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Application of Neural Network Scheme to Performance Enhancement of Rheotruder

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Abstract

Recently, in order to guarantee the quality of the final product from the production line, several equipments able to examine the polymer ingredients' quality are being used. Rheotruder is one of the equipments manufactured to measure the viscosity of the ingredient that is an important factor for the quality of final product. However, Rheotruder has nonlinear characteristics such as time delay which make systematic analysis difficult. In this paper, in order to enhance the performance of Rheotruder, a new scheme is introduced. It incorporates TDNN (Time Delay Neural Network) bank and Elman network to get a right decision on whether the tested ingredient is good or not. Furthermore, the proposed scheme is verified through real test execution

Key words : Elman network, Rheotruder, TDNN bank, time-delay

1. Introduction

Recently, many companies are undergoing some problems such as short product life cycle and maintenance of good qualified product. Generally, inferior quality ingredients result in deterioration of the final product quality. Therefore, in order to get good products, some equipment for evaluation of the ingredients' quality is required. For example, many companies try to test the characteristics of ingredients before they are used in the product line. LG Chemical Corporation designed the test equipment called Rheotruder for the quality evaluation of the polymer ingredients which are used in plastic injection molding system [1]. Currently, Rheotruder is manipulated by human expert to determine whether the material is good or not. However, it is very difficult to get a right decision on whether the ingredient is good or not. It is partly because Rheotruder has some nonlinear characteristics.

In last years, ANNs (Artificial Neural Networks) have achieved a high degree of importance. Because ANN is cost-effective and easy to understand, it has found many applications in nonlinear process modeling and control. Especially, the TDNN, which is a dynamic neural network, was proposed to effectively learn the characteristic of nonlinear systems. TDNN is a multilayer feed-forward network whose hidden neurons and output neurons are replicated across time [2-3]. Furthermore, a recurrent neural network which is known as Elman network was proposed to effectively memorize and recognize the pattern found in multiple input variables. It also has the characteristics of robustness against noisy input, learning ability of nonlinear relationships between input and output and generalization [4].

In this paper, a new scheme for enhancing the performance of Rheotruder is proposed. It incorporates the TDNN bank and Elman network to get a right decision on whether the tested material is good or not. In section 2, the description of Rheotruder is given. In section 3 and 4, TDNN and Elman network are briefly discussed. In section 5, a new scheme based on TDNN and Elman is discussed. Finally, in section 5 and 6, application of proposed scheme to Rheotruder and results are discussed.

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2. Rheotruder System

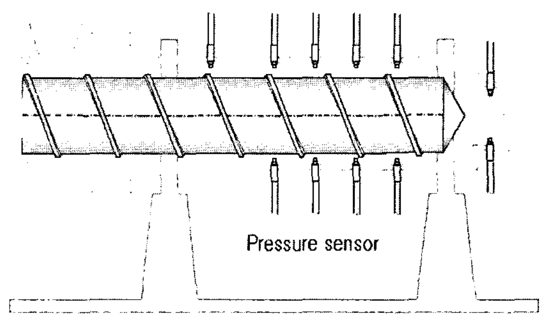

Fig. 1. Structure of Rheotruder system

Fig 1 shows the Rheotruder system designed by LG Chemical Corporation. On principle, it is a simple process in which the barrel is equipped with temperature and pressure sensors installed on the vertical axis [5]. A thermoplastic ingredient, in the form of granules, passes from a feed hopper into the barrel where it is heated and melted. As the other side of barrel is closed, it stays inside of the barrel. If the speed of screw increases, the corresponding pressure values can be continuously changed. By measuring the trend of each pressure values, the quality of the ingredient can be estimated. If the ingredient is not good, the trend of each pressure value is different. As this kind of decision scheme can be erroneous, an enhanced system is required to get a good decision rate.

3. Time Delay Neural Network (TDNN)

TDNN represented in Fig 2 is a dynamic neural network able to study nonlinear systems and to perform temporal processing having the noise removal feature as well. These neural networks are multilayer feed-forward networks whose hidden neurons and output neurons are replicated across time [6]. The output is associated with input and it depends on time context. The connections have time delays that postpone the forwarding of a unit's activation to another unit. In this way, the output depends on (and uses) the current inputs as well as the past inputs. TDNN enables efficient interpolation of the output data about input data which are not used in training and is able to perform the modeling of nonlinear system by using time-delayed input/output data from the actual system. [7]

