Abstract: In light of fine learning ability in the existing uncertainties, a sage revised reiterative even Zernike polynomials neural network (SRREZPNN) control with modified fish school search (MFSS) method is proposed to control the six-phase squirrel cage copper rotor induction motor (SSCCRIM) impelled continuously variable transmission assembled system for obtaining the brilliant control performance. This control construction can carry out the SRREZPNN control with the cozy learning law, and the indemnified control with an assessed law. In accordance with the Lyapunov stability theorem, the cozy learning law in the revised reiterative even Zernike polynomials neural network (RREZPNN) control can be extracted, and the assessed law of the indemnified control can be elicited. Besides, the MFSS can find two optimal values to adjust two learning rates with raising convergence. In comparison, experimental results are compared to some control systems and are expressed to confirm that the proposed control system can realize fine control performance.

Keywords: even Zernike polynomials neural network; fish school search; Lyapunov stability theorem; six-phase squirrel cage copper rotor induction motor

1. Introduction

Artificial intelligent systems have been widely used in many commercial and industrial applications. Artificial neural networks (ANNs) [1–4] were one of the popular methods in modeling, control, estimation and prediction of nonlinear systems with better learning ability. However, these ANNs need longer time to process training and learning procedures. Hence, a lot of orthogonal polynomials neural networks (NNs) [5–8] were proposed to apply to various kinds of modellings, identifies, approximations and controls of nonlinear systems because of faster computing ability. However, these NNs combined with some controllers have not appeared to have any adjustable mechanisms of weights. The approximated models for nonlinear systems appeared with a larger difference. Thereby, the even Zernike polynomials (EZPs) that are orthogonal on the unit disk found in the extended Nijboer–Zernike theory of diffraction and aberrations [9] with a sequence of polynomials combined with NNs are not yet proposed in modellings, estimations, predictions and controls for nonlinear systems. The feedforward even Zernike polynomials neural network (FEZPNN) may not be able to approximate nonlinear dynamic uncertainties effectively in light of lacking reiterative loop.

The recurrent NNs [10–13] have been broadly applied in prediction, identification, estimation and control of nonlinear systems as result of high certification and fine control performance lately. On the basis of more benefits than the feedforward EZPNN, the revised reiterative even Zernike polynomials neural network (RREZPNN) control has, as yet, not been used for expelling the nonlinear continuously variable transmission assembled system to enhance the certification property of the nonlinear system and cut down calculation complexity.

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Fish school search (FSS) firstly proposed by Carmelo et al. [14] is a unimodal optimization algorithm inspired by the collective behavior of fish schools. It is a population-based search algorithm inspired by the behavior of swimming fishes that expand and contract while looking for food. Each fish n-dimensional location represents a possible solution for the optimization problem. Salomao et al. [15] proposed the density-based fish school search (DBFSS) method that includes modifications of the previous operators: feeding and swimming, as well as new: memory and partition operators. Fernando and Marcelo [16] proposed the weight-based fish school search (WBFS) method that is a weight-based niching version of FSS intended to produce multiple solutions. However, these FSS methods absented the updated mechanisms of weights so that led to the sluggish astringent. Thereby, so as to speed up the convergent speed of weights, the novel modified fish school search (MFSS) method is proposed to adjust two learning rates in this paper.

A six-phase induction motor [17–19] has been broadly applied in various kinds of industrial applications [20,21] because it has higher efficiency, higher reliability and lower torque ripple in comparison with a three-phase squirrel cage aluminum rotor induction motor. Moreover, the nonlinear dynamics continuously variable transmission systems [22,23] driven by the six-phase squirrel cage copper rotor induction motor (SSCCRIM) that adopted the orthogonal polynomials neural network controls were proposed by Lin [24,25]. However, those control systems with neural networks proposed by Lin [24,25] need longer calculation time to carry out the nonlinear system. Thereby, the main objective and motivation of the proposed sage revised reiterative even Zernike polynomials neural network (SRREZPNN) control with the MFSS method for the SSCCRIM impelled continuously variable transmission assembled system is to develop the RREZPNN control with the cozy learning law, and the indemnified control with an assessed law to reduce computing time as well as speed up convergence of weights in the RREZPNN. This control method has a faster learning ability and better generalization. The SRREZPNN control with MFSS can carry out the handler control, the RREZPNN control with a cozy learning law, and the indemnified control with an assessed law. In accordance with the Lyapunov stability, the cozy learning law for training parameters in the RREZPNN is derived online. Therefore, the RREZPNN with learning ability online can respond to nonlinear uncertainty. Besides, the MFSS is proposed to search for two optimal values to revise two learning rates in the connecting weights and recurrent weights of the RREZPNN and to speed up convergent speed of weights regulation. Finally, tested results are demonstrated to confirm that the SRREZPNN control with MFSS method can reach a fine control performance.

The main aims of this paper are as below. Section 2 presents the descriptions of entire system including the continuously variable transmission assembled system, the SSCCRIM modeling system and the SSCCRIM impelled system. Section 3 presents the explanations of applied methods including the SRREZPNN control method and the MFSS method. Section 4 presents the tests and experimental results for the SSCCRIM impelled continuously variable transmission assembled system by using three control methods. Section 5 presents the discussions and analyses for experimental results. Section 6 presents the conclusions.

2. Descriptions of Entire System

The entire system is composed of three subsystems that are the continuously variable transmission assembled system, the SSCCRIM modeling system and the SSCCRIM impelled system. Three subsystems are described as below.

2.1. Continuously Variable Transmission Assembled System

Owing to the effects of nonlinear uncertainties, the SSCCRIM impelled continuously variable transmission assembled system conducted seriously abnormal performance variation in the entire system. The tracking responses of torque and speed control in the SSCCRIM impelled continuously variable transmission assembled system especially deteriorated under nonlinear uncertainties. Therefore, the better models in the SSCCRIM impelled continuously variable transmission assembled system are
important in system modelling and control performance. The conformation of the SSCCRIM impelled continuously variable transmission assembled system is shown in Figure 1 [22,26]. Considering that the belt curve effects loss, power loss and sliding loss, which are insignificant in Figure 1, the four drive equations with simplified kinematics of the continuously variable transmission assembled system in the subordinate driven flank and the foremost driving flank by using the law of safekeeping are described as

\[
T_x = J_1 \frac{d\omega_x}{dt} + B_1 \omega_x + T_w
\]  
(1)

\[
T_w = \mu_y (v_x, v_y) \omega_y T_z / \omega_z
\]  
(2)

\[
T_z = J_z \frac{d\omega_y}{dt} + B_z \omega_y + T_y
\]  
(3)

\[
T_y = J_y \frac{d\omega_y}{dt} + B_y \omega_y + T^\prime_y (v_{xy}, T_{xy}, F_{yl}, B_y, \omega^2_y)
\]  
(4)

