Original Article

Web tension control of multispan roll-to-roll system by artificial neural networks for printed electronics

KyungHyun Choi, Muhammad Zubair and Ganeshthangaraj Ponniah

Abstract

The mass production of printed electronic devices can be achieved by roll-to-roll system that requires highly regulated web tension. This highly regulated tension is required to minimize printing register error and maintain proper roughness and thickness of the printed patterns. The roll-to-roll system has a continuous changing roll diameter and a strong coupling exists between the spans. The roll-to-roll system is a multi-input-multi-output, time variant, and nonlinear system. The conventional proportional–integral–derivative control, used in industry, is not able to cope with roll-to-roll system for printed electronics. In this study, multi-input-single-output decentralized control scheme is used for control of a multispan roll-to-roll system by applying regularized variable learning rate backpropagating artificial neural networks. Additional inputs from coupled spans are given to regularized variable learning rate backpropagating artificial neural network control to decouple the two spans. Experimental results show that the self-learning algorithm offers a solution to decouple speed and tension in a multispan roll-to-roll system.

Introduction

The roll-to-roll (R2R) processing for electronics is also known as web processing or reel to reel processing, which is the process of making electronic devices on flexible substrates. This is the future of electronic devices as the process is carried out at normal room conditions. The flexible substrate used in this system can be of plastic such as polyethylene terephthalate (PET), paper or metal sheet. R2R system is simpler and cost effective method as compared to the conventional manufacturing processes currently adopted in electronic industry. R2R process comprises of selecting suitable ink, a printing system for printing the ink on the substrate such as direct gravure, gravure offset, microgravure, electrohydrodynamics, slot die printing method, and finally curing of the ink.

The roughness and layer thickness defines the performance of a device.[1] Lee et al.[2] showed that the print thickness and roughness depend on the tension while keeping all other parameters constant in a R2R process. Hence printed electronics require highly regulated tension in R2R process. Electronic devices comprise of more than one layer, so in printed electronics, new layer must be printed on top of the previous layer

in a way that both layers are aligned. The alignment error of two layers is known as register error. Fluctuation in tension causes register error[3] which ultimately result in failure of the device. Graphic media uses the R2R system for printing with acceptable tension error of $\pm 10\%$ of reference tension in steady running state[4] and register control error up to $76.2\,\mu m$.[5,6] Song and Sul[7] presented the tension control for metal processing line. For printed electronics, highly regulated tension is required as compared to graphic printing.

R2R system is a multi-input multi-output (MIMO), time variant, and nonlinear system. The roll diameter of the unwinder roll decreases whereas diameter of rewinder increases when the R2R system operates and web is moved from unwinder to rewinder. This makes R2R system a time variant system.

Department of Mechatronics Engineering, Jeju National University, South Korea

Corresponding author:
KyungHyun Choi, Department of Mechatronics Engineering, Jeju National University, Jeju-si, Jeju-do 690756, Korea.
Email: amm@jejunu.ac.kr

The interactions between two spans make the system nonlinear. Disturbances of R2R system include the slip of web in NIP rolls, friction of the idle rolls, printing processes tension disturbances, and backlash in the gears. R2R system is a modular machine. Many printed devices with different layer structures have to be made on R2R system. A single device may require different printing processes such as gravure offset, electrohydrodynamic printing (EHD), or slot die.

Many researchers[7–19] worked on tension control. In control theory, there are two approaches for the tension control of web. First, is mathematical modeling of the system and applying conventional control and second is the optimization or tuning regulator techniques. For mathematical modeling and conventional control, a highly precise model of the system is required. Modeling error between a system's mathematical model and the real-world system, parameter variations, assumptions, and the external disturbances in the practical control are the factors that have to be taken into account for highly regulated tension.[9] Pagilla et al.[10] used proportional–integral (PI) control for a model based decentralized control with assumption that there is no slip between rolls and ignoring time variant factor of diameter of rolls. Liu and Davison[4] described control approaches for MIMO systems. Pagilla et al. and Kang et al. modeled the system considering it nonlinear and time variant but assumed that there is no slip between NIP rolls and web materials and the idle rollers have no rotational inertia. [11,12] Sakamoto and Fujino[13] developed a mathematical model and performed PI control. Ebler et al.[14] performed a tension control comparison between load cells and dancers systems. Dwivedula et al.[15] presented a comparative study of active and passive dancers. Lin[16] developed an observer based tension control for friction and inertia compensation. Okada and Sakamoto[17] simulated an adaptive fuzzy based control on a model. Sakamoto[18] estimated the interaction between different spans for tension control for a decentralized control scheme.

PI–derivative (PID) control once tuned has constant parameters thus a critically damped system can go into unstable oscillation once any disturbance arises. Atherton and Majhi[19] presented the limitations of PID controller. Fuzzy controller can perform better as the membership functions can be quantified in a nonlinear way by the expert opinion but fuzzy controller is a pre-tuned system which limits its capabilities. The fuzzy control is equivalent to feed forward neural networks (NNs).[20] This gives a clear advantage to BPNs over the fuzzy control scheme. Wang et al.[21] simulated a NNs control for tension control for a single span R2R system compared with conventional PID control.

In this article, the web tension of a three span R2R system is controlled by applying regularized backpropagating artificial neural networks (BPNs) with variable learning rate (VLR). BPN with VLR offers a multi-input-single-output (MISO) control system that has the ability of auto tuning. The auto tuning takes care of time variant nature of R2R system. The inputs of BPN are tension from load cells, position, and speed from encoders and roll diameters measured by ultrasonic sensors. The coupling between spans is minimized by introducing inputs of one span to next span. The VLR BPN control is implemented on speed control simulation and web tension control on a three span R2R system. This self-learning algorithm provides a solution to the web tension control of multispan R2R system for printed electronics.

Experimental setup

Hardware

R2R system used during the experiments is shown in Figure 1. This R2R system has an unwinder, infeed, outfeed, and rewinder spindles connected to servomotors housed in an industrial machine frame. There are many idle rolls helping in guiding the web. Load cells are used to measure the tension in the spans. Ultrasonic sensors provide the diameter of the unwinder and rewinder rolls. The web (PET) unwinds at unwinder and is passed through a load cell and idle rolls to the infeed comprising of first span, where span is a web length between two adjacent driven rolls. From infeed, the web passes through a load cell and a lateral web control unit to gravure offset printer and from gravure offset printer to a load cell and to the outfeed. The web from the outfeed passes through a load cell and a lateral web control and is rewound on the rewinder making it the last span. In this study, the gravure printer was not utilized which makes this a three span system. Figure 2 shows the web path through the R2R system.

PET substrate is elastic in nature so the printing was performed with low values of tension. If the printing is performed with high values of tension it can cause shrinkage problems after its removal which eventually causes failure of the device. The drying temperature of PET may be from 50°C to 120°C depending on the ink properties. The PET is dried in infrared (IR) heating chamber. The temperature changes causes variations in strain, Young's modulus and thermal coefficient in this part of the PET.[8] This causes the web to surpass its yield strength and enter into the plastic region hence causing permanent failure. Ultimately the tension was kept low for the above mentioned reasons and was 0.56% of the yield strength which is 5 N.