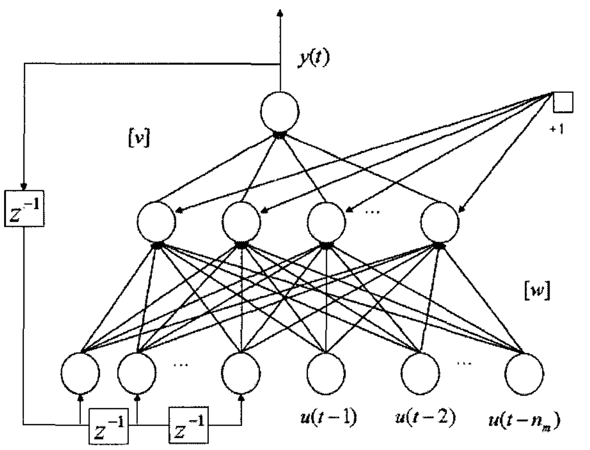

Fig. 2. Structure of TDNN

Back-propagation algorithm used for TDNN's training is as follows:

Step 1: Input $u_1, u_2, \ldots, u_{(t-2)}, \ldots, y_{(t-1)}, \ldots, y_{(t-m)}$ and the desired output $y_{(t)}$ makes pattern
Step 2: Initialize the weight and counter.
v, w ← small random value (weight)
p ← epoch
k ← 1 (counter)
E ← 0 (the error rate)
Step 3: Set up learning rate (α>0) and maximum error E_{max}.
Step 4: Yield the sum of weight by input at each node and calculate the output value from the nonlinear activation function. When $E > E_{max}$, E ←0, counter k increases; the process is repeated until $E < E_{max}$ is achieved.

4. Elman Network

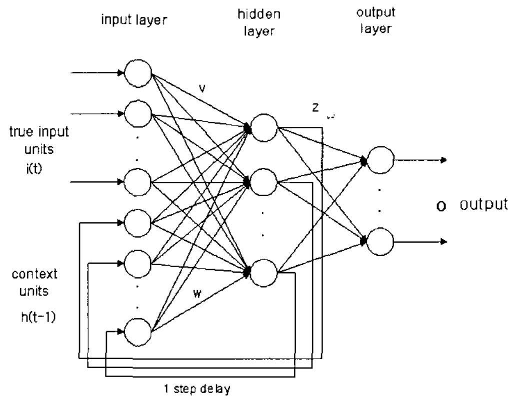

Fig. 3. Structure of Elman network

Generally, Elman network may be described in analogy to three layer feed-forward network, except, it has a feedback connection from the output of hidden layer to input layer, as shown in Fig 3. The output of the hidden units at time-step t-1 are copied as context units and used together with the new inputs at time-step t to yield the next hidden units output. The architecture of the units in input-hidden-output layer and context units should be carefully selected. The number of context units is the same as the number of units in hidden layer [8]. The output of hidden layer is calculated as follows:

$$h(t) = f(w(t), v(t), x(t)) \tag{1}$$

$$x(t) = [i(t), h(t-1)]^T \tag{2}$$

where, h(t) is the output of hidden layer at time t and w(t),v(t) are the weights matrix (from context unit to hidden layer and from input unit to hidden layer). x(t) is the input training pattern consisting of the true input i(t) and the output h(t-1) of hidden layer at time-step t-1. Also, h(t-1) is the input of a context unit.

Function f is a standard sigmoid activation function as follows:

$$f(x) = 1/(1+e^{-ax}) \tag{3}$$

Where,

$$a \in [-\infty, +\infty] \tag{4}$$

The detailed calculation of the output of hidden layer and the output of Elman network is as follows:

$$h_j(t) = f(\sum_i v_{ij} \cdot i_i(t) + \sum_k w_{kj} \cdot h_k(t-1)) \tag{5}$$

$$o_p(t) = f(\sum_p z_{jp} \cdot h_j(t)) \tag{6}$$

Where $h_j(t)$ is the output of j-th unit hidden layer, v_{ij} is the weight from the input layer to the hidden layer, w_{kj} is the weight from the context units to hidden layer, $o_p(t)$ is the output of p-th unit output layer and z_{jp} is the weight from the hidden units to output.

In training, Elman network is using the Back-propagation algorithm with momentum.

5. Enhanced evaluation system for Rheotruder

The whole structure of the performance enhancement form Rheotruder that uses TDNN and Elman network is shown in Fig 4.