where \(T_x, T_w, T_z\) and \(T_y\) are the electromagnetic torque in the SSCCRIM, the input driving torque in the foremost pulley flank, the output driven torque in the subordinate pulley flank and the impelled torque in the wheel, respectively; \(J_1 = J_x + J_w\) and \(B_1 = B_x + B_w\) are the synthesized moment of inertia and the synthesized viscous friction coefficient, respectively; \(J_{xy}, J_{yw}, J_z\) and \(J_y\) are the moment of inertia in the SSCCRIM, the moment of inertia in the foremost pulley flank, the moment of inertia in the subordinate pulley flank and the moment of inertia in the wheel, respectively; \(B_{xy}, B_{yw}, B_z\) and \(B_y\) are the viscous frictional coefficient in the SSCCRIM, the viscous frictional coefficient in the foremost pulley flank, the viscous frictional coefficient in the subordinate pulley flank and the viscous frictional coefficient in the wheel, respectively; \(\mu_y (v_x, v_y), (v_x, v_y), (\rho_x, \rho_y), (T_y, T^\prime_y)\) are the transposition ratios in connection with the foremost flank and subordinate pulley flank in the continuously variable transmission assembled system, the slip arcs in connection with driving torque transmission under low speed, the wrap angles that are the contacted arcs between belt and pulley, the input transmitting torque and the output load torque on the foremost driving pulley and the subordinate driven pulley, respectively; \(T^\prime_y (v_{xy}, T_{xy}, F_{yl}, B_y, \omega^2_y)\) is the intact nonlinear extrinsic disturbances in the subordinate driven pulley; \(v_{xy}, T_{xy}, F_{yl}, \omega_x\) and \(\omega_y\) are the rolling resistance, the wind resistance, the braking force, the speed in the foremost pulley flank and the speed in the subordinate pulley flank, respectively. Then, the torque equation can be transformed from the subordinate pulley flank to the foremost pulley flank by use of speed ratio and sliding ratio. For simplification, the modeling of the continuously variable transmission assembled system can be assumed negligible with regard to power and slip losses. Thus, the synthesized dynamic equation in the SSCCRIM impelled continuously variable transmission assembled system from Equation (1) to Equation (4), including the synthesized torque, can be described as

\[
J_1 \frac{d\omega_x}{dt} + B_1 \omega_x + T^\prime_y (v_{xy}, T_{xy}, F_{yl}, B_y, \omega^2_y) + T_f = T_x
\]  
(5)

where \(T^\prime_y (v_{xy}, T_{xy}, F_{yl}, B_y, \omega^2_y) = \Delta T_w + T_{al}\) is the large nonlinear extrinsic disturbances and parameter variations; \(T_f = T_f (T_{ls}, T_{sr}, T_{cs}, T_{rs})\) is the synthesized torque; \(T_{ls}, T_{sr}, T_{cs}\) and \(T_{rs}\) are the external load torque, the Striebeck effect torque, the cogging torque and the coulomb friction torque, respectively; \(\Delta T_w = \Delta T_1 \frac{d\omega_x}{dt} + B_1 \omega_x\) and \(T_{al} = T^\prime_y (v_{xy}, T_{xy}, F_{yl}, B_y, \omega^2_y)\) are the entire parameter variations and the entire nonlinear extrinsic disturbances, respectively.
2.2. SCCRIM Modeling System

For simplicity in the six-phase \(a_1 - b_1 - c_1 - a_2 - b_2 - c_2\) axes coordinate frames via the Clarke and Park transformations, the voltage equations in the coordinate frames transformation from the six-phase \(a_1 - b_1 - c_1 - a_2 - b_2 - c_2\) axes to the \(q_1 - d_1 - q_2 - d_2\) axes in the SCCRIM can be represented by [17–19]

\[
v_{d1} = r_1 i_{d1} - \omega_s \lambda_{q1} + \frac{d\lambda_{q1}}{dt} \tag{6}
\]

\[
v_{q1} = r_1 i_{q1} + \omega_s \lambda_{d1} + \frac{d\lambda_{d1}}{dt} \tag{7}
\]

\[
v_{d2} = r_1 i_{d2} + \frac{d\lambda_{d2}}{dt} \tag{8}
\]

\[
v_{q2} = r_1 i_{q2} + \frac{d\lambda_{q2}}{dt} \tag{9}
\]

\[
0 = r_2 i_{dr} + \omega_s \lambda_{qr} + \frac{d\lambda_{dr}}{dt} \tag{10}
\]

\[
0 = r_2 i_{qr} + \omega_s \lambda_{dr} + \frac{d\lambda_{qr}}{dt} \tag{11}
\]

where \(\lambda_{q1} = L_1 i_{q1} + L_2 i_{qr}, \lambda_{d1} = L_1 i_{d1} + L_2 i_{dr}\) and \(\lambda_{q2} = L_1 i_{q2}, \lambda_{d2} = L_1 i_{d2}\) are the \(q_1 - d_1\) axes and \(q_2 - d_2\) axes flux linkages, respectively. \(\lambda_{qr} = L_3 i_{qr}, \lambda_{dr} = L_3 i_{dr}\) are the \(q_r - d_r\) axes flux linkages.

\(v_{q1}, v_{d1}, v_{q2}, v_{d2}\) are the \(q_1 - d_1 - q_2 - d_2\) axes voltages. \(i_{q1}, i_{d1}, i_{q2}, i_{d2}\) are the \(q_1 - d_1 - q_2 - d_2\) axes currents. \(i_{qr}, i_{dr}\) are the \(q_r - d_r\) axes currents. \(r_1\) and \(r_2\) are the stator resistance and rotor resistance, respectively; \(L_1, L_2\) and \(L_3\) are the stator-coil self-inductance, the mutual inductance between stator coils and rotor coils and the rotor-coil self-inductance, respectively. \(\omega_s, \omega_{sl} = \omega_s - \omega_b = r_2 L_2 i_{q1}/(|\lambda_{dr}|L_3)\) are the electrical angular speed of synchronous flux and the slip angular speed, respectively. \(\omega_b\) is the electrical angular speed of rotor. \(P_1\) is the number of poles. The electromagnetic torque \(T_x\) in the SCCRIM can be described as

\[
T_x = k_s [\lambda_{dr} i_{q1} - \lambda_{qr} i_{d1}] \tag{12}
\]
where \( k_s = 3P_1L_2/(4L_s) \) is the torque constant. Besides, the dynamic equation for speed-torque of the SSCCRIM can be described as

\[
T_x = T_f(T_{ls}, T_{ss}, T_{cs}, T_{rs}) + J_x \frac{d\omega_x}{dt} + B_x \omega_x
\]

where \( \omega_x = 2\omega_r/P_1 \) is the mechanical angular speed of rotor in the SSCCRIM.