Load cells were used to measure the tension values in each span and ultrasonic sensors were used to measure the diameter of the rolls at rewinder and unwinder. National instrument analog to digital converter modules were used to read the values of load cells and ultrasonic sensors. The Mitsubishi servopack MRJ-2S-70A and motors HC-KFS-73 were used.
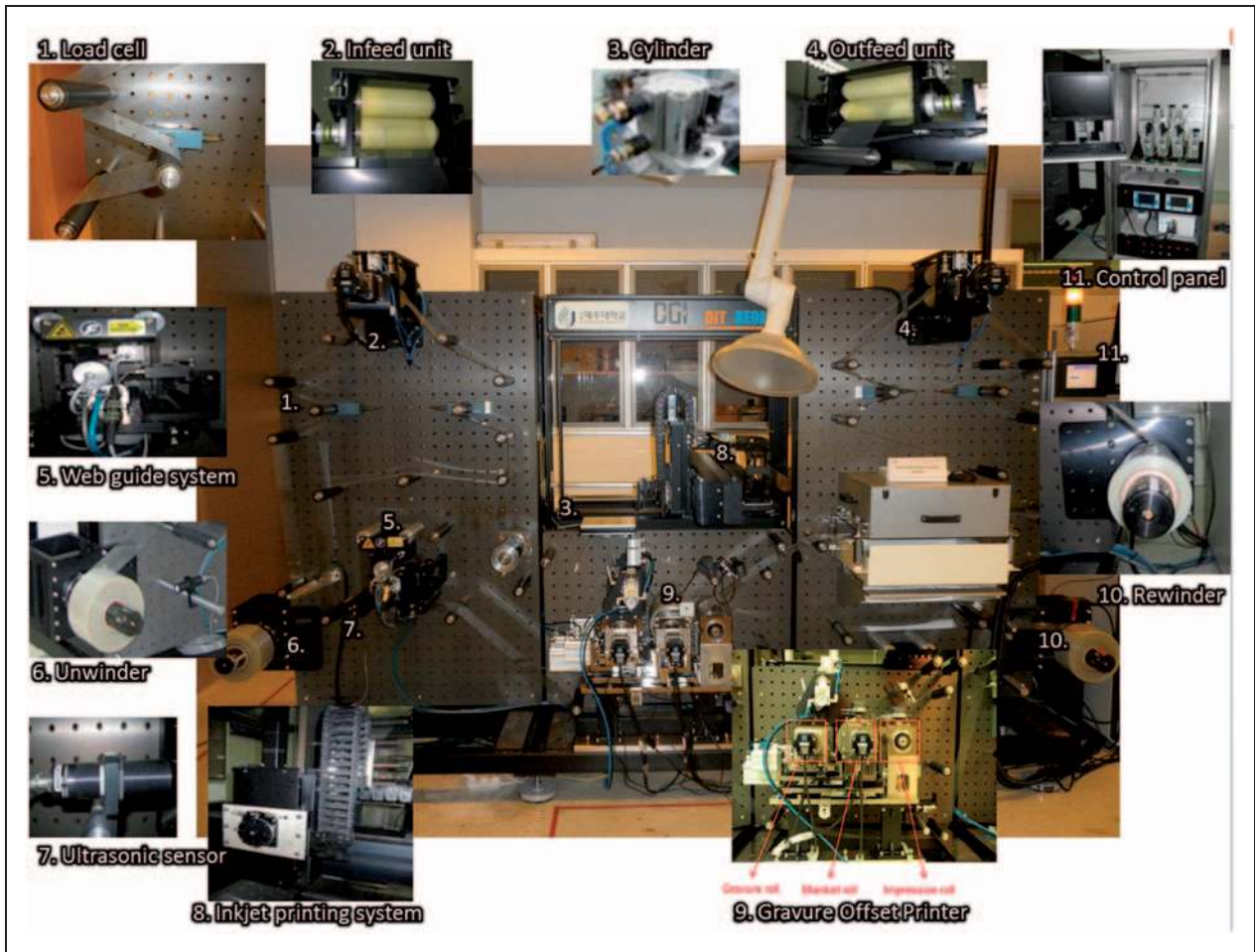
Figure 1. R2R system showing load cells, infeed unit, pneumatic cylinder, outfeed unit, web guide system (lateral control), unwinder, ultrasonic sensors, inkjet printing system, gravure offset printer, rewinder, and control panel.
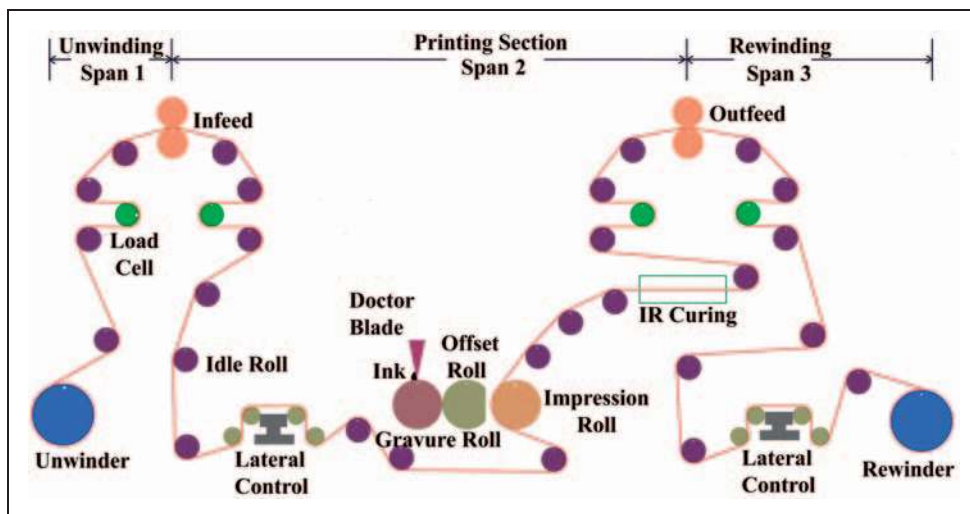R2R: roll-to-roll.

Figure 2. Web path and tension spans in the R2R system where all three spans of R2R system are shown.
Infeed motor acts as master velocity control where other three motors are in tension control. Two lateral control units keep the lateral position of the web in check.
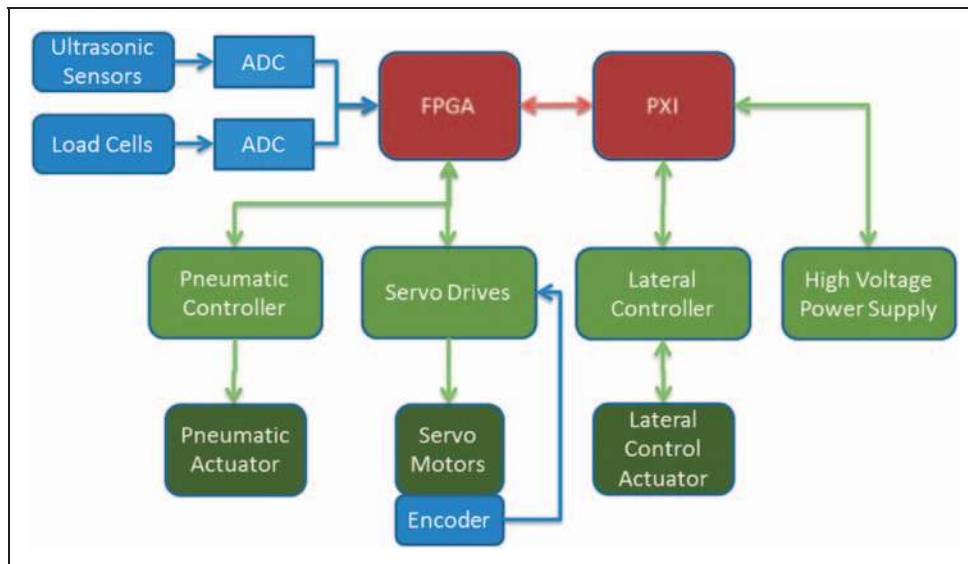R2R: roll-to-roll.

Figure 3. Electrical connection diagram of R2R system is shown where connections of ultrasonic sensors, load cell, pneumatic actuators, and servodrives are connected to a FPGA which is inserted in PXI.
PXI directly controls lateral control units and high power supply for electro-hydrodynamics printing system.
FPGA: field-programmable gate array; R2R: roll-to-roll.

The two lateral control units were connected to the PXI by Profibus interface and are responsible for the lateral control of web. A high-voltage power supply was controlled by PXI via USB, for EHD. The electrical circuit diagram of the system is shown in Figure 3. The rotational angle and speed of AC servomotors was calculated from the incremental encoder pulses. A field-programmable gate array (FPGA) was used to find the motion and speed of all motors. A rugged PC-based platform (PXI) processes all the data and artificial neural networks is implemented to get the appropriate torque control signals for AC servomotors.

Programming software

National Instrument Laboratory Virtual Instrumentation Engineering Workbench (LabVIEW 8.6) was used to program the FPGA and PXI. Hardware interfacing, code compilation, large libraries, and parallel programming are the key features of Labview. Multitasking in LabVIEW enables the users to make different control loops.

Control scheme

The web tension control was achieved by deploying artificial neural networks control algorithm. Unwinder, outfeeder, and rewinder servomotors were made to run in tension control while the infeeder was made to run as the master velocity control of the system. The inputs of BPN of one span were used for the BPN of next span to minimize the interaction between the spans. This control scheme is shown in Figure 4 where 'TA' is the tension output from

control to servomotor, 'VA' the master control velocity, 'V' the velocity of servomotor, 'E' the encoder count, 'T' the tension measured by load cell in Newtons, and 'U' the roll diameter measured in centimeters by ultrasonic sensor. The speed of the web was controlled by the master velocity control motor all other motors were set to match the speed while keeping the web at the prescribed tension of 5 N.

Artificial NN

Artificial neural network can also be called as NN. NN is nonlinear and adaptive system hence NN can take care of the disturbances and time variant characteristics of the R2R system. NN consists of networks of artificial neurons in which the data flows through and their weights are changed to reduce the root mean square of error, during the learning phase. A single neuron is shown in Figure 5 in which the inputs are multiplied by the weights, the product is added to bias and resultant is subjected to activation function where an activation function is the mathematical formulation that is used to calculate the output of a neuron.

