressed as:

$$Y_u^{(4)} = \frac{Y_u^{(3)}}{\sum_{u=1}^{125} Y_u^{(3)}}, \quad u = 1,2,\ldots,125 \tag{6}$$

▪ Layer 5: output layer

The layer node represents the actual system output variables. This is calculated using the center of the gravity method

$$Y_l^{(5)} = \sum_{u=1}^{125} \omega_{ul} \cdot Y_u^{(4)},\ u = 1,2,\cdots,125,\ l = 1,2,3, \quad (7)$$

where ω_{ul} is the connection weight between the rule layer and output layer. c_{ij}, σ_{ij} and ω_{ul}, which are network adjustable parameters, can be obtain by seeking the minimum of the error function values.

4.3 Design of Neural network

By using a first order delay with output feedback forward network, making the structure of input and output equal to system identification, the system dynamics identification can be derived. In this study, the serial-parallel predictive model has been adopted. The learning objective function is the error sum of squares of the system's actual output and output of the predictor network. By using the BP algorithm along with an adaptive learning rate to train the network, the predictive model can have similar input and output characteristics as the actual controlled object in a certain error range, as shown in Fig. 4.

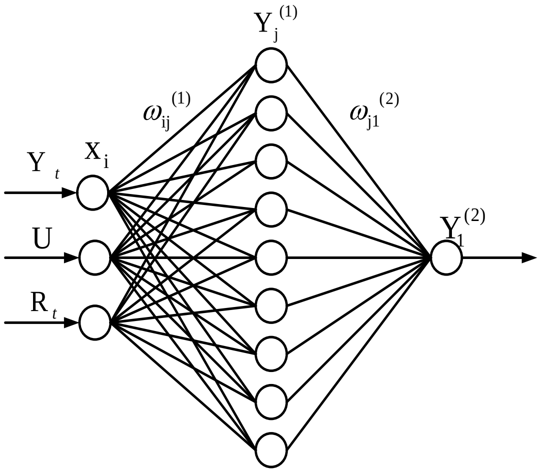


Figure 4. The structure of neural network in predictor.

The network consists of three layers: there are three input layer neurons, input servo motor speed, the yarn group radius and fiber tension; there are nine neurons in the hidden layer; the output layer has one neuron, and the output is the tension in the fiber.
Select the S-type function to be the activation function in the hidden layer:

$$Y_j^{(1)} = f(\omega_{ij}^{(1)} x_i + \theta_i^{(1)}) \quad (8)$$

where, x_i is the input of the input layer, $\omega_{ij}^{(1)}$ are the weights from the input layer to hidden layer, $\theta_i^{(1)}$ is the threshold value of the hidden layer, $Y_j^{(1)}$ is the output of the hidden layer.
Select the linear function to be the motivate function in the output layer:

$$Y_l^{(2)} = f(\sum_{j=1}^{9} \omega_{jl}^{(2)} Y_j^{(1)} + \theta_j^{(2)}) \quad (9)$$

where $\omega_{jl}^{(2)}$ are the weights from the hidden layer to the output layer, $\theta_j^{(2)}$ is the threshold value of the output layer, $Y_l^{(2)}$ is the output of the output layer. In Eq. (8) and Eq. (9), $i = 1,2,3$, $j = 1,2,\ldots,9$, $l = 1$.
It can be adjusted following the gradient of the network weights. The weight after training and learning of k steps can be expressed as:

$$\omega_{ul}(k+1) = \omega_{ul}(k) - \eta \frac{\partial J}{\partial \omega_{ul}} + \alpha \Delta \omega_{ul}(k) \quad (10)$$

$$\frac{\partial J}{\partial \omega_{ul}} = -\frac{1}{n} \sum_{k=1}^{n} \sum_{c=1}^{l} \delta'_{\ln}(k) y_u^{(4)}(k) \quad (11)$$