### 2.3. SSCCRIM Impelled System

The composition of the SSCCRIM impelled continuously variable transmission assembled system shown in Figure 2 is composed of three subsystems as the SSCCRIM impelled system, the continuously variable transmission assembled system and the digital signal processor (DSP) control system. The continuously variable transmission assembled system is composed of the continuously variable transmission system and the wheel. The SSCCRIM impelled system is comprised of the voltage-fed converter with six arms–twelve switches insulated-gate bipolar transistor power elements, the isolated circuit, the interlocked circuit, the analog–digital converter and the current sensing circuit. The DSP control system can realize a speed control, an indirect field-oriented control (FOC) and a proportional-integral (PI) current control. The indirect FOC is composed of a \( \sin \theta_1 / \cos \theta_2 \) production, a table production, a coordinate transformation, an inverse coordinate transformation and a space vector pulse-width modulation control. \( k_{ip} = 18.6 \) and \( k_{il} = k_{ip}/T_{1i} = 7.6 \) are two gains of the PI current control via certain heuristic comprehension [26–28] so as to obtain a significant dynamic response. The SSCCRIM impelled system was controlled by the DSP control system under entire nonlinear extrinsic disturbances and entire parameter variations.

![Figure 2. Composition of the SSCCRIM impelled continuously variable transmission assembled system.](image-url)
3. Explanations of Applied Methods

The applied methods that are composed of the SRREZPNN control method and the MFSS method are as below.

3.1. SRREZPNN Control Method

The dynamic equation in Equation (5) via systems simplification can be described as

\[
d\omega_x = G_x \omega_x + G_y T_t + G_z f_x
\]  

(14)

where \( T_t = T_y(\Delta T_w, T_{ls}(\omega_y), \omega_{yw}) + T_f(T_{ls}, T_{rs}, T_{cs}) = \Delta T_w + T_{d1} + T_f \) is the entire system’s disturbances; \( G_x = -B_t/J_t \) is an intimate ratio constant that \( |G_x \omega_x| \leq Q_x(\omega_x) \) is assumed to be bounded and \( Q_x(\omega_x) \) is the functional-bounded value; \( G_y = -1/J_t \) is a constant with regard to the synthesized moment of inertia that \( |G_y T_t| \leq Q_y \) is assumed to be bounded; \( G_z = 1/J_t \) is an intimate constant the synthesized moment of inertia that \( G_z \leq Q_x \) is assumed to be bounded and \( Q_x \) and \( Q_y \) are two bounded intimate values. \( f_x = T_x \) is the control torque, i.e., the electromagnetic torque of the SSCCRIM. The speed difference is defined by

\[
b_x = \omega^* - \omega_x
\]  

(15)

where \( b_x \) is the speed difference.

If the entire nonlinear extrinsic disturbances and the entire parameter variations are well intimate, the unflawed control rule can be described as

\[
f_x^* = \frac{d\omega^*}{G_z dt} + \frac{k_x b_x}{G_z} - \frac{G_x \omega_x}{G_z} - \frac{G_y T_t}{G_z}
\]  

(16)

where \( k_x \) is a control gain that is a positive constant. When \( f_x^* = f_x \) in Equation (16), and it is substituted into Equation (14). Then Equation (17) can be obtained as

\[
\left( \frac{d}{dt} + k_x \right) b_x = 0
\]  

(17)

In general, when \( t \to \infty \) as well as \( b_x(t) \to 0 \) in Equation (17), the system’s state will track the desired trajectory. Nevertheless, the control performance of system’s state will result in sluggish tracking under the occurrence of uncertainty. Therefore, the SRREZPNN control with the MFSS method is developed for controlling the SSCCRIM impelled continuously variable transmission assembled system so as to improve speed tracking response. The control frame of the proposed control system that is depicted in Figure 3 is described as

\[
f_x = f_1 + f_2 + f_3
\]  

(18)

We can first obtain differential Equation (15), then we can substitute Equations (14) and (16) into the differential equation of (15). A difference dynamic equation can be described as

\[
\frac{db_x}{dt} = f_x^* G_z - f_1 G_z - f_2 G_z - f_3 G_z - k_x b_x
\]  

(19)
controller so as to compensate the difference between the unflawed control and the RREZPNN control. Then, the handler control $f_1$ can be represented by

$$f_1 = I_x \left[ \frac{1}{G_z} \frac{d\omega_x}{dt} \right] + \left| k_x b_x \right| + \frac{Q_x (\omega_x)}{G_z} + \frac{Q_y}{G_z} \text{sgn}(b_x G_z)$$  \hspace{1cm} (20)

where $\text{sgn}(\cdot)$ is a sign function. When the RREZPNN approximation properties cannot be guaranteed, the handler control with the changed index $I_x = 1$ will result in appropriate action.

![Figure 3. Block diagram of the SRREZPNN control with MFSS method.](image)

The RREZPNN control $f_2$ shown in Figure 4 is the three-layer RREZPNN structure that is composed of a foremost layer, a middle layer and a last layer. The message disseminations in each node of each layer are described below:

Firstly, the input message and the output message in the foremost layer can be described as

$$v_{x_a}^1 = \prod_c g^1_c (M) \phi_{ac}^1 (M) \bar{b}_x^1 (M - 1) b_x^1 (M - 1) b_x^1 (M) = g^1_{a0} (v_{x_a}^1) = v_{x_a}^1, \ a = 1, 2$$  \hspace{1cm} (21)

where $\Pi$ is the multiplication factor; $g^1 = \omega \ast -\omega_x = b_x$ and $\bar{g}_s^1 = b_x (1 - z^{-1}) = \Delta b_x$ are the speed difference and speed difference alteration, respectively; $M$ is the iteration number; $\phi_{ac}^1 (M)$ is the reiterative weight between the last layer and the foremost layer; $g_{a0}^1$ is the linear activation function; $\bar{b}_x^1 (M)$ is the output message of node in the last layer.
\[ f_2 = l_c^2(M) = A^T B \]

Secondly, the input message and the output message in the middle layer can be described as

\[ \nu x_h^2 = \sum_{a=1}^{2} \phi_{cb}^2(M) \xi_a^2(M) + \epsilon l_b^2(M - 1), \quad l_b^2(M) = q_b^2(\nu x_h^2) = EZ_b(\nu x_h^2;s), \quad b = 0, 1, \cdots, n - 1 \] (22)

where \(\Sigma\) is the summation factor; \(\epsilon\) is the reiterative gain in the middle layer; \(n\) is the activation function. 

Even Zernike polynomials function [9,29] is adopted as the activation function. 

\(EZ_j(x,s)\) is the even Zernike polynomials function with \(-1 < x < 1\). \(EZ_0(x,s) = 1, \quad EZ_1(x,s) = 1 + x\) and \(EZ_2(x,s) = (1 + x)(1 + x) + x(s - 1)\) are the zero-, one- and two-order even Zernike polynomials functions, respectively. The even Zernike polynomials function in the recurrence relation [9,29] is given by \(EZ_{m+1}(x,s) = (1 + x)EZ_m(x,s) + x(s - 1)EZ_{m-1}(x,s)\).

Thirdly, the input message and the output message in the last layer can be described as

\[ \nu x_h^3 = \sum_{b=0}^{n-1} \phi_{cb}^2(M) \xi_a^2(M), \quad l_c^2(M) = q_c^2(\nu x_h^3) = \nu x_h^3, \quad c = 1 \] (23)

where \(\phi_{cb}^2(M)\) is the linking weight between the middle layer and the last layer; \(q_c^2\) is the linear activation function. 

