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Prediction of Shanghai Index based on Additive Legendre Neural Network

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Abstract. In this paper, a novel Legendre neural network model is proposed, namely additive Legendre neural network (ALNN). A new hybrid evolutionary method besed on binary particle swarm optimization (BPSO) algorithm and firefly algorithm is proposed to optimize the structure and parameters of ALNN model. Shanghai stock exchange composite index is used to evaluate the performance of ALNN. Results reveal that ALNN performs better than LNN model.

1 Introduction

Artificial neural networks (ANNs) are powerful mathematical methods that can be used to learn complex linear and non-linear continuous functions, and have been successfully applied to many areas in the past decades [1]. Due to that traditional neural network has some disadvantages such as low efficiency, long learning time and easy to fall into the local minimum solution, Legendre neural network (LNN) was proposed. LNN modle has no hidden layer and could add dimensionality of the input layer with a set of nonlinear functions. Patra et al. proposed a Legendre neural network model for equalization of nonlinear communication channels with 4-QAM signal constellation [2]. Patra et al. also propose a computationally efficient Legendre neural network for identification of nonlinear dynamic systems [3]. Pei et al. forecastedand investigated the stock prices of the financial model by an improved Legendre neural network–Legendre neural network with random time strength function [4].

The structure of Legendre neural network is very simple and learning speed is fast. But the number of input Legendre polynomials is large due to the fact that each input variable has n order Legendre polynomials. The stucture of LNN is fixed and only task is to optimize the paramters of LNN. To reduce the optimization complexity and improve efficiency, in this paper, a novel Legendre neural network model is proposed, namely additive Legendre neural network (ALNN). Binary particle swarm optimization (BPSO) algorithm is proposed to select proper input Legendre polynomials in order to construct proper structure. Firefly algorithm is used to optimize the parameters of ALNN. Shanghai stock exchange composite index is used to evaluate the performance of ALNN.

2 Method

2.1 Structure of ALNN

Legendre neural network (LNN) was first proposed by Yang and Tseng for function approximation in 1996 [5]. LNN has less parameter and does not have hidden layer, which uses Legendre orthogonal polynomials as the activation functions of hidden layer neurons. Due to the absence of hidden layer, LNN provides computational advantage over the MLP.

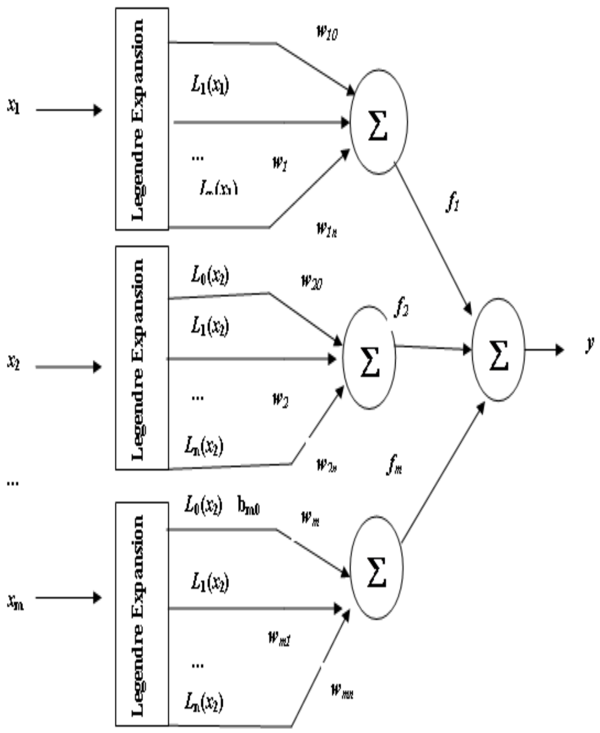

Figure 1. The structure of ALNN.

In order to select proper Legendre polynomials for specific problems, additive Legendre neural network (ALNN) is proposed. The structure of an ALNN is shown in Figure. 1. Suppose that input vector [$x_1, x_2, \ldots x_m$] and *n* order Legendre polynomials.

The Legendre polynomials of each input variable are described as followed.

$$\begin{cases} L_0(x) = 1 \\ L_1(x) = x \\ L_2(x) = \frac{1}{2}(3x^2 - 1) \\ \vdots \\ L_n(x) = \frac{1}{n}[(2n-1)xL_{n-1}(x) - nL_{n-2}(x)] \end{cases} \tag{1}$$

The output of f_i is defined as followed.

$$f_i = \tanh(\sum_{k=0}^{n} L_0(x_k) \times b_{ik} \times w_{ik}) \tag{2}$$

where $\tanh()$ is Hyperbolic tangent, b_{ik} is boolean value (0 or 1). When b_{ik} is equal to 1, Legendre polynomial $L_0(x_k)$ is selected as input data and weight w_{ik} is assigned.

The final output y is defined as followed.

$$y = \sum_{k=1}^{m} f_k \tag{3}$$

2.2 Structure optimization of ALNN

Additive Legendre neural network could not allow all Legendre polynomials as input data. It uses evolutionary method to select proper Legendre polynomials. In this paper, binary particle swarm optimizaiton (BPSO) is used to gain the optimal vector $[b_{10,}b_{11}, \ldots, b_{1n}, \ldots, b_{m0}b_{m1}, \ldots, b_{mn}]$.