The connection weight between the rule layer and the output layer is:

$$\omega_{ul}(k+1) = \omega_{ul}(k) + \eta \frac{1}{n} \sum_{k=1}^{n} \sum_{c=1}^{l} \delta'_{\ln}(k) y_u^{(4)}(k) + \alpha \Delta \omega_{ul}(k) \quad (12)$$

where $\delta'_{\ln}(k) = \frac{2}{n}[d_l(k) - y_l(k)] \operatorname{sgn} \frac{y_l(k) - y_l(k-1)}{r_l(k) - r_l(k-1)} y_u^{(4)}(k)$.
The correction values of input variable membership functional parameters c_{ij} and σ_{ij} can be expressed as:

$$\Delta c_{ij} = -\frac{\partial J}{\partial c_{ij}} = -\frac{\partial J}{\partial Y_{ij}^{(2)}} \cdot \frac{\partial Y_{ij}^{(2)}}{\partial c_{ij}} = \delta_{ij}^{(2)} \cdot \frac{2(x_i - c_{ij})}{\sigma_{ij}^2} \quad (13)$$

$$\Delta \sigma_{ij} = -\frac{\partial J}{\partial \sigma_{ij}} = -\frac{\partial J}{\partial Y_{ij}^{(2)}} \cdot \frac{\partial Y_{ij}^{(2)}}{\partial \sigma_{ij}} = \delta_{ij}^{(2)} \cdot \frac{2(x_i - c_{ij})^2}{\sigma_{ij}^3} \quad (14)$$

$$c_{ij}(k+1) = c_{ij}(k) + \eta \Delta c_{ij} + \alpha[c_{ij}(k) - c_{ij}(k-1)] \quad (15)$$

$$\sigma_{ij}(k+1) = \sigma_{ij}(k) + \eta \Delta \sigma_{ij} + \alpha[\sigma_{ij}(k) - \sigma_{ij}(k-1)] \quad (16)$$

where, η is learning rate, $0 \leq \eta < 1$, α is a momentum factor, k is a number of learning steps.

5 Results and analysis

In the MATLAB based simulation environment, a fiber tension control system model can be expressed with one order inertia. The model of the transfer function of the temperature can be determined by the experiments as:

$$G(s) = \frac{k}{Ts+1}, \tag{17}$$

where taking the inertia time constant T to be 0.12, the gain factor K of 150.

The temperature and humidity of the drying process after training and optimization has been simulated. Temperature and humidity of the drying system model are replaced by the generated identification model, enabling online calculation and simulation to obtain fast output characteristics. In order to verify the performance of the designed controller, a fuzzy neural network controller has been simulated. The results will be compared with the simulation results of a conventional PID controller and fuzzy controller. Tension deviation E_t, tension deviation change rate E_c and the yarn group radius R_t are inputs. Servo motor control voltage Y_t is output, and its final quantization is the servo motor speed. Set the initial PID regulator proportional coefficient to be K_p = 0.2, integration time constant K_i = 0.3, and derivative time constant K_d = 0.5.

Using the Gaussian function to be the membership function of the fuzzy controller, the input and output variables of the domain have taken {NS, NB, Z, PS, PB}. The fuzzy linguistic terms of the inputs and output are used as negative big (NB), negative small (NS), zero (Z), positive small (PS) and positive big (PB). The discrete universe of input is {-3,-2, -1, 0, 1, 2, 3}; for the input is {-1, -0.5, 0, 0.5, 1}, and for the output is {-12, 6, 0, 6, 12,}. Membership functions according to the basic principles must be followed to achieve the tension change E_c ("e"), and the membership function is shown in Fig 5. The performance comparison can be illustrated as Figs. 6 and 7.

Fig. 6 a) shows that the normalized tension force changes with the ordinary PID and the presented fuzzy neural networks. The FNN method can effectively adjust the parameters of the controller and thus the smooth and stable tension force is derived without any response delay, which has advantage over the ordinary PID method.

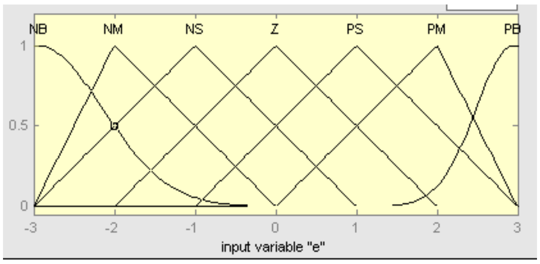
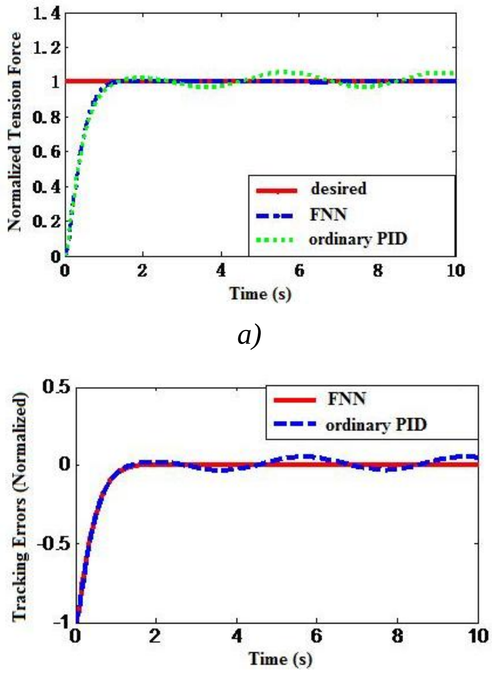