The output message in the last layer can be represented by \(l_c^2(M) = f_2\). Thus, the RREZPNN control can be described as

\[ f_2 = l_c^2(M) = A^T B \] (24)

where \(A = [\phi_{1a}^2 \cdots \phi_{1,n-1}^2]^T \) and \(B = [l_0^2 \cdots l_{n-1}^2]^T\) are the weight vector in the last layer and the input vector in the last layer, respectively.

In addition, a minimum difference \(\zeta\) so as to realize the indemnified control can be described as

\[ \zeta = (f_a^* - f_2) - (f_2^* - f_2) \] (25)
where \( f_2^* = (A^*)^T B \) is the unflawed control law of the RREZPNN control; \( A^* \) is the unflawed weight vector; \( |c| < \beta < \kappa, \kappa < (Q_x(\omega_x) + Q_y + |d\omega_x/\eta| + |k_3 b_x|)/G_z \) and \( \kappa \) is a small real number that is greater than zero. By using Equation (25), \( f_2 = f_2^*(M) = A^T B \) and \( f_2^* = (A^*)^T B \), then Equation (19) can be described as

\[
d\eta_1 \over dt = G_z \eta_1 - G_z f_2 - G_z f_3 - G_z f_1 - k_4 b_x
\]

\[
d\eta_2 \over dt = G_z (f_2^* - f_2^2) - G_z (f_2 - f_2^2) - G_z f_1 - k_4 b_x
\]

\[
d\eta_3 \over dt = G_z (f_2^* - f_2^2) + G_z [(A^*)^T B - A^T B] - G_z f_3 - G_z f_1 - k_3 b_x
\]

\[
d\eta_4 \over dt = G_z \zeta + G_z (A^* - A)^T B - G_z f_3 - G_z f_1 - k_3 b_x
\]

In order to obtain the indemnified control, the assessed law and the cozy learning law, the Lyapunov function is described as

\[
F_1 = 0.5b_2^2 + 0.5\beta^2 \over \eta_1 + 0.5\kappa^2 \over \eta_2 + 0.5(A^* - A)^T (A^* - A) \over \sigma_1
\]

where \( \eta_1 \) and \( \eta_2 \) are the cozy value that are greater than zero. \( \beta = \beta - \tilde{\beta} \) and \( \kappa = \kappa - \tilde{\kappa} \) are the assessed differences. \( \sigma_1 \) is the learning rate of the linking weight. By using Equations (25) and (26), then differential equation of the Lyapunov function can be described as

\[
d\tilde{\eta}_1 \over dt = b_x \tilde{\eta}_1 - \tilde{\eta}_2 \tilde{\eta}_2^{\beta \over \eta_1} - \tilde{\eta}_1 \tilde{\eta}_2^{\beta \over \eta_2} - (A^* - A)^T \over \sigma_1 dA
\]

\[
= b_x (G_z \zeta + (A^* - A)^T B - f_3 - f_1) - k_4 b_x - \tilde{\eta}_1 \tilde{\eta}_2^{\beta \over \eta_1} - \tilde{\eta}_1 \tilde{\eta}_2^{\beta \over \eta_2} - (A^* - A)^T \over \sigma_1 dA
\]

For realizing \( dF_1/\eta \leq 0 \), then the indemnified control \( f_3 \), the assessed law \( d\eta / dt \) and the cozy learning law \( dA / dt \) can be described as

\[
dA \over dt = \sigma_1 B b_x G_z
\]

\[
f_3 = (\beta - \tilde{\beta}) \sigma_2(b\zeta G_z)
\]

\[
= (\beta - \tilde{\beta}) \tilde{\eta}_1 b_x G_z - (\kappa - \tilde{\kappa}) \tilde{\eta}_2 b_x G_z - (A^* - A)^T \over \sigma_1 dA
\]

By using Equations (29)–(31) and (20) with \( I_x = 1 \), then Equation (28) can be described as

\[
d\tilde{\eta}_1 \over dt = b_x \tilde{\eta}_1 - \tilde{\eta}_2 \tilde{\eta}_2^{\beta \over \eta_1} - \tilde{\eta}_1 \tilde{\eta}_2^{\beta \over \eta_2} - (A^* - A)^T \over \sigma_1 dA
\]

\[
= -k_4 b_2^2 + \left\{ \zeta + (A^* - A)^T B - (\beta + \tilde{\beta}) \sigma_2 b_x G_z \right\} b_x G_z
\]

\[
= -k_4 b_2^2 + \left\{ \zeta + (A^* - A)^T B - (\beta + \tilde{\beta}) \sigma_2 b_x G_z \right\} b_x G_z
\]

By using \( |c| < \beta < \kappa \) and \( \kappa < (Q_x(\omega_x) + Q_y + |d\omega_x/\eta| + |k_3 b_x|)/G_z \), then Equation (32) can be described as

\[
d\tilde{\eta}_1 \over dt = -k_4 b_2^2 + (\zeta - \beta) b_x G_z + \left[ |b_x G_z - \sigma_1 b_x G_z| \right] b_x G_z
\]

\[
= -k_4 b_2^2 + (\zeta - \beta) b_x G_z + \left[ |b_x G_z - \sigma_1 b_x G_z| \right] b_x G_z
\]

\[
= -k_4 b_2^2 + (\zeta - \beta) b_x G_z + \left[ |b_x G_z - \sigma_1 b_x G_z| \right] b_x G_z
\]

\[
= -k_4 b_2^2 + (\zeta - \beta) b_x G_z + \left[ |b_x G_z - \sigma_1 b_x G_z| \right] b_x G_z
\]

when \( dF_1/\eta \leq 0 \) in Equation (33) that is a negative semi-definite, and then \( b_x \) and \( (A^* - A) \) are represented as bounded. Additionally, for the sake of proof of the proposed SRREZPNN control
with the MFSS method to be gradually stable, \( \mu(t) \) that is the uniformly continuous function can be defined by

\[
\mu(t) = \frac{dF_1}{dt} = k_3 b_x^2
\]

(34)

Then the integral equation of \( \mu(t) \) can be described as

\[
\int_0^t \mu(\tau) d\tau = \int_0^t \left[ \frac{dF_1}{dt} \right] dt = F_1(0) - F_1(t)
\]

(35)

The differential equation of \( \mu(t) \) can be described as

\[
\frac{d\mu}{dt} = 2k_1 b_x \frac{db_x}{dt}
\]

(36)

The limitation of Equation (35) under \( F_1(0) \) and \( F_1(t) \) being bounded can be described as

\[
\lim_{t \to \infty} \int_0^t \mu(\tau) d\tau < \infty
\]

(37)

As all variables in the right side of Equation (26) are bounded, it is implied that \( \frac{db_x}{dt} \) is also bounded. By using Barbalat’s lemma [30,31], it can be shown that \( \lim_{t \to 0} \mu(\tau) dt = 0 \), thus \( b_x(t) \to 0 \) as \( t \to \infty \) under \( \mu(t) \) can be a uniformly continuous function. Therefore, the SRREZPNN control with the MFSS method is gradually stable from proof. Moreover, the tracking error \( b_x(t) \) of the system will converge to zero.

