

인공 신경망을 이용한 방적사 굵기 신호의 모델링

김주용

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Modeling and Prediction of Yarn Density Profiles Using Neural Networks

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Abstract— A prediction model for yarn density profile was developed using the neural network methodology. The neural network model developed traces mass densities of a yarn within a section and predicts the mass profiles of the next yarn segment yet to be measured. The model does not require an assumption on the existence of a relationship between the past and future data sets. Four high-draft yarns made under different processing conditions were employed in order to test the performance of the model developed. It was shown that the model could predict the yarn density profiles without a significant error.

Keywords: yarn densities, neural network, uniformity, data acquisition, time-series

1. Introduction

In an earlier study, autocorrelation function analyses were performed to identify hidden periodicities in the signals captured from the Zweigle G-580 tester¹⁾. It was shown that the adjacent segments of a given yarn were strongly correlated with each other while exhibiting some periodicities as well. Based on these results, a time-series analysis approach was applied for modeling the density profiles of several high-draft yarns. The techniques used for analyzing these random signals include Kalman filtering, ARMA model, and spectral expansion technique. The Kalman filter approach requires an estimation of the covariance matrix. In this method, a possible high nonstationarity in the mass variation pattern

of the yarns can be a hindrance to accurate estimation.

The ARMA model, on the other hand, assumes that the density at a specific time point can be estimated by a linear combination of that from prior time points. Generally, the larger the data set, the better the results in terms of the accuracy. This model, however, may not be applicable to interpretation of a non-linear relationship between two adjacent time points. Finally, the spectral expansion technique utilizes Fourier series employing only a small fraction of the all possible orthogonal basis sets, and therefore is applicable only to slowly varying signals. On the other hand, an abrupt change of processing conditions may alter the yarn density profiles substantially, producing high frequency

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components in the frequency domain. Therefore, the spectral expansion technique cannot provide an accurate prediction for signals when they change much with time. In order to overcome the drawback of not being able to explain sudden changes in data trend, a variety of nonlinear models has been proposed in recent years²⁾. In spite of the significant progress during the last decade, however, formulation of a reasonable nonlinear model remains to be an extremely difficult task due to the simplifications one has to make during the modeling stage. Recently, the feedforward multi-layered neural network approach has been widely used in many areas of engineering and science³⁾.

Commonly, the neural networks can be employed in order to analyze some of the most complex non-linear relationships. The recent theoretical work has proven that the neural networks can be successfully applied to express most classes of continuous functions with bounded inputs and outputs with any specified precision⁴⁾. In this paper, we introduce a neural network algorithm for modeling the mass variations of high-draft spun yarns. As is the case with a time series approach, the neural network also traces the mass densities of a yarn within a section and predicts the mass profiles of the next yarn segment yet to be measured.

This approach does not require an assumption on the existence of a relationship between the past and future data sets. In this work, we applied the neural networks with varying weights for modeling the mass variations of four different types of yarns with different CV%.

2. Neural Network

A. Neural network methodology

In this research, the feedforward back propagation algorithm is applied to model the mass variation of high-draft yarns. The feedforward net has been found to be an effective structure for modeling the mass variation measured from evenness testers. A basic multi-layer neural network structure is shown in Fig. 1 depicting

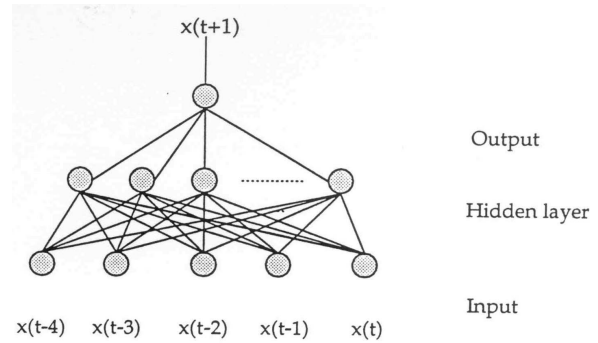


Fig.1. A neural network with one hidden layer, five input neurons(five time delays) and one input (predicted output).

