Application of Process Neural Network on Consumer Price Index Prediction

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Abstract. In this paper we present a prediction method of consumer price index (CPI) based on process neural network (PNN). In order to reduce errors, after the raw data was directly expressed as a set of orthogonal basis expanded form, we made use of time-varying input function feature of process neural network and trained process neural network with combined type improved BP algorithm. We achieved a multi-variable CPI prediction with non-linear model of process neural networks gotten by above-mentioned result and illustrated the advantage of process neural network compared to traditional neural network in economic time series prediction. We provide a new method for economic time series prediction in this paper.

Keywords: CPI, process neural network, time series, prediction.

1 Introduction

As an important indicator reflecting inflation (or deflation) degree, consumer price index is an important basis to analyze and formulate national economic policies and national economic accounting. Therefore, it has great significance to monitor in real-time and predict accurately CPI. CPI prediction not only depends on a country's overall macroeconomic situation, but also its own inherent characteristics of time series. However, the entire macroeconomic system is a complex and elusive nonlinear system; it is difficult to predict accurately CPI. Therefore, it is the key of economic time series prediction to simulate accurately the characteristics of the above two strands. Neural network is an effective prediction method, which has a good nonlinear mapping ability to simplify modeling process of time series. It is widely used in various fields. In particular, process neural network technology, the input is time-varying function; process neuron not only includes the space aggregate computing functions of traditional neuron, but also includes the extraction function of time cumulative effects. It coincides with time-related features of time series. Therefore, compared to the previous prediction method, it has its own unique advantages to fit the inherent laws between eight categories data of China's household consumption and CPI, and establish non-linear model of CPI time series using process neural network.

J. Luo (Ed.): Affective Computing and Intelligent Interaction, AISC 137, pp. 427–432.
springerlink.com

2 Process Neural Network Model

2.1 Process Neuron

The structure of process neuron is composed of weighted, aggregation and activation operator of three parts. The difference from the traditional neuron is that the input, output, and weights of process neuron can be time-varying, and its aggregation operations is composed of multi-input aggregation in space and cumulative aggregation of time. A process neural network is a network composed of some neurons in the certain topology structure. The structure of a process neuron as shown in Fig. 1, where $X(t) = (X_1(t), X_2(t),...X_n(t))^T$ is input function vector of process neuron, $w_1(t), w_2(t),...w_n(t)$ is weight function, $f(\cdot)$ is the activation function, which may take linear function, Sigmoid function, Gauss-type function, and so on.

The relationship between input and output of process neuron is

$$Y = f((w(t) \oplus X(t)) \otimes K(\cdot) - \theta) \tag{1}$$

Where " $\oplus$ " indicates a sort of spatial aggregation operation," $\otimes$ " indicates a sort of time (process) aggregation operation, " θ " indicates threshold value of process neuron, $K(\cdot)$ indicates an integrable function of [0, T] [1].

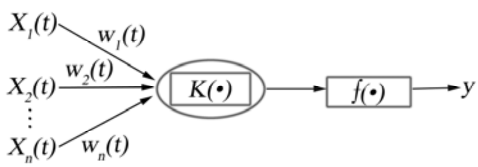

Fig. 1. Process neuron

2.2 Topology of Process Neural Network

Fig. 2 shows a topology structure of feedforward process neural network: the input is a time-varying function, the output is a constant, and the topology structure of network is n－m－L－1 .Input layer has n nodes used for n time-varying function input to the network. The first hidden layer is a process neuron hidden layer composed of m nodes to complete the n input function weighted aggregation in space and the aggregation operation of the time course, as well as the character extraction of sample process model. The second hidden layer is a non-time-varying hidden layer (Also known as normal neuron hidden layer), which have *L* nodes. The fourth layer is the output layer, whose output is y.