Additionally, in order to reduce chattering in the indemnified control, the sign function \( \text{sgn}(b_xG_z) \) was replaced by the continuous function \( b_xG_z/(|b_xG_z| + \delta) \). Then \( \delta \) equals to \( \delta_0 \) under \( |b_xG_z| < \delta \), and \( \delta \) equals to zero under \( |b_xG_z| \geq \delta \), where \( \delta_0 \) and \( \delta \) are two small real numbers that are greater than zero.

In order to train some parameters in the RREZPNN effectively, an on-line parameters training skill can be derived by using the cozy learning law \( dA/dt \) in Equation (29). Then the cozy learning law \( dA/dt \) of the parameters in the RREZPNN, the linking weight parameter by the gradient descent skill and the backpropagation skill can be denoted as

\[
\frac{d\phi_{cb}^2}{dt} = \sigma_1 b_x G_z \sigma_b^3
\]

(38)

So as to describe the online training process of the RREZPNN, an objective function can be defined by

\[
F_2 = 0.5b_x^2
\]

(39)

By using the gradient descent technique with the chain rule and the backpropagation technique, the cozy learning law of the linking weight \( \phi_{cb}^2 \) from Equation (39) can be expressed by

\[
\frac{d\phi_{cb}^2}{dt} = -\sigma_1 \frac{\partial F_2}{\partial \phi_{cb}^2} = -\sigma_1 \frac{\partial F_2}{\partial b_x} \frac{\partial b_x}{\partial \phi_{cb}^2} = -\sigma_1 \frac{\partial F_2}{\partial \phi_{cb}^2} \frac{\partial \phi_{cb}^2}{\partial \phi_{cb}^2} = -\sigma_1 b_x \frac{\partial F_2}{\partial \phi_{cb}^2}
\]

(40)

In comparison with Equations (38) and (40), it can be obtained as \( \frac{d\phi_{cb}^2}{dt} = -b_x G_z \). The updated law of the linking weight in the RREZPNN can be expressed by

\[
\phi_{cb}^2(M + 1) = \phi_{cb}^2(M) + \frac{d\phi_{cb}^2}{dt}
\]

(41)
By using the gradient descent technique with the chain rule and the backpropagation technique, the reiterative weight $\phi_{ac}^1$ from the cozy learning law can be expressed by

$$\frac{d\phi_{ac}^1}{dt} = -\sigma_2 \frac{\partial F_2}{\partial b_x^1} \frac{\partial b_x^2}{\partial b_y^2} \frac{\partial b_y^1}{\partial v_{k}^2} \frac{\partial v_{k}^1}{\partial v_{k}^2} \frac{\partial v_{k}^1}{\partial \phi_{ac}^1} = \sigma_2 G_z b_x^2 EZ_1(\cdot)g_2^1(M)F_1^2(M-1)I_z^2(M)$$

(42)

where $\sigma_2$ is the learning rate of the reiterative weight. The updated law of the reiterative weight in the RREZPNN can be expressed by

$$\phi_{ac}^1(M+1) = \phi_{ac}^1(M) + \frac{d\phi_{ac}^1}{dt}$$

(43)

So as to obtain better convergence, the MFSS method is used for looking for two adjusted learning rates of the two weights in the RREZPNN. The proposed MFSS method not only improved convergent speed but also searched for two optimal learning rates in this study.

3.2. MFSS Method

In the MFSS method, every fish in the school realizes a local search that looks for promising regions in the search space. An individual component of the movement algorithm with regard to the learning rate can be expressed by

$$x_{n,i}(t_1 + 1) = x_{n,i}(t_1) + \text{rand}(-1,1) \times Sp_{n,i}, \ n_1 = 1, 2, \ i = 1, \ldots, \ M_1, \ t_1 = 1, 2, \ldots, N_1$$

(44)

where $x_{n,i}(t_1 + 1)$ and $x_{n,i}(t_1)$ represent the position of the fish $i$ before and after the individual movement operator, respectively. $\text{rand}(-1,1)$ is a uniformly distributed random number varying between $-1$ and $1$. $Sp_{n,i}$ is the parameter that defines the maximum displacement for this movement. The new position $x_{n,i}(t_1 + 1)$ is only accepted if the fitness of the fish $i$ improves with the position change. If it is not the case, the fish $i$ remains in the same position, then $x_{n,i}(t_1 + 1) = x_{n,i}(t_1)$.

An average of the individual movements in the collective-instinctive component of the movement can be also expressed by

$$W_{n,av}(t_1) = \frac{\sum_{i=M_1}^{i=M_1} \Delta x_{n,i}(t_1) \Delta h_{n,i}}{\sum_{i=1}^{i=M_1} \Delta h_{n,i}}, \ n_1 = 1, 2, \ i = 1, \ldots, \ M_1, \ t_1 = 1, 2, \ldots, N_1$$

(45)

where the vector $W_{n,av}(t_1)$ represents the weighted average of the displacements of each fish. It means that the fishes that experienced a higher improvement will attract more fishes into its position. After the vector $W_{n,av}(t_1)$ is computed, every fish can be expressed by

$$x_{n,i}(t_1 + 1) = x_{n,i}(t_1) + W_{n,av}(t_1), \ n_1 = 1, 2, \ i = 1, \ldots, \ M_1, \ t_1 = 1, 2, \ldots, N_1$$

(46)

This operator in the collective-volitive component of the movement is used so as to regulate the exploration/exploitation ability of the school during the search process. First of all, the barycenter $B_{n_i}(t_1)$ of the school that is calculated based on the position $x_{n,i}(t_1)$ and the weight $W_{n,av}(t_1)$ of each fish $i$ can be expressed by

$$B_{n_i}(t_1) = \frac{\sum_{i=1}^{i=M_1} x_{n,i}(t_1) W_{n,i}(t_1)}{\sum_{i=1}^{i=M_1} W_{n,i}(t_1)}, \ n_1 = 1, 2, \ i = 1, \ldots, \ M_1, \ t_1 = 1, 2, \ldots, N_1$$

(47)
Besides, the movement operator was also defined as a feeding operator so as to update the weights of every fish by

\[ W_{n_1,t}(t_1 + 1) = W_{n_1,t}(t_1) - \frac{\Delta h_{n_1,t}}{\max(|\Delta h_{n_1,t}|)}, \quad n_1 = 1, 2, \quad i = 1, \ldots, M_1, \quad t_1 = 1, 2, \ldots, N_1 \]  

(48)

where \( W_{n_1,t}(t_1) \) is the weight parameter for fish \( i \). \( \Delta h_{n_1,t} \) is the fitness variation between the last and the new position. \( \max(|\Delta h_{n_1,t}|) \) represents the maximum absolute value of the fitness variation among all the fishes in the school. \( W_{n_1,t}(t_1) \) is only allowed to vary from 1 up to \( W_{n_1,\text{scale}} / 2 \), which is a user-defined attribute. The weights of all fishes are initialized with the value \( W_{n_1,\text{scale}} / 2 \). Finally, if the total school weight \( \sum_{i=M_1}^{n_1} W_{n_1,t}(t_1) \) has increased from the last to the current iteration, the fishes are attracted to the barycenter \( B_{n_1}(t_1) \) by using Equation (49) as

\[ x_{n_1,t}(t_1 + 1) = x_{n_1,t}(t_1) - Sp_{n_1,v} \times \text{rand}(0,1) \frac{x_{n_1,t}(t_1) - B_{n_1}(t_1)}{\text{distance}(x_{n_1,t}(t_1) - B_{n_1}(t_1))}, \quad n_1 = 1, 2, \quad i = 1, \ldots, M_1 \]  