the hidden layer, and output layer. This neural network has one input layer, one output layer, and any number of hidden layers. Each network consists of several nodes (neurons). The input layer of the neural network takes information from the outside world and sends it to the nodes in the hidden layers. Similarly, the output layer of the neural network transmits the processed information to the external world. To apply an m -variate signal input to a one-layer neural network consisting of n neurons each having m weights, we multiply an m -variate vector $X(x_1, x_2, \dots, x_{m-1}, 1)$ with the $(n \times m)$ -variate weight matrix W . The result is an n -variate net input vector $s(s_1, s_2, \dots, s_n)$. Then, we can show how each component s_j is calculated for layer l :

$$s_j = \sum_{i=1}^m w_{ji} x_i \quad j = 1, 2, \dots, n, \quad (1)$$

The index j spans the n neurons, while i spans the m weights in the j th neuron. The number of weights in the neuron is one of more than the number of input variables, the remaining one input variable is the bias, which is always equal to 1. The quantity s_j is processed by an activation function to give the output o_j of j th neuron:

$$o_j = f(s_j) \quad (2)$$

The input consists of time series $x(t)$ and a number of delay components $[x(t-1), x(t-2), \dots]$

$x(t-n)$]. The network output is the predicted value of the time series at the next sampling point, $x(t)$. The actual data calculated by the network is expressed by E . The network training is performed using the nonlinear least square methods. As a result, the error signal defined by

$$\delta_j = -\frac{\partial E}{\partial o_j} \quad (3)$$

leads to the result of general delta rule

$$\Delta w_{ji} = \eta \delta_j o_i \quad (4)$$

where η is an adaptation gain. δ_j is computed based on whether or not neuron j is in the output layer.

B. Neural Network Architecture

In this study, we used the feedforward back propagation algorithm based on the generalized delta rule and the minimum mean squared error (MSE) principle for the data sets. In a feedforward network, the processing units can be divided into several layers: input layer, hidden layers and output layer. The input components consist of time series $x(t)$ and an appropriate number of delays [$x(t-1)$, $x(t-2)$, $x(t-3)$ and $x(t-4)$] which are chosen by a trial and error method⁵⁾. The output of the network is the predicted value at the next sampling point. The number of units in the hidden layers were set to be 16 following a series of optimization experiments. The networks have been used for training four different time series sets, namely, the density profiles of four different high-draft yarns produced by varying the process conditions. The training was performed by using the first 500 points of the time series data, and then the next 150 points were predicted by the network models generated.

3. Experimental

A. Data acquisition system

Data acquisition system consists of DAS-1602[®], a plug-in board from MetraByte, an analog and

digital Interface board, the Streamers from MegaByte[®], a software for storing data into hard disk, and Matlab[®] for signal analysis. Meha-Byte's DAS-1602[®] board is a high performance analog and digital I/O board for IBM[®] PC/XT/AT and compatible computers. The DAS-1602[®] uses an AD774 successive approximation A/D converter which has an 8.5 microsecond conversion rate. At this conversion rate, the DAS-1602[®] performs conversions just over 100,000 times per second when combined with the 800 nanosecond sampling and holding time. The STREAMER[®] is a high speed data acquisition and control software package for use with MetraByte DAS-1602[®]. The STREAMER[®] allows the converted data from a DAS-1602[®] to be stored directly on a hard disk at a rate of up to 90,000 samples per second. The package also allows data streaming from hard disk to one or both of the D/A channels in a DAS-1602[®] board.

B. Experiments

For the analysis, we used four high-draft yarns produced under different process conditions. The four different yarns with sample names of UBLAC, UNON, UYEL and ULILA were used for analysis of density profiles. The yarns were analyzed to provide CV% of 15.6, 15.3, 15.1 and 15.6, respectively. The Uster Tester-3[®] measured the mass variations by a pair of electrode plates of the measuring condenser. The materials were preconditioned in room temperature for a week. The fiber assembly mass lying between the two measuring electrodes was determined by Uster Tester-3[®] at 200yds/min speed with a sampling rate of 379Hz in order to match the 8mm measuring field of the yarn. The total measured length of the yarns was 500yds each.

4. Results

In a series preliminary experiments, we fixed the number of delay components at 5 for an effective training and for a minimum MSE. The prediction result for UNON is shown in Fig. 2.