The input-output relationship of the network as follows:

$$y = \sum_{l=1}^{L} f_2(\sum_{j=1}^{m} v_{jl} f_1(\sum_{i=1}^{n} \int_0^T w_{ij}(t) x_i(t) dt - \theta_j^{(1)}) - \theta_l^{(2)}) \mu_l \tag{2}$$

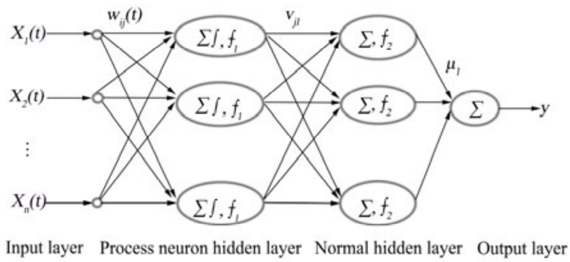

Fig. 2. Process neural network

Where $x_i(t)$ is system input, $w_{ij}(t)$ is the connection weight function between input layer and the first hidden layer, $\theta_j^{(1)}$ is the output threshold of j-neuron of the first hidden layer, $[0\ T]$ is sampling interval, f_1 is the activation function of the first hidden layer. v_{jl} is the connection weight between j-neuron of the first hidden layer and l-neuron of the second hidden layer, $\theta_l^{(2)}$ is output threshold of j-neuron in the second hidden layer, f_2 is the activation function of the second hidden layer, which can be taken as a linear function or S function. y is final output of network, μ_l is the connection weight between neuron of the second hidden layer and l-neuron in output layer [2].

3 CPI Prediction Based on Process Neural Network

3.1 Datasets

China's CPI data are composed of the eight categories residents' basic consumption data, and has very strong nonlinear characteristics. As a general rule, monthly economic time series is affected not just by the seasonal but also non-seasonal factors. In order to achieve a more accurate prediction result of CPI and extract sufficiently its non-linear variation characteristics, process neural network is introduced into CPI prediction. Making use of extraction capabilities of process neurons to time accumulative feature, the next month CPI data is gotten by prediction, after training set and test set are composed of historical data fully reflecting the characteristics of seasonal and non-seasonal factors, and make up for the deficiencies in past prediction methods. A sample structure is as follows:

$$\{x_1(t), x_2(t), \ldots, x_i(t), \ldots, x_n(t), d\} \tag{3}$$

Where $x_i(t)$ indicates an arbitrary input function, which is fitted by a series of consecutively discrete data, d is network expected output. In order to represent seasonal and non-seasonal characterizations, as well as time accumulate feature more fully, finally, CPI data of 10 consecutive months was selected as the data to fit input function, after repeated comparison and analysis. CPI data in the eleventh month was selected as expected output of PNN. Namely:

$$x_i(t) \approx \varphi(a_0, a_1, \ldots, a_m) \tag{4}$$

Where $(a_0, a_1,..., a_m)$ indicates consecutively discrete data, $m = 9$ in CPI prediction.

Data were specifically selected as follows: 22 samples are composed of the eight categories residents' basic consumption data published in National Bureau of Statistics of china web site from May 2007 to September 2009, then selected 17 of which as a training sample and 5 of which as the test samples.

3.2 Concrete Measures and Combined Type Improved BP Algorithm

In addition, in order to improve overall prediction accuracy, the following measures were adopted in CPI prediction:

1) The raw data were normalized.

2) The raw data normalized was directly expressed as a set of orthogonal basis expanded form so as to reduce errors and speed up network convergence. Thereinto, network orthogonal basis function selected Legendre polynomial [3], number of basis functions is 8 (The value is determined based on the status of network convergence at last).

3) Combined type improved BP algorithm was adopted to train PNN.

The concrete implements of combined type improved BP algorithm in PNN training are followed as:

There are three main measures of improving BP Algorithm: the momentum method [4], adaptive learning rate method and steepness factor method [5] [6]. But it often happens that the three methods used simultaneously can not get the best convergence results in the actual application, whereas using the above three ways alone or combined can get better convergence results in connection with different data characteristics. Therefore, using random combinations of the above three measures, PNN is trained by the above random combinations respectively, and finally decides the concrete improving measures of BP algorithm by convergence accuracy and test errors, which is a feasible improvements in the actual application. Specifically, Adaptive learning rate method is realized by using equation (5).

$$\eta(k+1) = \begin{cases} \alpha_1\eta(k), E(k+1) > \lambda_1 E(k) \\ \alpha_2\eta(k), E(k+1) < \lambda_2 E(k) \end{cases} \tag{5}$$

Where k is training number, η is learning rate, E is error function, α_1 is incremental factor used to increase learning rate of network, and α_2 is as reduction factor used to decrease learning rate. λ_1, λ_2 are amplitude control factors new added, which are used to indicate the changing magnitude of two successive error function and accelerate the network convergence speed.