(49)

If the total school weight has not improved, the fishes are spread away from the barycenter \( B_{n_1}(t_1) \) by using Equation (50) as

\[ x_{n_1,t}(t_1 + 1) = x_{n_1,t}(t_1) + Sp_{n_1,v} \times \text{rand}(0,1) \frac{x_{n_1,t}(t_1) - B_{n_1}(t_1)}{\text{distance}(x_{n_1,t}(t_1) - B_{n_1}(t_1))}, \quad n_1 = 1, 2, \quad i = 1, \ldots, M_1 \]  

(50)

where \( Sp_{n_1,v} \) defines the size of the maximum displacement performed with the use of this operator. \( \text{distance}(x_{n_1,t}(t_1) - B_{n_1}(t_1)) \) is the Euclidean distance between the fish position \( i \) and the school barycenter \( B_{n_1}(t_1) \). \( \text{rand}(0,1) \) is a uniformly distributed random number varying between 0 and 1. At last, \( x_{n_1,t}(t_1 + 1) \), \( n_1 = 1, 2 \) is the best solution in regard to the learning rates \( \sigma_{n_1}(t_1 + 1) \), \( n_1 = 1, 2 \) of the two weights in the RREZPNN. Hence, the better numbers could be optimized by using the MFSS method for adjusting two learning rates of two weights so as to find two optimal values and speed up the convergence of two weights.

**Remark 1.** The control design idea for constructing the proposed SRREZPNN control with MFSS method by using the Lyapunov function is the main key point. The proposed control system is shown in Equation (18) and Figure 3, which reduces the input dimensions of the RREZPNN.

**Remark 2.** RREZPNN approximation holds only in a compact set. Thus, the obtained result is semi-global in the sense that they hold for the compact sets, there exists the proposed SRREZPNN control MFSS method with a sufficiently large number of RREZPNN nodes such that all the closed-loop signals are bounded.

**Remark 3.** Owing to inherent uncertainty in the SSCCRIM drive system in Equation (14), it will be shown that we cannot conclude the convergence of the tracking error to zero. Therefore, it is only reasonable to expect that all errors defined on the proposed SRREZPNN control MFSS method with the indemnified control, the assessed law and the cozy learning law converge into a neighborhood with reachable radius, and remains within it thereafter, which is so-called uniformly ultimate boundedness.

4. Tests and Experimental Results

The conformation of the SSCCRIM impelled continuously variable transmission assembled system by using DSP control system is shown in Figure 2. The profile formats of the continuously variable transmission assembled system with conversion ratio as 4.8 are the V-belt length as 652.4 mm, the subordinate pulley diameter as 75.8 mm, the foremost pulley diameter as 34.4 mm. The rated specification of the SSCCRIM is given as six-phase two-poles 48 V, 2 kW, 3452 rpm. The mechanical
and electrical parameters of the SSCCRIM are as \( J_x = 18.24 \times 10^{-3} \text{ Nms} \), \( B_x = 2.16 \times 10^{-3} \text{ Nms/rad} \), \( k_x = 0.214 \text{Nm/A} \), \( r_1 = 1.58 \Omega \), \( r_2 = 1.21 \Omega \), \( L_1 = 19.28 \text{ mH} \), \( L_2 = 4.8 \text{ mH} \), \( L_3 = 19.12 \text{ mH} \). Due to the fixed uncertainty effect in the continuously variable transmission assembled system and the power output limitation in the 48 VDC battery power source, the SSCCRIM impelled continuously variable transmission assembled system is used in 3300 rpm (345.4 rad/s) so as to prevent the insulated-gate bipolar transistor power elements from burning down the SSCCRIM impelled system. Figure 5 is shown in the flowchart of the carried out control method by DSP control system in the experimental tests with real-time implementation that is composed of the main program (MP) and the minor interrupt routine (MIR). The MP realizes all settings and initializations for some parameters and input/output interfaces. The MIR realizes the interrupt process inner 2 ms. The MIR with 2 ms interrupt time processes the following works as capturing six-phase currents from analog-digital converters, capturing rotor position of the SSCCRIM from encoder, computing rotor speed, computing speed difference, enforcing lookup table and coordinate translations, enforcing PI current control, enforcing the proposed control system, and outputting six-phase space vector pulse-width modulation signals to switch the voltage-fed converter with six arms–twelve switches insulated-gate bipolar transistor power elements. Three identifiers \( b_1 \), \( b_2 \) and \( b_{1_{mx}} \) are set as 0, 0, and 3, respectively. The DSP control system with the indirect FOC applied the identifier \( b_2 \) to serve as the enforcing number of the proposed control scheme. If the indirect FOC is enforced in less than three times, i.e., \( b_1 < b_{1_{mx}} \), the indirect FOC needs to be enforced repeatedly. When the proposed control scheme is enforced one time and the indirect FOC is enforced three times, then the MIR will return the MP.