The input of NN is scaled to be within 0.1 to 0.9 to get the maximum efficiency of backpropagation method. NN is designed in layers. First layer is called the input layer and last is called the output layer. In-between layers are termed as the hidden layers. Figure 6 shows the layers of a NN. A single neuron in a layer is also called as a node. Its output is given by equation

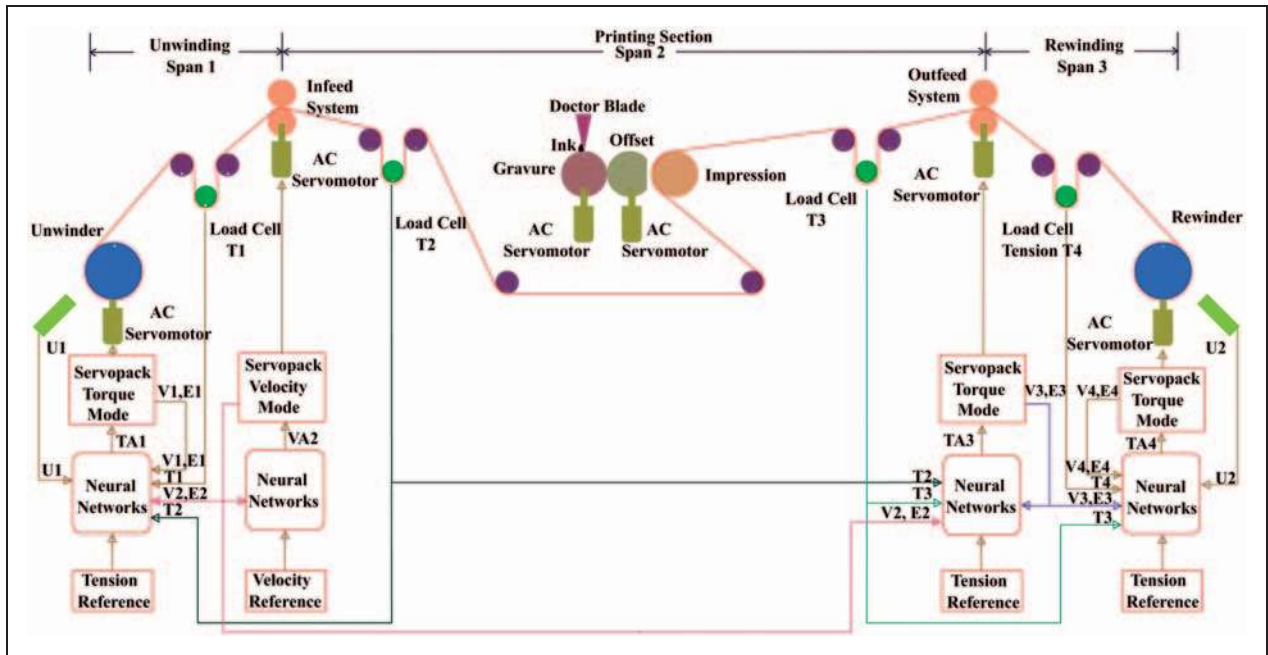$$a_j^{(l)} = f\left(W_j^{(l-1)} a_j^{(l-1)} + b_j^l\right)$$

Figure 4. Control architecture of R2R system is shown, where *E* and *V* are the servomotors encoders calculated position and velocity, respectively, *U* the ultrasonic sensor to find roll diameter, *T* the tension by load cell, *TA* the NN calculated torque input to motors, and *VA* the master velocity control signal given to infeed motor.
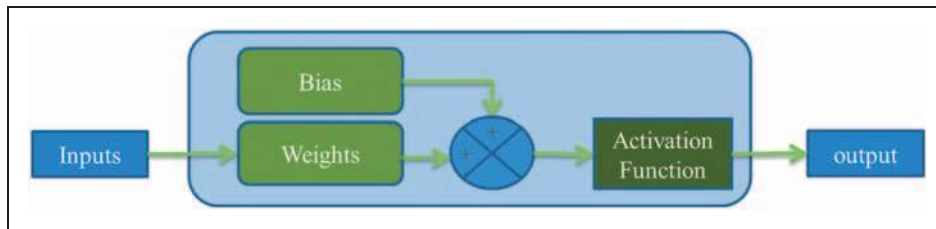NN: neural network; R2R: roll-to-roll.

Figure 5. Structure of a single neuron is shown where inputs are multiplied to their corresponding weights and are added with bias value.
This result is subjected to the activation function to get the output of a neuron.

where '*f*' is the activation function, '$W_j^{(l-1)}$' the weights, 'b_j^l' the bias, and '$a_j^{(l-1)}$' the input of neuron '*j*' of layer '*l*'. For R2R system, the inputs of the NN control are the feedback from load cells, roll diameter at the winder and unwinder, position from encoder pulses of servomotors and velocity of servomotors calculated from the encoder counts. The position from encoder counts, velocity calculation of the motors, and load cells calibration was performed in FPGA. For first layer with input '*x*' the output becomes

$$a_j^{(1)} = f\left(W_j^{(1)}x + b^1\right)$$

Same activation function must be used on all nodes in a layer but different activation functions can be used for different layers. Sigmoid activation function was employed in this article. Sigmoid activation

function is a nonlinear function as shown in equation (1). A nonlinear activation function allows the network to compensate for the nonlinearity present within the system.[20]

$$f(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

The derivative of equation (1) is as follows

$$\frac{d}{dt}f(x) = f'(x) = f(x) \cdot (1 - f(x))$$

'z^l' is the intermediate value in a neuron before the activation function is applied. So for the first layer 'z^l' is described by the following equation
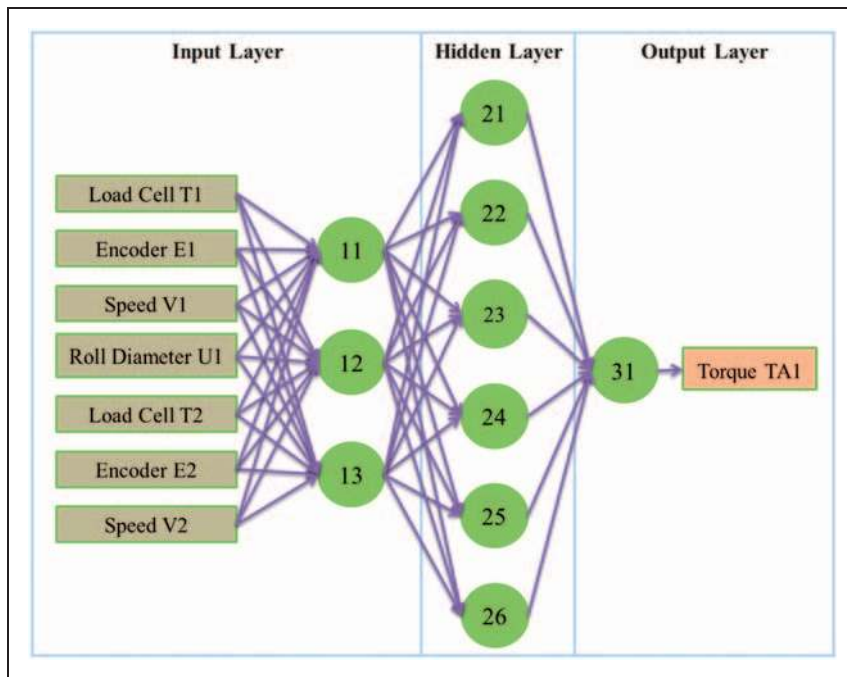
$$z^{(1)} = W^{(1)}x + b^1$$

Figure 6. NNs layer architecture is shown where inputs go into first layer known as input layer and outputs come from the last layer known as output layer while in-between layers are known as hidden layer.
In this case there are three neurons in first layer, six in hidden layer, and a single neuron in output layer.
NNs: neural networks.

When the activation function is applied then the output of the neuron is readily available and is given as equation (2)

$$a_j^{(1)} = f\big(z^{(1)}\big) \tag{2}$$

Feedforward NNs

In feedforward NNs, the data flow is one directional that is from the input layer to next layers so the process completes at the output layer. There is no loop or feedback of data flow. A well-tuned feedforward system acts like a fuzzy system[20] and can handle nonlinear systems as well but as the weights of the system remains constant hence for a time variant system the weights working for one instant may not perform well under other. For a three layer NN, as shown in Figure 6, the output of first layer is given by equation (2). Following the same sequence, the output at last layer, i.e. third layer is stated as

$$a_j^{(3)} = f\big(z^{(3)}\big) \tag{3}$$

The output equation for feedforward NNs shown equation (3) can be expanded into

$$a_j^{(3)} = f^3\big(W^{(3)}f^2\big(W^{(2)}f^1\big(W^{(1)}x + b^1\big) + b^2\big) + b^3\big)$$

Backpropagation method

A backpropagation NN (BPN) is the method of feedback system or loop in NN. This process[22] has two steps, the first step calculates the error from the desired output to the actual output and then keeps on calculating the error for each neuron in the NN and the second step updates the weights for all the neuron according to that error. The BPN scheme is shown in Figure 7.

Calculation of error

Calculation of error starts from the difference between the desired output value of the system from training set 'y_j' and the value of output layer 'a_j^l'. The error is represented by '$\delta_j^{(l)}$' where 'δ' is the error in layer 'l' and at neuron (node) 'j'.