Figure 5. Membership function of the tension change E_c.



a)

b)

Figure 6. The comparison of the performance of the methods: a) Normalized tension force, b) Tracking errors.

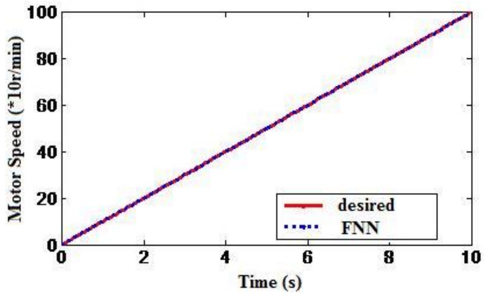


Figure 7. The motor speed tracking performance comparison.

The motor speed tracking performance comparison effects are illustrated. In Fig. 7, it can be seen that the presented method can make the drive servo motor a satisfied acceleration process that almost coincides with the desired speed control signal, which is a key dynamic measure point for real applications. The results have given a reasonable and practical solution to be implemented in the proposed fuzzy neural network control scheme for industrial winding processes.

In order to validate the performance of the presented scheme, the experiments and tests are also conducted on the machine. Fig. 8 illustrates the structure of the test platform as a modified winding machine for Fiber Reinforced Polymer (FRP).

Figure 8. Photo of the composite filament winding machine.

The diameter of the product can be ϕ 500-2500 mm, the length can be ≤12000 mm, the winding angle is 45°-90°, and the maximum rotation speed for the main axis is 45 r/min. The maximum width of the yarn sheet is 200mm. The repeat positioning accuracy is 0.2 mm. Figs. 9 and 10 show the experiment results of tension force measurements with their step variation conditions. It can be seen that the presented FNN control scheme can effectively enhance the dynamic performance of the step response and interference suppression abilities.

6 Conclusion

This study uses the advantages of the fuzzy logic and neural network, and designs the fuzzy neural network controller of a fiber tension control system. Using the BP algorithm to train a fuzzy neural network controller and a tension control system prediction model, the fuzzy neural network with optimal structure and parameters as well as predictive models with good dynamic characteristics are obtained. The comparison by differentiating between simulation and experiment results made with a conventional PID controller proved that the proposed fuzzy neural network controller has the advantages of fast convergence, good dynamic response, robustness, small overshoot, control high accuracy and good stability. The proposed controller design scheme can meet the requirements of the fiber glass winding system.

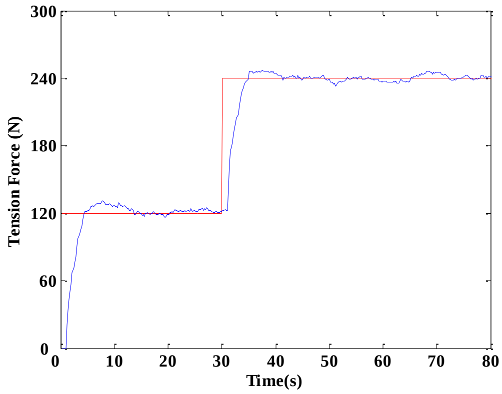


Figure 9. Experimental tension force variation with time by PID control.

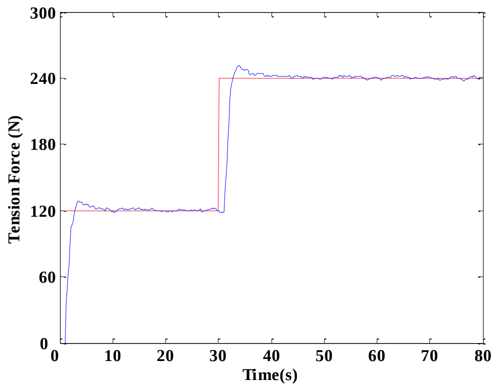


Figure 10. Experimental tension force variation with time by FNN control.

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