Three tested instances with experimental results are illustrated to demonstrate various control performances. Firstly, the one entire parameter variation and entire nonlinear extrinsic disturbances \( \Delta T_{ag} + T_{a1} \) case at 1650 rpm (172.7 rad/s) is the examination Y1 instance. Secondly, the double entire parameter variations and entire nonlinear extrinsic disturbances \( 2\Delta T_{ag} + T_{a1} \) case at 3300 rpm (345.4 rad/s) is the examination Y2 instance. Thirdly, the adding external load torque disturbance and entire nonlinear extrinsic disturbances \( 2N\eta(T_{ag}) + T_{a1} \) at 3300 rpm (345.4 rad/s) speed is the examination Y3 instance. Three adopted controllers are the prominent PI controller as the controller CD1, the Mixed modified recurring Rogers-Szego polynomials neural network (MMRRSPNN) control with mended grey wolf optimization (MGWO) [13] as the controller CD2 and the proposed SRREZPNN control with the MFSS method as the controller CD3 so as to compare with control performances. Firstly, two gains \( k_{2p} = 21.2 \) and \( k_{2i} = k_{2p}/T_{2i} = 5.2 \) in the controller CD1 can be obtained by using the Kronecker method [26–28] that is used to narrow down the region for iterative selection of values of the parameters of \( k_{2p} \) and \( k_{2i} \) on the tuning of the PI controller with one entire parameter variations and entire nonlinear extrinsic disturbances \( \Delta T_{ag} + T_{a1} \) case at 1650 rpm (172.7 rad/s) for the speed tracking to achieve better stability boundary in the \( k_{2p} \) and \( k_{2i} \) plane so as to get better transient-state and steady-state control performance. Secondly, some control gains \( k_a = 4.52 \), \( \eta = 0.08 \) and \( \gamma = 0.18 \) in the controller CD2 can be obtained to show better transient control performance under the requirement of stability consideration. Additionally, the neuron’s numbers of the MRRSPNN are 2, 3 and 1 nodes in the first layer, the second layer and the third layer of MRRSPNN, respectively. Thirdly, some control gains by using the controller CD3 are given as \( k_x = 4.52 \), \( \epsilon = 0.08 \), \( \eta_1 = 0.18 \) and \( \eta_2 = 0.18 \) to attain better transient control performance under the requirement of stability consideration. In addition, the neuron’s numbers of the RREZPNN are 2, 3 and 1 nodes in the foremost layer, the middle layer and the last layer of the RREZPNN, respectively.
Firstly, Figures 6 and 7 display some experimental results by using the controller CD1 for the SSSCRRIM impelled continuously variable transmission assembled system at the examination Y1 instance and at the examination Y2 instance. The speed responses for mandate speed $\omega_c$, reference model speed $\omega^*$, and gauged speed $\omega_x$ at two tested instances are shown in Figures 6a and 7a. The speed difference $b_2$ responses at two tested instances are shown in Figures 6b and 7b. The enlargements of speed difference responses at two tested instances are shown in Figures 6c and 7c. The electromagnetic torque $T_\tau$ responses are shown in Figures 6d and 7d. Figure 6a at the examination Y1 instance demonstrated better speed tracking performance because small disturbance is the same with the rated instance. Figure 7a demonstrated dilatory speed responses because of absent gains adjustment appropriately. Moreover, Figures 6d and 7d in the electromagnetic torque $T_\tau$ responses demonstrated...
large torque ripple because of large nonlinear operation in the continuously variable transmission assembled system.

![Graph of speed response](image)

**Figure 6.** Tested instances with experimental results obtained by using the controller CD1 for the SSCRRIM impelled continuously variable transmission assembled system at the examination Y1 instance: (a) speed response, (b) speed difference response, (c) enlargement of speed difference response, (d) electromagnetic torque response.
Figure 7. Tested instances with experimental results obtained by using the controller CD1 for the SSCCRIM impelled continuously variable transmission assembled system at the examination Y2 instance: (a) speed response, (b) speed difference response, (c) enlargement of speed difference response, (d) electromagnetic torque response.

Secondly, Figures 8 and 9 display some experimental results by using the controller CD2 for the SSCCRIM impelled continuously variable transmission assembled system at the examination Y1 instance and at the examination Y2 instance. The speed responses for mandate speed $\omega_c$, reference model speed $\omega^*$, and gauged speed $\omega_x$ at two tested instances are shown in Figures 8a and 9a. The speed difference $b_x$ responses at two tested instances are shown in Figures 8b and 9b. The enlargements of
speed difference responses at two tested instances are shown in Figures 8c and 9c. The electromagnetic torque \( T_x \) responses are shown in Figures 8d and 9d. Figure 8a at the examination Y1 instance demonstrated better speed tracking performance because small disturbance is the same with the rated instance. Figure 9a demonstrated better speed responses owing to the online adjustable method of the MRRHPNN control system with MGWO and the compensated controller action. Moreover, Figures 8d and 9d in the electromagnetic torque \( T_x \) responses demonstrated middle torque ripple because of large nonlinear action in the continuously variable transmission assembled system.

**Figure 8.** Tested instances with experimental results obtained by using the controller CD2 for the SSCCRIM impelled continuously variable transmission assembled system at the examination Y1 instance: (a) speed response, (b) speed difference response, (c) enlargement of speed difference response, (d) electromagnetic torque response.
Figure 9. Tested instances with experimental results obtained by using the controller CD2 for the SSCCRIM impelled continuously variable transmission assembled system at the examination Y2 instance: (a) speed response, (b) speed difference response, (c) enlargement of speed difference response, (d) electromagnetic torque response.

Thirdly, Figures 10 and 11 display some experimental results by using the controller CD3 for the SSCCRIM impelled continuously variable transmission assembled system at the examination Y1 instance and at the examination Y2 instance. The speed responses for mandate speed $\omega_c$, reference model speed $\omega_*$, and gauged speed $\omega_x$ at two tested instances are shown in Figures 10a and 11a. The speed difference $b_x$ responses at two tested instances are shown in Figures 10b and 11b. The enlargements of speed difference responses at two tested instances are shown in Figures 10c and 11c. The electromagnetic torque $T_x$ responses are shown in Figures 10d and 11d. Figure 10a at the examination Y1 instance
demonstrated better speed tracking performance because small disturbance is the same with the rated instance. Figure 11a displayed better speed responses because of the online cozy mechanism of the RREZPNN and the indemnified control’s motion. Moreover, the smaller torque ripple responses displayed in Figures 10d and 11d for the electromagnetic torque $T_x$ are due to online adjustment of the SRREZPNN control with the MFSS method to overcome the unmodeled dynamic of continuously variable transmission assembled system such as V-belt torsion and push–pull frictions.

![Graphs showing speed and torque responses](image_url)

**Figure 10.** Tested instances with experimental results obtained by using the controller CD3 for the SSSCRRIM impelled continuously variable transmission assembled system obtained at the examination Y1 instance: (a) speed response, (b) speed difference response, (c) enlargement of speed difference response, (d) electromagnetic torque response.
Figure 11. Tested instances with experimental results obtained by using the controller CD3 for the SSCCRIM impelled continuously variable transmission assembled system at the examination Y2 instance: (a) speed response, (b) speed difference, (c) enlargement of speed difference response, (d) electromagnetic torque response.

Besides, Figure 12a,b demonstrate the convergent responses for learning rate $\sigma_1$ of linking weight and learning rate $\sigma_2$ of reiterative weight in the SRREZPNN control with the MFSS method as the controller CD3 at the examination Y1 instance, respectively. Figure 12c,d demonstrate the convergent responses for learning rate $\sigma_1$ of linking weight and learning rate $\sigma_2$ of reiterative weight.
in the SRREZPNN control with the MFSS method as the controller CD3 at the examination Y2 instance, respectively.

![Graphs showing learning rates](image)

**Figure 12.** Tested instances with experimental results obtained by using the controller CD3: (a) convergent response of learning rate $\sigma_1$ of linking weight at the examination Y1 instance, (b) convergent response of learning rate $\sigma_2$ of reiterative weight at the examination Y1 instance, (c) convergent response of learning rate $\sigma_1$ of linking weight at the examination Y2 instance, (d) convergent response of learning rate $\sigma_2$ of reiterative weight at the examination Y2 instance.

At last, the speed-regulated responses and the gauged phase current $a_1$ responses obtained by using the controller CD1, the controller CD2 and the controller CD3 under adding external load torque disturbance and entire nonlinear extrinsic disturbances $2Nm(T_{ls} + T_{d1})$ at 3300 rpm speed as the
The tested instances with experimental results of gauged speed $\omega_x$ and gauged phase current $i_1$ at the examination Y3 instance when the controller CD1, the controller CD2 and the controller CD3 are shown in Figures 13 and 14. The tested instances with experimental results display that the degenerated responses at the examination Y3 instance are fairly improved when the controller CD3 was used. Besides, transient response of the controller CD3 displays better convergence and better load regulation than the controller CD1 and the controller CD2.