For the NN shown in Figure 6, the error 'δ_j^3' of output layer is

$$\delta_j^{(3)} = y_j - a_j^{(3)}$$

After the output layer, the error is calculated back from output layer to input layer, layer by layer, thus the error is propagating back from last layer to the first layer

$$\delta_j^{(l)} = \big(W^{(l)}\big)\delta^{(l)} * f'\big(z^{(l)}\big)$$
$$f'\big(z^{(l)}\big) = a_j^{(l)} * \big(1 - a_j^{(l)}\big)$$
$$\delta_j^{(l)} = \big(W^{(l)}\big)\delta^{(l)} * a_j^{(l)} * \big(1 - a_j^{(l)}\big)$$
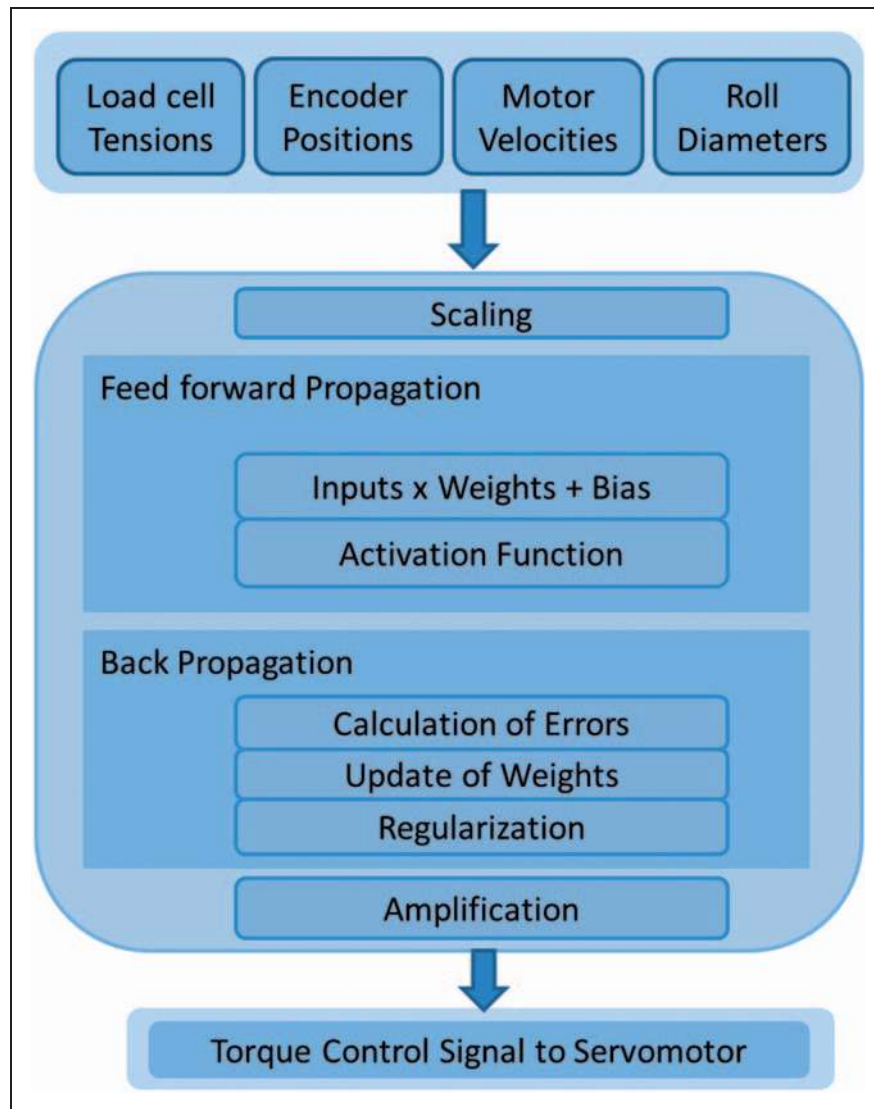
Figure 7. NN programming design is shown where inputs of NN are tension, position, velocity, and roll diameter while using a VLR BPN torque inputs for all motors are calculated.
NN: neural network; BPN: backpropagating artificial neural network; VLR: variable learning rate.

The error in second and first layers for NN in Figure 6 is given in equations (4) and (5), respectively.

$$\delta_j^{(2)} = \left(W^{(2)}\right)\delta^{(3)} * a_j^{(2)} * \left(1 - a_j^{(2)}\right) \tag{4}$$

$$\delta_j^{(1)} = \left(W^{(1)}\right)\delta^{(2)} * a_j^{(1)} * \left(1 - a_j^{(1)}\right) \tag{5}$$

Training and learning rate

Training is the process of updating weights. Initially, the system is started by random values of weights and bias values between 0 and 1. With BPN the weights are auto tuned which makes BPN capable of dealing with time variant nature of any system. After each feedforward networks output, error value for each neuron is calculated. These error values are used to update the weights so the root mean square error is minimized

$$W_{New}^{(l)} = W^{(l)} + \alpha\left(a_j^{l-1}\delta_j^{(l)}\right)$$

here, '$\delta_j^{(l)}$' is the error and 'α' the learning rate which is the ratio effecting the speed and quality of learning. After first cycle of tuning, all weights are updated so that for the next tuning the system can start with weights closer to the actual converging weights[23] instead of random values.

Constant learning rate consumes more training cycles. Also, the constant learning rate has to be optimized because if the learning rate is high the system may oscillate and become unstable while a low learning rate causes may cause the system to converge after a long time thereby increasing the rise time.
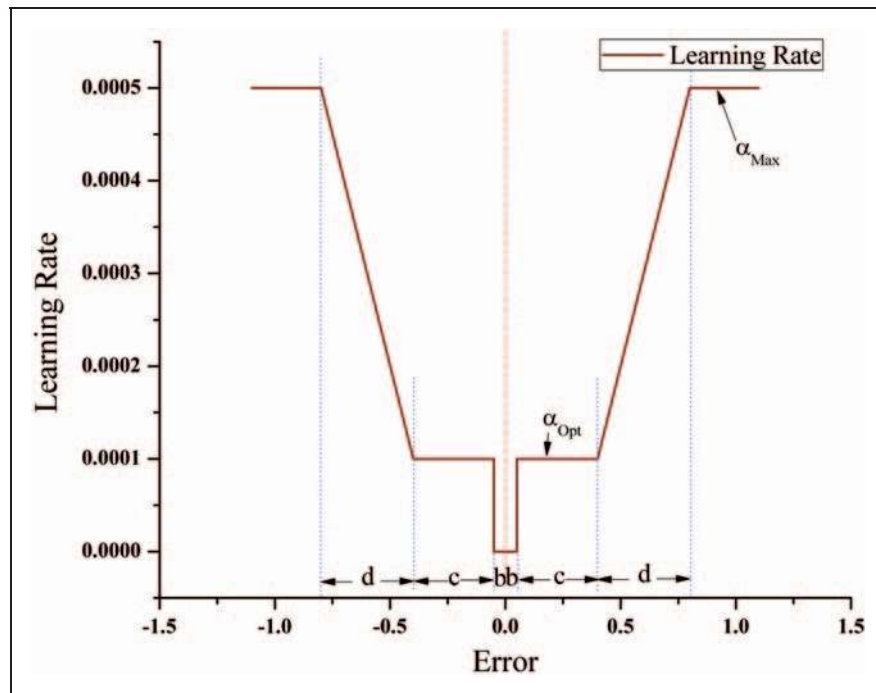
Figure 8. Limits set on VLR corresponding to error so that the system may not go in unstable region.
Here, learning rate is zero if error is within acceptable range of *b*, an optimal learning rate is applied for error range of *c*, a proportional learning rate is applied for range *d*, and beyond this range a maximum learning rate is applied.
VLR: variable learning rate.

Variable learning rate

For decreasing the rise time, a VLR approach[24] is adopted. The learning rate is proportional to the error between the user prescribed value and the system output. When the error is large the learning rate is higher than optimum value so that the system can train itself faster but for a smaller error the learning rate stays at the optimum value. The learning rate 'α' is presented as

$$\alpha = \begin{cases} 0, & -b \geqslant E \geqslant b \\ \alpha_{opt}, & -c \geqslant E \geqslant -b \\ & b \geqslant E \geqslant c \\ |\alpha_{opt} \times E|, & -d \geqslant E \geqslant -c \\ & c \geqslant E \geqslant d \\ \alpha_{Max}, & \text{otherwise} \end{cases}$$

where *E* is the error, 'α_{opt}' the optimized learning rate, 'α_{Max}' the maximum limit for learning rate and error margin ranges *b*, *c*, and *d* are shown in Figure 8.

Overfitting

R2R has a complex system model and in initial training BPN tries to memorize the data rather than learning from the trend. This makes the system to perform well on training data but on unseen data the system will have poor predictive performance. This state is known as overfitting. As a remedy, limits are applied for the training of system so that after getting a

suitable accuracy the training procedure stops. Regularization term has been added to overcome the overfitting problem. So with regularization term the weight update equation become

$$W_{New}^{(l)} = W^{(l)} + \alpha \left(a_j^{l-1} \delta_j^{(l)} \right) + \lambda W^{(l)}$$

where 'λ' is the regularization parameter which is a penalty on the weights and hence keeps the NN out of over fitting.

Simulations

To get optimized values of learning rate and regularization, speed control of motor was simulated in LabVIEW environment. A sinusoidal reference velocity pattern is created. The BPN makes the motor to track the speed pattern. Simulation shows that the learning rate was initially high but it reaches the optimum value as the system goes to a steady state. The reference speed signal, speed of the motor, output of BPN, and learning rate are shown in Figure 9. It should be noted that speed control of a motor is a SISO and time invariant system. This simulation was done to check the abilities of the control algorithm.