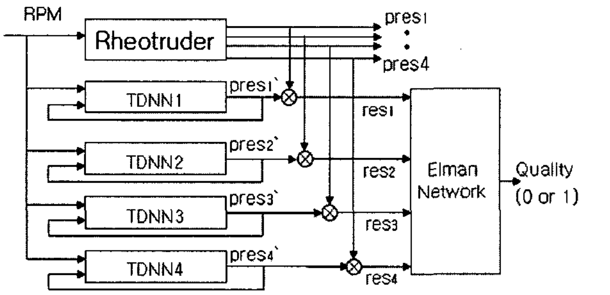

Fig. 4. Performance enhancement system for Rheotruder based on TDNN bank and Elman network

Fig 4 represents the performance evaluation system for Rheotruder consisting of TDNN bank and Elman network. Generally, the input (RPM) and the corresponding output values (pressure values) can be obtained by several experiments with a good ingredient. Furthermore, the time-delayed input and the time-delayed output values are used to form training data for TDNN as in equation (11).

$$\begin{aligned} pres_1'(k) &= f_1(RPM(k),..,RPM(k-d), \\ &\quad pres_1'(k-1),...,pres_1'(k-d_1)) \\ pres_2'(k) &= f_2(RPM(k),..,RPM(k-d), \\ &\quad pres_2'(k-1),...,pres_2'(k-d_2)) \\ pres_3'(k) &= f_3(RPM(k),..,RPM(k-d), \\ &\quad pres_3'(k-1),...,pres_3'(k-d_3)) \\ pres_4'(k) &= f_4(RPM(k),..,RPM(k-d), \\ &\quad pres_4'(k-1),...,pres_4'(k-d_4)) \end{aligned} \tag{11}$$

Each TDNN is trained to generate the corresponding output (i.e., pres1') using the time-delayed input (RPM) and its time-delayed output (pres1' (k-1)... pres1' (k-n)). If the training of TDNNs is successfully finished, each TDNN can generate its corresponding output value (i.e.: pres1', pres4') which is similar to the real value from Rheotruder. Therefore, some residuals between Rheotruder and TDNNs can be obtained. If a certain tested ingredient is of good quality, the residuals are zero or very close to zero. Otherwise, if the ingredient is of inferior quality, the residuals are not zero. Furthermore, the residual shows different behavior according to the change of RPM. Generally, it is very difficult to decide whether the tested ingredient is of good quality or not. In order to overcome this difficulty, Elman network having the feature of memorizing the trend is introduced. Elman network can be trained to output a right decision on good ingredient (according to RPM). By incorporating Elman network, the decision rate can be further improved.

6. Application of the proposed scheme to Rheotruder

This section wishes to confirm the usefulness of the proposed system. Fig 5 shows pressure sensor values according to the change of the barrel speed (RPM). Each TDNN is trained with the time-delayed RPM values and pressure values as in equation (11). For its learning, we used 1200 data collected from each pressure sensor. For training, the time-delay degree of RPM, d, is set to 4 and the time-delay degree of output (d_1, d_2, d_3, d_4) is set to (3, 4, 6, 3). Generally, the degree of time-delay for TDNN is empirically determined through various training.

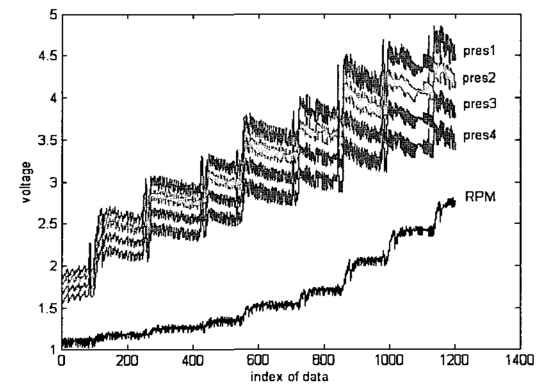

Fig. 5. Input/output characteristics of Rheotruder

When the training is completed, the output of each TDNN is shown in Fig 6. As it can be seen in Fig 6, trained TDNN shows the characteristic of a low pass filter which can remove noise in output values.

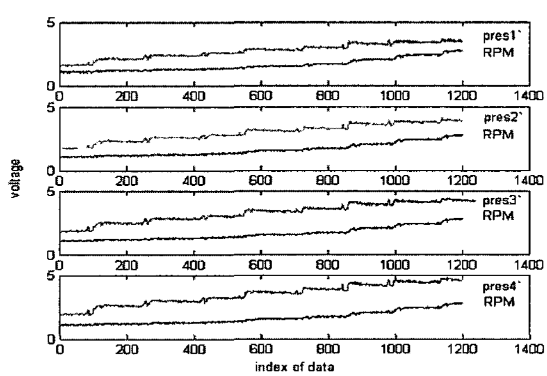

Fig. 6. Output characteristics of trained TDNN

The modeling errors of TDNNs are shown in Fig 7.