In CPI prediction, weight functions in process neural hidden layer were firstly expressed as the same set of orthogonal basis expanded form (which is identical to orthogonal basis in input function expansion), so weight function training is transformed into a set of weights (orthogonal basis parameters) training problem. Moreover, all parameters of orthogonal basis and the weights in normal neuron hidden layer were initialized in (-1, 1).

Secondly, PNN used in CPI prediction was trained by combination of the above three measures. After repeated combination training and comparative analysis, finally, identify the momentum method to train PNN, momentum factor is 0.8, learning rate is 0.8, and steep factor is 1.

The correlation parameters in CPI prediction were selected as follows: 8 input nodes, 15 hidden layer neurons in process neuron hidden layer, 1 normal neural node, and 1 output node. The largest iterative number is 50, and learning accuracy is 0.01.The activation function in the first hidden layer is tangent sigmoid function. The activation function in the second layer is a linear function.

3.3 Prediction Result and Comparison Analysis

Network has convergence, after it operated 3 generations. The error during the training stage for sample was shown in Fig. 3, prediction values and real data of test samples as shown in Table 1.The average of relative errors is 0.3623%, the average of relative errors absolute value is 0.6842%.

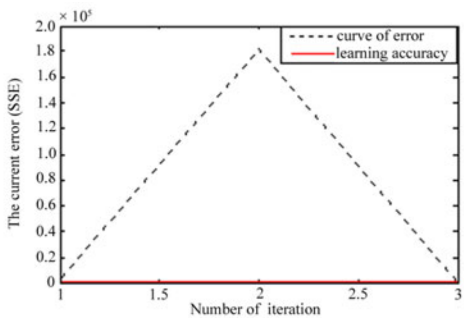

Fig. 3. The error value during the training stage for sample

For the same training samples and test samples (Discrete real data were used as input), traditional neural network method was adopted to make model. After repeated adjust the network structure and repeated training using the same learning algorithm a model with the best test error was choose as the end result. Its test errors are shown in Table 1. Training parameters selected are as follows: 8 input nodes, 100 the first hidden layer nodes, 1 the second hidden layer nodes, learning rate is 0.01, the largest iteration number is 10000, learning accuracy is 0.001, momentum factor is 0.8,activation function of the first hidden layer is the tangent sigmoid function, activation function of the second layer is a linear function, the minimum run gradient is 1e-010.The network was terminated after 305 generations, because the gradient does not meet the minimum run gradient value.

Table 1. Prediction values of test samples on different prediction ways

Test Samples	Real Data	Prediction Values of Traditional Neural Network	Prediction Values of Process Neural Network
1	98.8	103.7647	98.7438
2	99.5	103.7647	98.9253
3	98.3	103.7647	98.6142
4	101	103.7647	99.3142
5	98.5	103.7647	98.666

Can be seen from Table 1, the average relative error of test samples in the traditional neural network model is -4.591%, the average of relative errors absolute value is 4.591%. Thus, under the premise of the same learning algorithm, the test result of PNN is superior to the traditional neural network result. This shows that PNN with time-varying input has advantage in CPI short-term prediction.

4 Conclusions

Aiming at CPI multivariable prediction problem in economic domain, a short-term prediction method of economic time series based on process neural network is presented. Its concrete realization process is given in this paper. A multivariable and nonlinear PNN prediction model of CPI was established, and was compared to traditional neural network perdition model using the same learning algorithm, the result illustrates that process neural network method has advantage in short-term prediction of time series. It provides a new way for other prediction problem in economic domain.

Acknowledgment. This work was supported by Harbin Technology Innovation Research Special Fund (2008RFQXG072) and Heilongjiang Province Science and Technology Project (GC05A118).

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