Experiments

Different configurations of NNs layer structures were used to control R2R system. Final configuration is
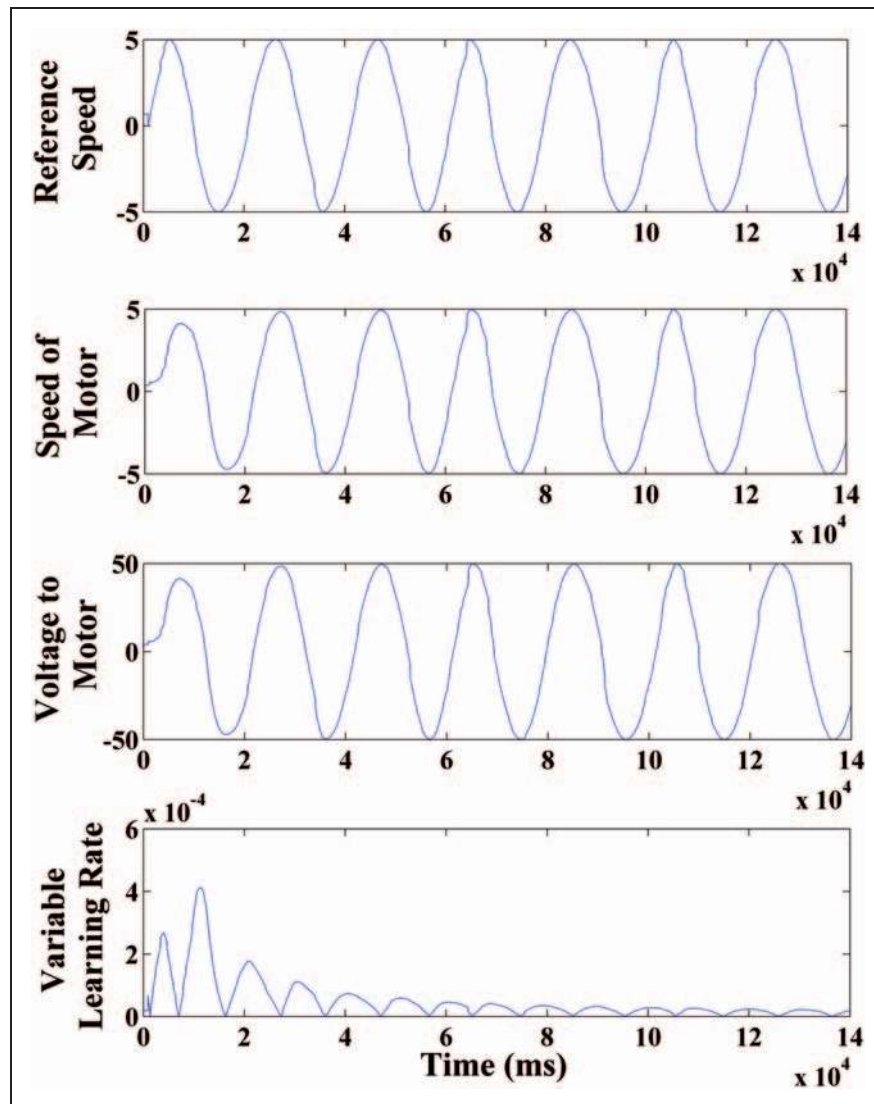
Figure 9. Simulation of speed control using regularized VLR backpropagation NNs showing the decrease of learning rate as the NN is trained and error is decreased.

NNs: neural networks; VLR: variable learning rate.

shown in Figure 6 which has three layers. First layer has three neurons and seven inputs. Second layer has six neurons and last layer has one neuron. Regularized VLR BPN is applied on the R2R system for tension and velocity control in a fashion described in Figure 4.

Infeed is the master velocity control of the system and was set to increase the speed from 0 to 1 rad/s in a ramp form, where 1 rad/s is equal to 2.4 m/min. A ramp form is a good test signal as the inputs of system are gradually changing function of time. The unwinder, outfeed, and rewinder are set in tension control mode and these motors make sure that the tension of the system is at 5 N. Printing system as gravure offset printer, slot die, EHP, and electrohydrodynamics atomization systems are installed in second span known as printing span. The experimental parameters used are mentioned in Table 1. The optimum

Table 1. Experimental parameters for R2R system control using regularized VLR backpropagation NNs.

Parameter	Value
Web width	120 mm
Web thickness	0.5 mm
Reference tension	5 N
Master control speed	2.4 m/min
Optimized learning rate	1E − 4
Optimized regularization rate	1E − 4
Learning rate error margins	±0.05
Maximum learning rate	1E − 3
Diameter of infeed roll	80 mm
Control loop time	1 ms

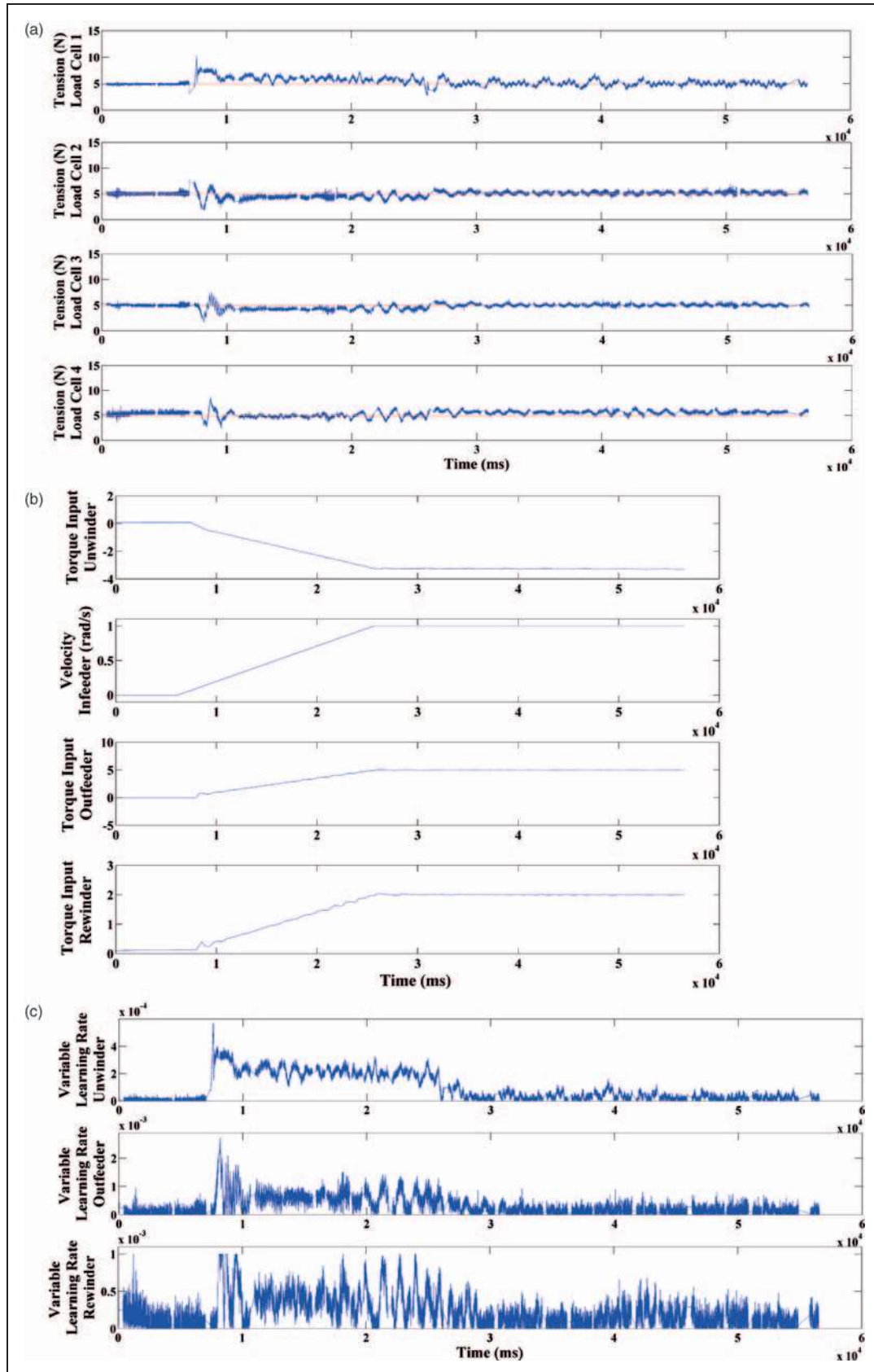NNs: neural networks; R2R: roll-to-roll; VLR: variable learning rate.

Figure 10. (a) Web tension control of R2R system at velocity ramp input by BPN control where the reference tension is set at 5 N; (b) the torque control inputs of motors corresponding velocity ramp input using BPN control scheme with tension, position, velocity, and roll diameter are used as inputs of NN; and (c) VLR corresponding to the changes in tension in BPN where a proportional learning rate with respect to error is selected to increase rise time.