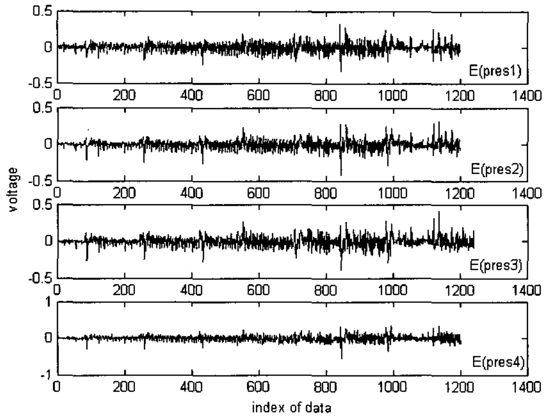

Fig. 7. Residuals between output of TDNN and output of Rheotruder

Fig 8 shows the output characteristic of trained TDNN and the output of Rheotruder. As it can be seen, the trained TDNN can precisely represent the characteristic of Rheotruder.

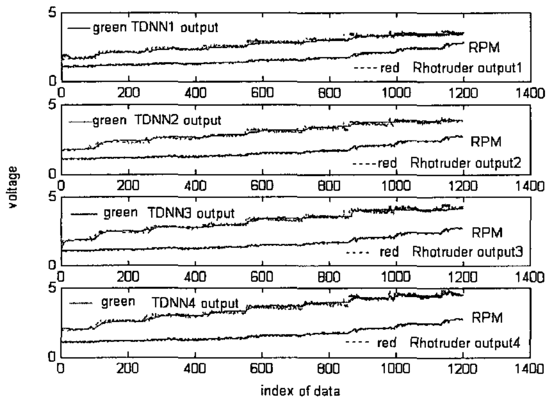

Fig. 8. Output characteristics of TDNN (green) and output characteristic of Rheotruder in case of good ingredient

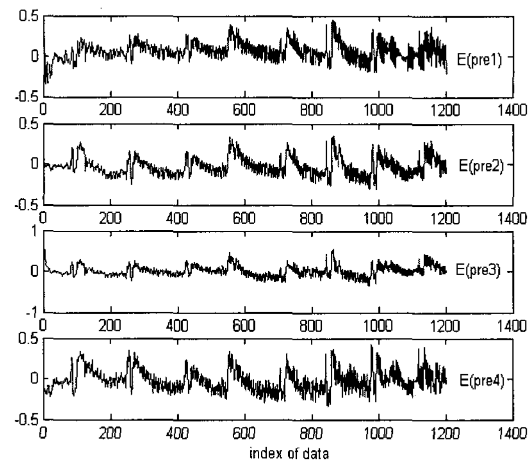

Fig. 9. Residuals between output of TDNN and output of Rheotruder

Fig 9 shows the residuals between the output of Rheotruder and the output of TDNN. It can be easily seen that the residuals are in the vicinity of zero, indicating that the tested ingredient is of good quality. That is, the characteristic of tested ingredient is almost the same as that of a good ingredient which was used for training.

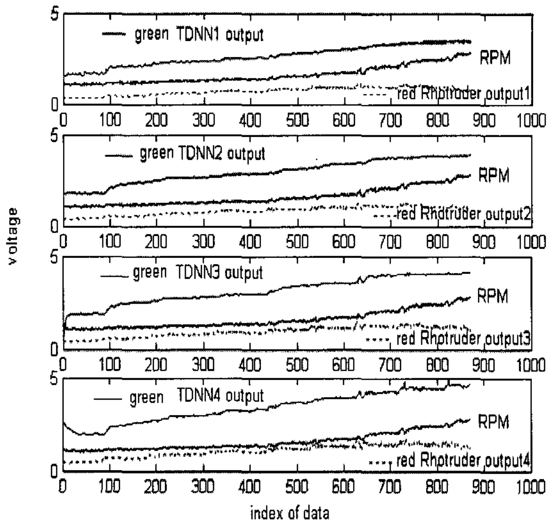

Fig. 10. Output characteristics of TDNN and Rheotruder in case of inferior quality ingredient

Fig 10 shows the output of TDNN and Rheotruder in case of other ingredient which can be thought of inferior polymer ingredient. There is a big difference between each output.

Fig 11 shows the residuals between output of TDNN and output of Rheotruder in case of inferior quality ingredient, when the residuals are not zero or close to zero. However, even though tested ingredients are of good quality, it reveals slightly different characteristics. Therefore, it is not desired to determine the quality of tested ingredient just by checking the residuals.