The test results for the UNON shown in Fig. 2 are based on samples of 150 data points which are seemingly much more irregular than other sections of the same yarns. This was to show the worst possible fit with the neural network models developed. In spite of these tough tests, the fit is shown to be strikingly good for each yarn. As shown in the figure, both the short and long term variations were predicted quite well with small errors. The four neural network models are much more and versatile in establishing the relationships between the previous data and future data. For the UYEL data set, neural network model was shown to be somewhat poor perhaps due to the irregular nature of the series. In this case, the neural network models provided over-smoothed curves, ignoring the small fluctuations.

The results may be improved by a better selection of the training parameters. Namely, the number of delay components, the number of nodes in the hidden layer and the number of data points in the training data sets can be further experimented in achieving a better fit. Our limited experimentation, however, shows that the effects of various setting were most negligible. This may be a serious problem at the presence of a highly irregular data set.

There can be a considerable debate as to the size of optimal data set for training. In general, when more data points for reliable training are needed, this also provides more smoothed density profiles. For checking the possibility of overfitting, correlation function was calculated for the data set. As shown in Fig. 3, there is no clear evidence for any periodic correlation

Table 1. Comparisons of actual and predicted values

Sample	Training error ⁺	Prediction error ⁺	Actual CV% [*]	P
UBLAC	0.0030	0.0042	15.6	
UNON	0.0025	0.0041	15.3	
UYEL	0.0032	0.0058	15.2	
ULILA	0.0003	0.0049	15.6	

⁺ Average mean squared error

^{*} Values obtained from test equipment

among various lags, which represents the randomness of residuals. The results can be either a plus or minus depending on our objectives. The neural network models are in general less sensitive to noise due to its inherent robustness.

The actual and predicted values of yarn densities are presented in Table 1 for the four different data sets. The MSE values limited were found to be extremely small, demonstrating the power of the neural network models. As expected, all neural networks have produced the

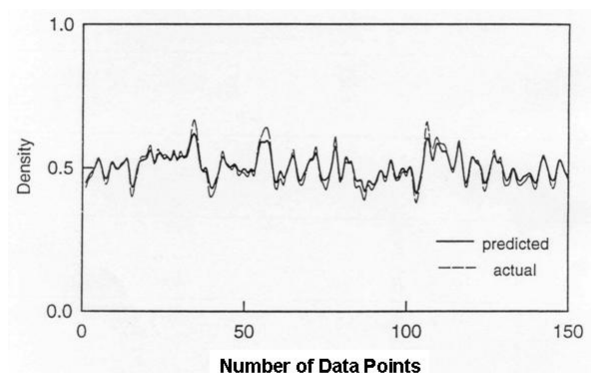


Fig. 2. Prediction of density profiles by neural network. (UNON)

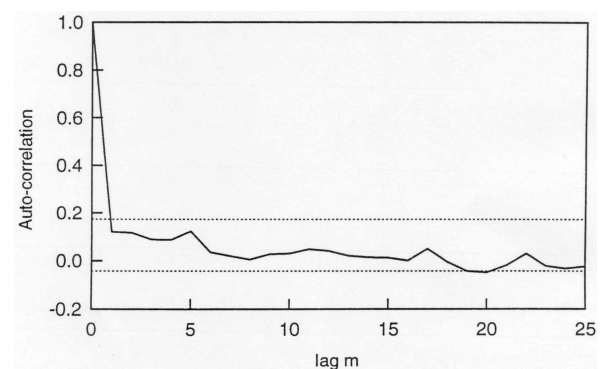


Fig. 3. Residual test for neural network model. (UNON) (the dashed lines gives the 95% confidence interval)

lower CV% values than actual yarn CV%. It is conceivable that the UYEL data set with the lowest CV% is associated with the poorest fit with the neural network models.

5. Conclusions

The analog signals representing the mass per unit length of a yarn have been converted to digital signals by a data acquisition system. Neural networks have been employed for the mass variation modeling of four different high-draft yarns. The results show that the neural network models predict well the actual density profiles of high-draft yarns. As a nonlinear approximator⁶⁾, the neural network models outperformed the statistical models based on the linear recurrence of previous values. The prediction results show that the neural network models performed much better than the previous statistical models. The validity tests also showed that the neural network models are quite insensitive to the number of inputs compared to the statistical models. For a more accurate prediction, comprehensive studies involving structural relationships are needed in order to link the material properties to the process variables. The structural modeling approaches are expected to improve the conventional time-series methods by providing them the system identification capabilities through dynamics of materials and processes.

Acknowledgement

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