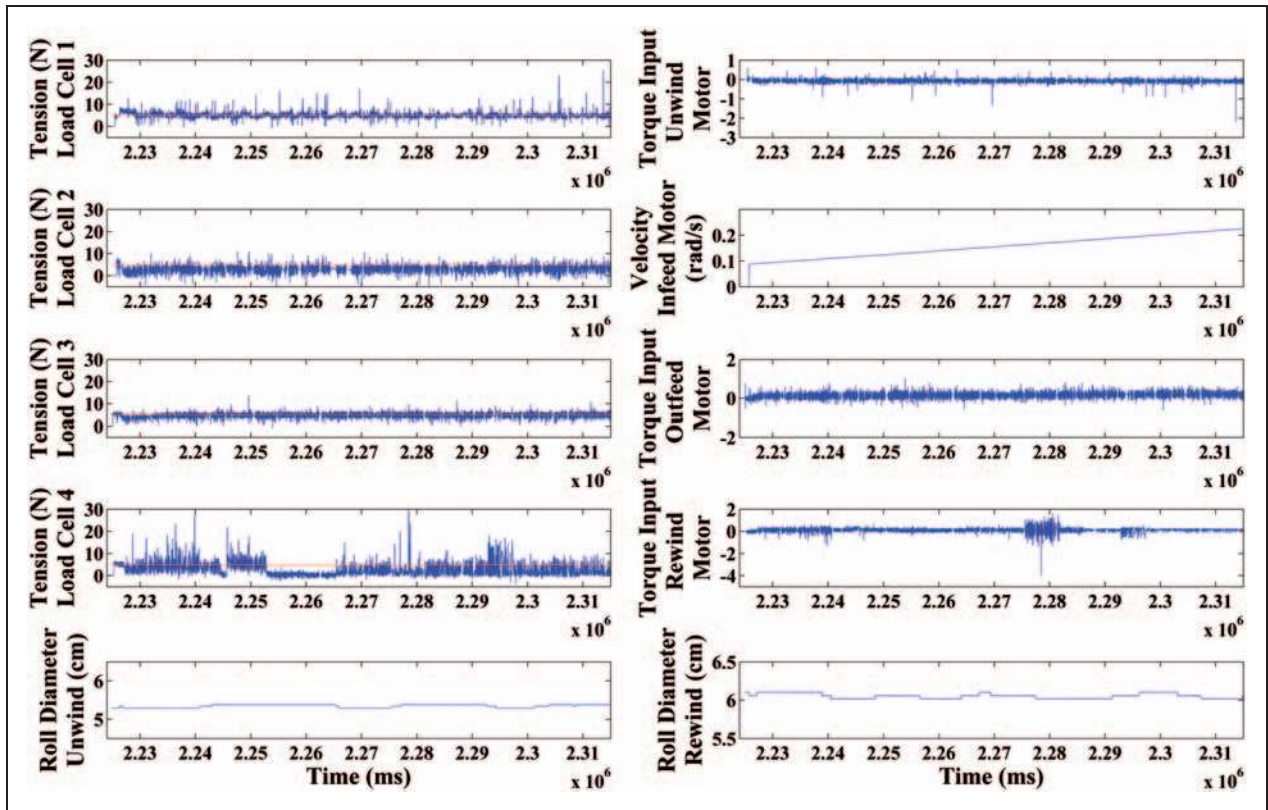BPN: backpropagating artificial neural network; R2R: roll-to-roll; VLR: variable learning rate.

Figure 11. PID web tension control of R2R system where reference tension is 5 N and master velocity control of system is increasing.

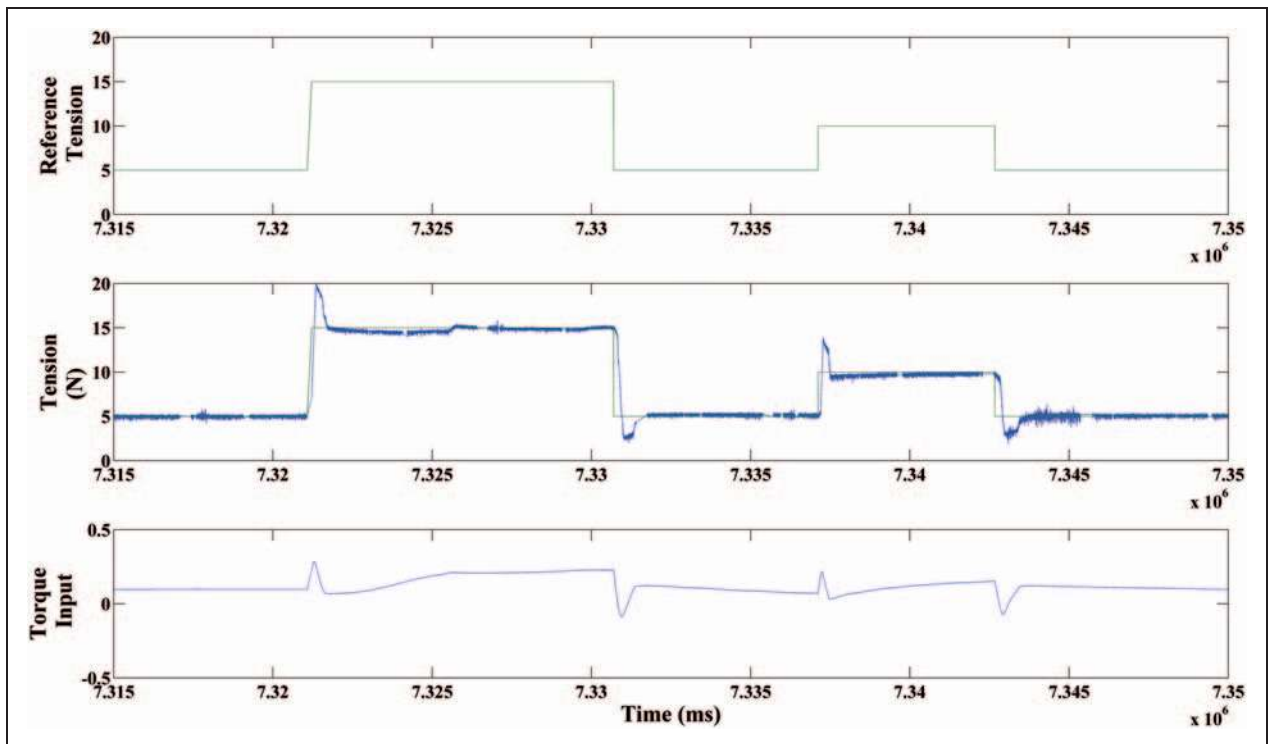PID: proportional–integral–derivative; R2R: roll-to-roll.

Figure 12. BPN web tension control of R2R system where reference tension is changed from 5 N to 10 N, 15 N, and back in static mode.

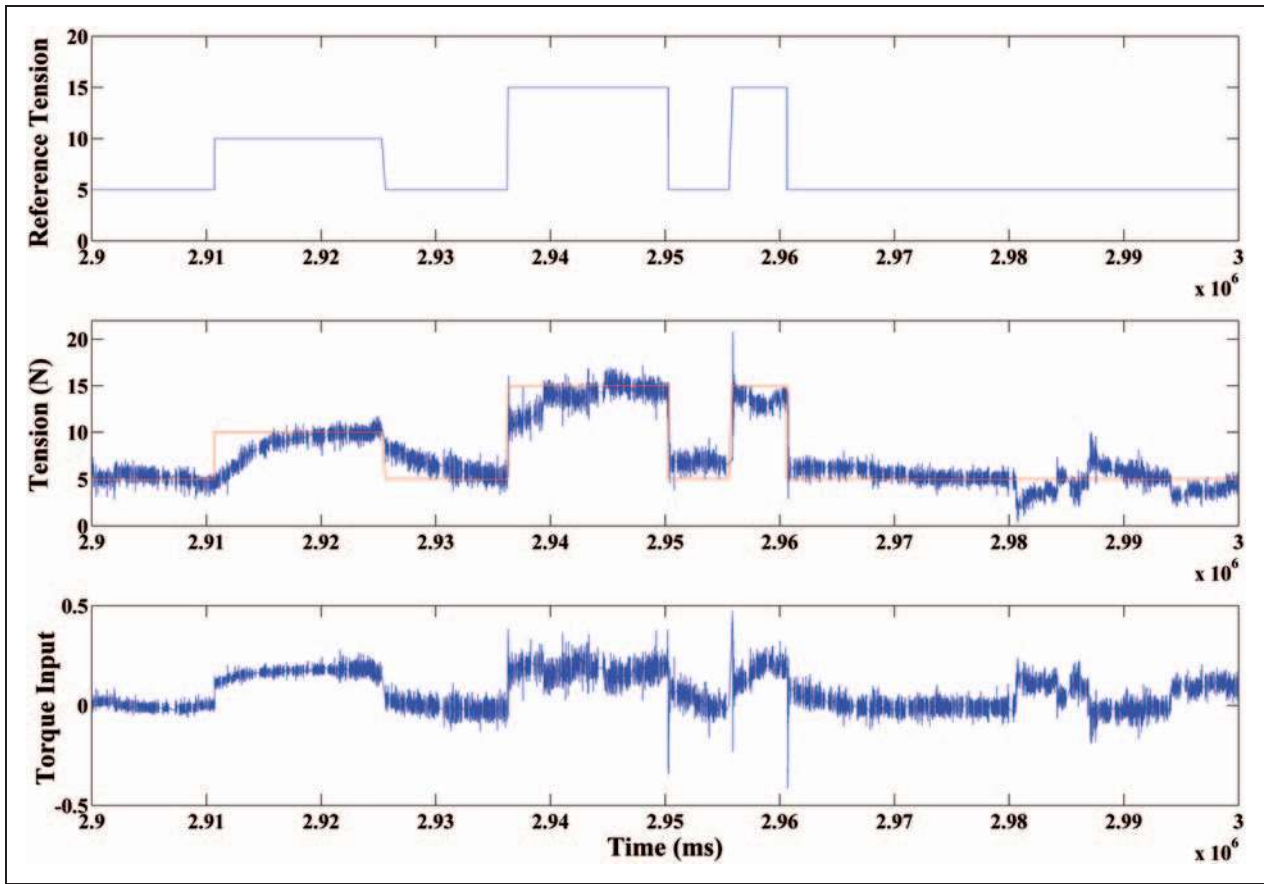BPN: backpropagating artificial neural network; R2R: roll-to-roll.