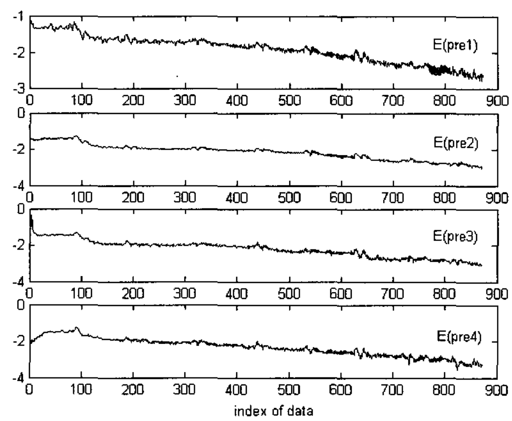

Fig. 11. Residuals between output of TDNN and output of Rheotruder in case of ingredient of inferior quality

To solve the above-mentioned problem, Elman network having the feature of memorizing the trend, is utilized. The input of Elman network consists of the residuals between the

TDNN and Rheotruder. The output of Elman is '0'which shows the tested ingredient is of good quality and '1' which shows the tested ingredient is of inferior quality. Each corresponding trends are used in training of Elman network. The quality of tested ingredient can be determined by just watching the output of Elman network. Fig. 12(a) shows the Elman network's output in case of good quality ingredient and Fig.12(b) shows the output of Elman network in case of inferior quality ingredient. Fig 12 shows that the decision on whether the tested ingredient is of good quality or of inferior quality is effectively carried out.

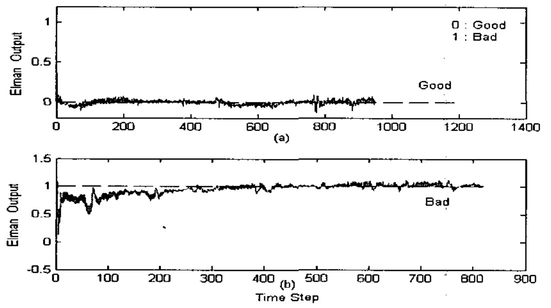

Fig. 12. Output of Elman network (a) in case of good quality ingredient (b) in case of inferior quality ingredient

7. Conclusion

In this work, a new scheme based on TDNN bank and Elman network is proposed to improve the decision rate on whether the tested ingredient is in good state or not. As it can be seen from the experimental results, the good quality of the tested ingredient can be easily determined simply by checking the output of Elman network. Therefore, the proposed system can be effectively used for improving the performance of Rheotruder system.

Reference

[1] Y.H.Kim J.K.Baek S.S.Kim "Development of Real Time Manufacturing Control System for Plastic Extrusion Factories", *Journal of the KIIE(Korean Institute of Industrial Engineers)*, No. 12-2, 254, 1999.

[2] Robert Hecht Nielsen, *Neuro-computing*, Addison Wesley, pp124-137, 1990.

[3] A.Waibel, T.Hanazawa, G.Hinton, et al., "Phoneme recognition using time-delay neural network", *IEEE Trans. on Acoustics, Speach, and Signal Processing*, Vol. 37, pp. 328-339, 1989.

[4] D.P. Mandic, J.A. Chambers, *Recurrent Neural Networks for Prediction*, John Wiley & Son, NY, 2001.

[5] Choi Won Jun, Shin Hyo Cheol, Gwak Shin Wung, "Optimization of Process Condition of Injection Molding using heredity algorithm", *Thesis version A of KSME(Korean Society of Mechanical Engineers)*, Vol.24 No.10, pp.2543-2551, 2000.

[6] K.NAIT BAHLOUL, "TDNN For Prediction of Position of Glycine on the Ramachandran map", *Proc. International Conference on Neural Information Processing*, Seoul, Korea, Vol. 3, pp. 1932-1936, Octobre 1994.

[7] Ing.Jozef Voftko, "Use of Time Delay Neural Networks for Sensor Errors Elimination", *ElectronicsLetters.com ISSN 1213-161X*, #2/5/2004.

[8] E.Michael Azoff, *Neural Network Time Series Forecasting of Financial Market*, John Wiley & Son, NY, 1994.

[9] J.L. Elman, *Finding structure in time*, Cognitive Sci. 14, 179-211, 1990.

[10] J.Zhou S.Bennett, "DYNAMIC SYSTEM FAULT DIAGNOSIS BASED ON NEURAL NETWORK MODELLING", *IFAC Conference SAFEPROCESS'97*, vol. 1, pp. 54-59, Hull, UK, 1997.

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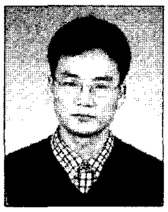

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