Figure 13. Tested instances with experimental results at the examination Y3 instance: (a) speed-regulated response obtained by using the controller CD1, (b) speed-regulated response obtained by using the controller CD2, (c) speed-regulated response obtained by using the controller CD3.
Figure 14. Tested instances with experimental results at the examination Y3 instance: (a) gauged phase current $a_1$ response obtained by using the controller CD1, (b) gauged phase current $a_1$ response obtained by using the controller CD2, (c) gauged phase current $a_1$ response obtained by using the controller CD3.

Finally, the photo of the test rig and experimental setup is shown in Figure 15.
5. Discussions and Analyses

Dynamic responses for control performances in comparison with the prominent PI controller as the controller CD1, the MMRRSPNN with MGWO [13] as the controller CD2, and the proposed SRREZPNP control with the MFSS method as the controller CD3 for three tested instances with experimental results are explained as below. The maximum differences of $b_x$ obtained by using the controllers CD1, CD2 and CD3 at the Examination Y1 instance are 73 rpm (7.64 rad/s), 58 rpm (6.07 rad/s) and 31 rpm (3.24 rad/s), respectively. The root mean square differences of $b_x$ obtained by using the controllers CD1, CD2 and CD3 at the Examination Y1 instance are 37 rpm (3.87 rad/s), 18 rpm (1.88 rad/s) and 13 rpm (1.36 rad/s), respectively. The maximum differences of $b_x$ obtained by using the controllers CD1, CD2 and CD3 at the Examination Y2 instance are 136 rpm (14.23 rad/s), 79 rpm (8.27 rad/s) and 41 rpm (4.29 rad/s), respectively. The root mean square differences of $b_x$ obtained by using the controllers CD1, CD2 and CD3 at the Examination Y2 instance are 52 rpm (5.44 rad/s), 28 rpm (2.93 rad/s) and 19 rpm (1.99 rad/s), respectively. The maximum differences of $b_x$ obtained by using the controllers CD1, CD2 and CD3 at the Examination Y3 instance are 264 rpm (27.63 rad/s), 114 rpm (11.93 rad/s) and 96 rpm (10.05 rad/s), respectively. The root mean square differences of $b_x$ obtained by using the controllers CD1, CD2 and CD3 at the Examination Y3 instance are 49 rpm (5.13 rad/s), 24 rpm (2.51 rad/s) and 16 rpm (1.67 rad/s), respectively.

Moreover, the feature performances in comparison with the controllers CD1, CD2 and CD3 on the basis of three tested instances with experimental results are recapitulated as below. The oscillation values in the control laws obtained by using the controller CD1, the controller CD2 and the controller CD3 are the 12% of rated value, the 9% of rated value and the 5% of rated value at the Examination Y2 instance, respectively. The movement responses obtained by using the controller CD1, the controller CD2 and the controller CD3 are the 2.1 s rising time, the 1.7 s rising time and the 1.5 s rising time at the Examination Y2 instance, respectively. The adjustment capabilities for external load torque disturbance obtained by using the controller CD1, the controller CD2 and the controller CD3 are the 264 rpm (27.63 rad/s) maximum difference, the 144 rpm (11.93 rad/s) maximum difference and the 96 rpm (10.05 rad/s) maximum difference at the Examination Y3 instance, respectively. The convergent speeds obtained by using the controller CD1, the controller CD2 and the controller CD3 are the 2.4 s settle time, the 2.1 s settle time and the 1.7 s settle time at the Examination Y2 instance, respectively. The speed tracking differences obtained by using the controller CD1, the controller CD2 and the controller CD3 are the maximum difference as

Figure 15. A photo of the test rig and experimental setup.
136 rpm (14.23 rad/s), the maximum difference as 79 rpm (8.27 rad/s) and the maximum difference as 41 rpm (4.29 rad/s) at the Examination Y2 instance, respectively. The repudiation abilities for parameter disturbance obtained by using the controller CD1, the controller CD2 and the controller CD3 are the maximum difference as 136 rpm (14.23 rad/s), the maximum difference as 79 rpm (8.27 rad/s) and the maximum difference as 41 rpm (4.29 rad/s) at the Examination Y2 instance, respectively. The two learning rates obtained by using the controller CD1, the controller CD2 and the controller CD3 are the none, the two varying values as two optimal learning rates and the two varying values as two optimal learning rates, respectively. The calculation times of NN obtained by using the controller CD1, the controller CD2 and the controller CD3 are the none, the 0.18 ms and the 0.12 ms, respectively. The torque ripples with belt trembling and torsional fluctuation obtained by using the controller CD1, the controller CD2 and the controller CD3 are the 12% of rated value, the 8% of rated value and the 8% of rated value at the Examination Y2 instance, respectively. From these performances with respect to the oscillation values in the control laws, the movement responses, the adjustment capabilities for external load torque disturbance, the convergent speeds, the speed tracking differences, the repudiation abilities of parameter disturbance, the calculation times of NN and torque ripples in the controller CD3 are better than the controllers CD1 and CD2.

6. Conclusions

The SRREZPNN control with the MFSS method has been successfully applied to control the SSCCRIM impelled continuously variable transmission assembled system with better robustness. The SRREZPNN control with MFSS method that can realize the handler control, the RREZPNN control and the indemnified control were proposed to reduce the control intensity with smoothing when the system’s states are within the predictive bounded region.

The core contributions of this study are described below. (1) The mathematic models of SSCCRIM impelled continuously variable transmission assembled system with nonlinear uncertainties have been successfully reduced by the four simplified dynamic models. (2) The SSCCRIM impelled continuously variable transmission assembled system under intact nonlinear extrinsic disturbances effect has been successfully controlled by using the SRREZPNN control with the MFSS method. (3) According to the Lyapunov stability theorem, the cozy learning law in the RREZPNN control and the assessed law in the indemnified control have been successfully derived. (4) The MFSS method was well utilized to adjust two learning rates of linking and reiterative weights in the RREZPNN to obtain optimal values and speed up convergence of linking and reiterative weights. (5) The SRREZPNN control with MFSS method as the controller CD3 is better than the prominent PI controller as the controller CD1 and the MMRRSPNN with MGWO [13] as the controller CD2 in torque ripple demotion.

Finally, the controller CD3 is more excellent than the controller CD1 and the controller CD2 from all experimental results and control performances for the SSCCRIM impelled continuously variable transmission assembled system.

The research’s directions in future works are as below. (1) The advancement of more accurate modellings in the continuously variable transmission assembled system will be derived so as to obtain more exact experimental results. (2) High performance of the DSP control systems will be adopted to reduce execution time and enhance computation efficiency. (3) The more advanced control methods combined with this study will be adopted so as to heighten robustness in the SSCCRIM impelled continuously variable transmission assembled system. (4) The advanced control structures with tracking for some different reference trajectories will be developed so as to enhance feasibility of the control systems.

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