Figure 13. PID web tension control of R2R system where reference tension is changed from 5 N to 10 N, 15 N, and back in static mode.

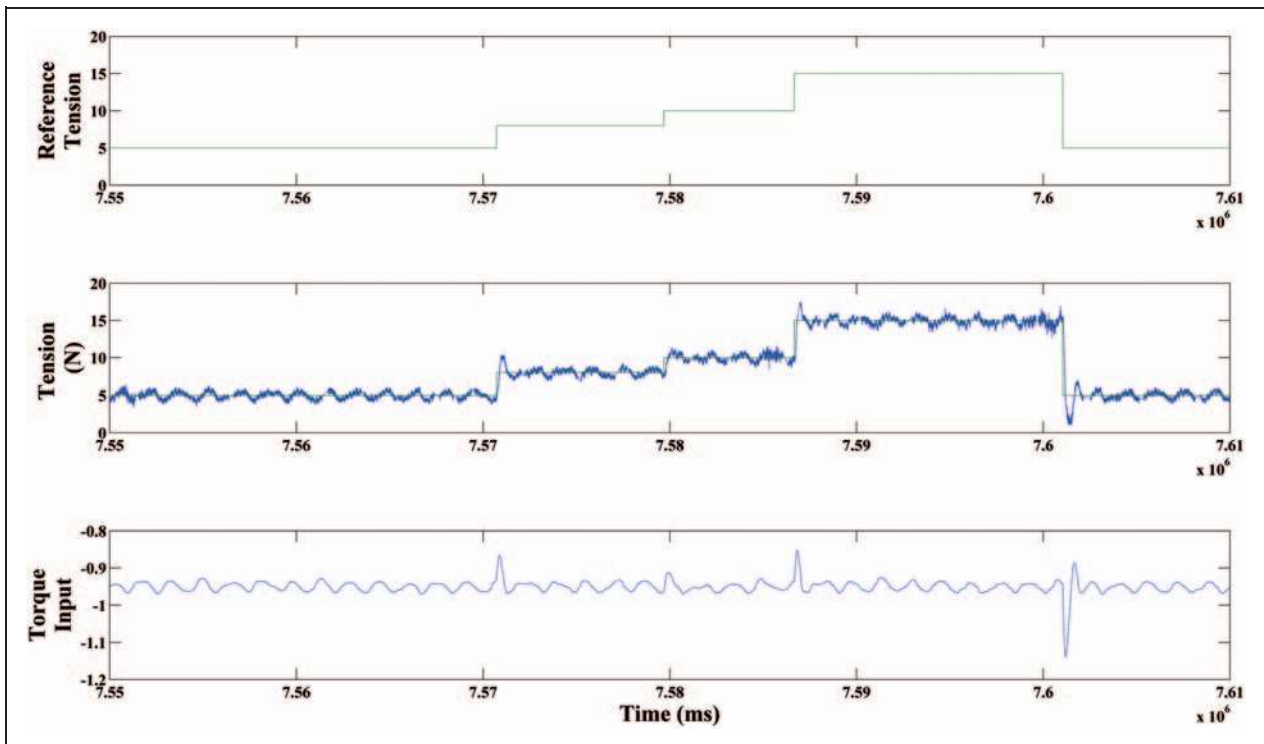PID: proportional–integral–derivative; R2R: roll-to-roll.

Figure 14. BPN web tension control of R2R system where reference tension is changed from 5 N to 10 N, 15 N, and back in dynamic mode with master velocity control set at 2.4 m/min.

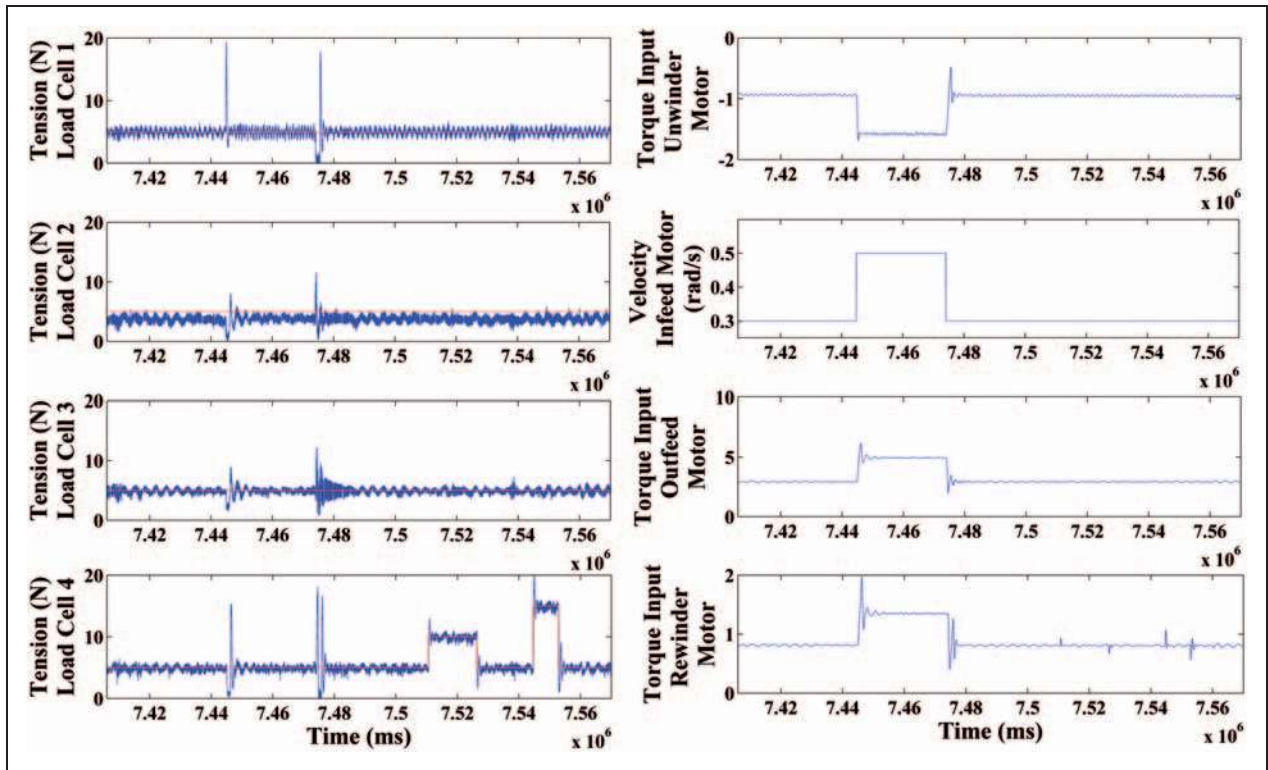BPN: backpropagating artificial neural network; R2R: roll-to-roll.

Figure 15. BPN web tension control of R2R system where speed of system is changed from 0.72 to 1.2 m/min in a step form. BPN: backpropagating artificial neural network; R2R: roll-to-roll.
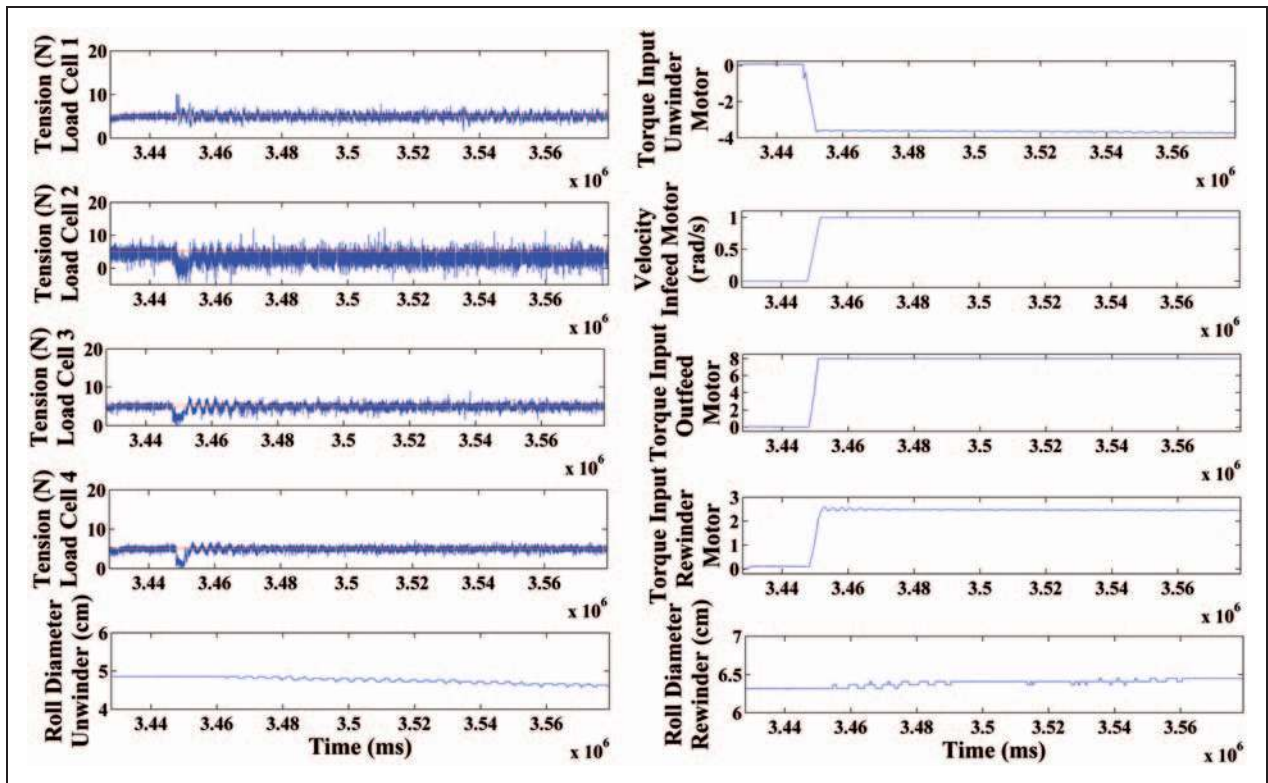

Figure 16. Fast start of R2R system increasing speed of system from 0 to 2.4 m/min in less than 4 s using BPN control scheme. BPN: backpropagating artificial neural network; R2R: roll-to-roll.
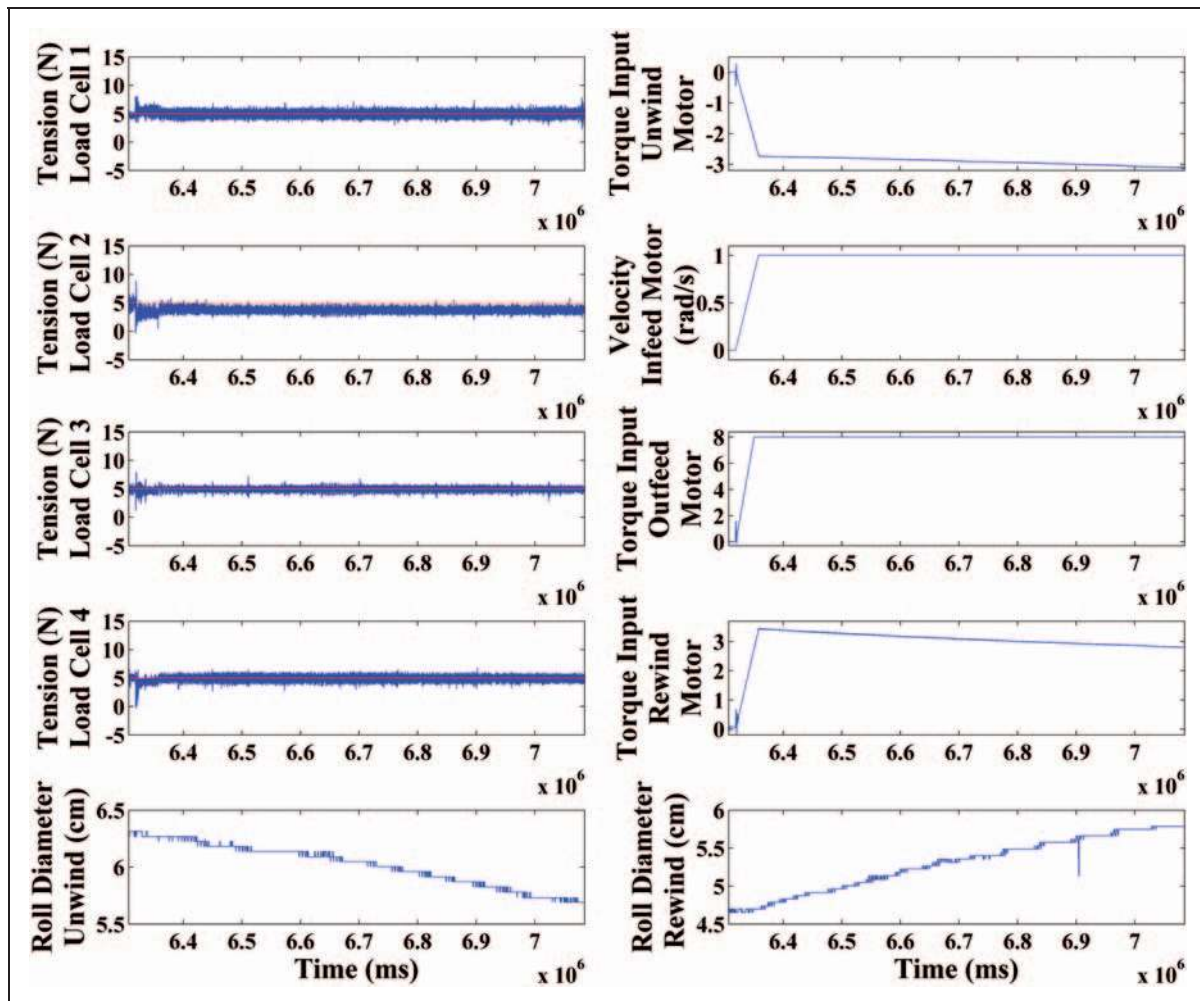
Figure 17. R2R system with master velocity control increasing from 0 to 2.4 m/min using BPN control scheme. The changing roll diameter causes the corresponding change in the torque input of the unwind and rewind motors is shown. BPN: backpropagating artificial neural network; R2R: roll-to-roll.

learning rate is the highest possible value of learning rate. Figure 10(a) shows the experimental tension control of R2R with change in master velocity control. The corresponding changes in output torques and VLR are shown in Figure 10(b) and (c), respectively. A conventional control PID is implemented for a comparison with BPN. The tension control with PID using a ramp input is shown in Figure 11, where the reference tension was kept at 5 N and master velocity control was made to increase.

Step response study is a universal method to compare different control systems, it provides data such as overshoot, undershoot, settling time, etc. The steps of 5, 10, and 15 N tension were chosen because 5 N is the minimum possible tension on the machine and step sizes smaller than 5 N did not produce significant difference between the response of the two control systems (i.e. PID and BPN). The tension changes in static mode form 5 N to 10 N, 15 N, and back in BPN control are shown in Figures 12 and 13 shows the PID tension control with step response in static mode from 5 N to 10 N and 15 N and back.

In dynamic mode where the master velocity control of the system is set at 2.4 m/min tension changes from 5 N to 10 N, 15 N, and back controlled by BPN are shown in Figure 14. A step response change in master velocity control of R2R system is shown in Figure 15. Here, the speed of system was varied from 0.72 to 1.2 m/min in a step form. The tension was kept constant at 5 N.

A high-speed change in master velocity control from 0 to 2.4 m/min in a ramp form was achieved in less than 4 s using BPN, as shown in Figure 16. The time variant behavior of R2R system is shown in Figure 17 where the changing diameters of unwind and rewind rolls give a corresponding change in BPN outputs.

Results and discussion

From experimental results, a high VLR for large error makes the system converge faster. With the decrease in error VLR is also shifted back to the optimum value. The learning rate is equal to the optimum

value when the system is in steady state condition of 2.4 m/min velocity. Figure 10 shows that the weights are tuned and in steady-state BPN gives a smooth tension control result where there are no spikes in the response. Web tension controlled by PID control is shown in Figure 11. Here, PID seems to be seen struggling to maintain the tension control on a very low value of 5 N tension. There are many spikes of more than 10 N. These figure show that BPN offers better control with multi-inputs and online tuning as compared to conventional PID control.

When PID control is compared to BPN control in step response of tension changes, BPN offers better compensations to step responses of tension from 5 N to 10 N and 15 N, as shown in Figures 12 and 13. If the sensitivity of PID is increased in this static mode than PID control goes in oscillation in dynamic mode. BPN is offering a good sensitivity in static mode without going into oscillation in dynamic mode, as shown in Figures 12, 14, and 15. In order to make the system sensitive for controlling web tension at a low value of 5 N, a high learning rate has been used in VLR BPN. The use of the high learning rate is the main cause of the spikes in initial tension during step changes.

The PID response in second span was much better than first and third spans as in second span the time variant nature of R2R system does not come into play. While in Figure 17 BPN changes the input torque of the rewind and unwind motor to cater for the changing roll diameters of rewind and unwind rolls. Here, it can be seen that in second span, the torque for the outfeed motor remains the same as it has no effect of changing roll diameters.

The experiments show that at constant speed the tension in second span is within ±1 N. It should be noted that noise of load cells is ±0.7 N. The VLR in BPN make the system converge faster hence the rise time of the system is improved. The coupling between the spans is minimized by introducing the inputs relating first span to the next one. Keeping the system tension low at 5 N helps the web to stay in elastic mode even in higher temperatures in IR curing module. This low tension will also insure that the electronic devices printed on web will not crack when the web shrinks. The tuning by BPN takes care of time variant nature of R2R system which is introduced by the continuously changing roll diameter of the unwind and rewind rolls.

Conclusion

In this article, web tension control of a multispan R2R system for printed electronics is achieved by applying regularized VLR on BPN. An optimum NN layer scheme for this task has been found which has 3 layers and 10 neurons. The R2R is a MIMO, time variant, and nonlinear system with a strong coupling that exists between the spans. The BPN has MIMO interface, nonlinear activation functions, and auto tuning scheme. The MIMO system is controlled by decentralized MISO scheme. The nonlinearity of interaction of spans is minimized with introducing multiple inputs from the corresponding interacting spans and nonlinear activation functions. The auto tuning of weights cater for the time variant nature of the system. The steady-state error of second span is within ±1 N where the load cells noise is ±0.7 N. The experimental result of regularized VLR using backpropagation neural networks control scheme gives fast auto tuning while avoid system instability hence giving a solution for a R2R system for printed electronics.

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