In BPSO, the moving trajectory and velocity of each particle is defined in term of probability. The moving trajectory represents changes of probabilities of a certain value. The moving velocity is defined as probability of a state or another state. Thus each bit $x_i(t)$ of one particle is restricted to 0 or 1. Suppose that ALNN has m input variables and *n* order Legendre polynomials. The length of each particle is *m**(*n*+1). Each $v_i(t)$ represents the probability of bit $x_i(t)$ taking the value 1. A new velocity $v_i(t)$ for particle *i* is updated as same as PSO, which is defined as followed.

$$\begin{aligned} v_i(t+1) &= w * v_i(t) + c_1 r_1 (Pbest_i - x_i(t)) + \\ & c_2 r_2 (Gbest - x_i(t)). \end{aligned} \tag{4}$$

where w is the inertia weight, c_1 and c_2 are positive constants and r_1 and r_2 are uniformly distributed random number. $Pbest_i$ is the best fitness of particle i and $Gbest$ is the best position among all particles.

xi(*t*) is calculated as followed [6].

$$x_i(t) = \begin{cases} 1, & r < Sig(v_i(t)) \\ 0, & other. \end{cases} \tag{5}$$

where r si created randomly from range [0,1], and the function Sig is defined as followed.

$$Sig(v_i(t)) = \frac{1}{1 + e^{-v_i(t)}}. \tag{6}$$

2.3 Parameters optimization of ALNN

According to the optimal structure of ALNN, tally the number (p) of 1 in the optimal particle $[x_1, x_2, \ldots, x_{m*(n+1)}]$ of BPSO. p parameters $[w_1, w_2, \ldots, w_p]$ need be optimized. Firefly algorithm (FA) is an efficient optimization algorithm which was proposed by Xin-She Yang in 2009 [7]. It is very simple, has few parameters and easy to apply and implement, so this paper uses firefly algorithm to optimize the parameters of Legendre neural network.

Firefly algorithm is the random optimization method of simulating luminescence behavior of firefly in the nature. The firefly could search the partners and move to the position of better firefly according to brightness property. A firefly represents a potential solution. In order to solve optimization problem, initialize a firefly vector $[x_1, x_2, \ldots, x_n]$ (*n* is the number of fireflies). As attractiveness is directly proportional to the brightness property of the fireflies, so always the less bright firefly will be attracted by the brightest firefly.

The brightness of firefly *i* is computed as

$$B_i = B_{i0} * e^{-\gamma r_{ij}} \tag{7}$$

where B_{i0} represents maximum brightness of firefly i by the fitness function as $B_{i0} = f(x_i)$. γ is coefficient of light absorption, and r_{ij} is the distance factor between the two corresponding fireflies i and j.

The movement of the less bright firefly toward the brighter firefly is computed by

$$x_i(t+1) = x_i(t) + \beta_i(x_j(t) - x_i(t)) + \alpha\varepsilon_i \tag{8}$$

where α is step size randomly created in the range [0, 1], and ε_i is gaussian distribution random number.

2.4 Fitness function

Root mean squared error (*RMSE*) is used to search the optimal ALNN according to actual data and predicted data.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y^i_{actual} - y^i_{predicted})^2} \tag{9}$$

Where N is the number of data points, y^i_{actual} is the actual output of i-th data point and $y^i_{predicted}$ is the predicting output of i-th data point.

3 Experiments

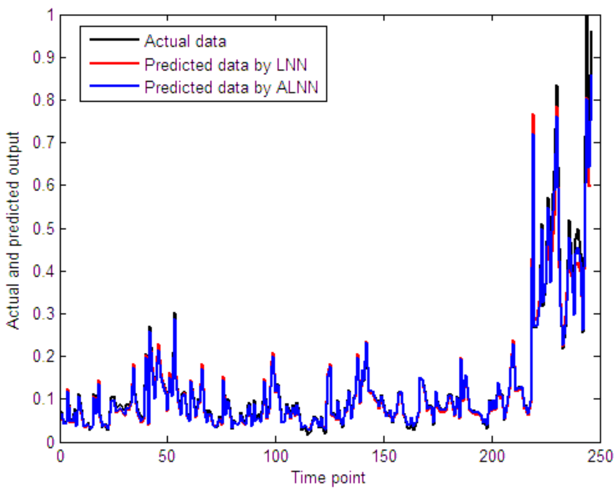

Figure 2. Actual data and predicted data by LNN and ALNN

We choose the Shanghai stock exchange composite index (Shanghai index, stock id: 000002) from 04 January, 2011 to 01 January, 2015 as the samples for validating the model.

We make the comparison between ALNN and LNN models. Through several runs, the predicted data by two methods are described in Figure 2. The predicted errors are illustrated in Figure 3. From two figures, we can see that ALNN and LNN models could predict stock index accurately and the error of ALNN is less than LNN.

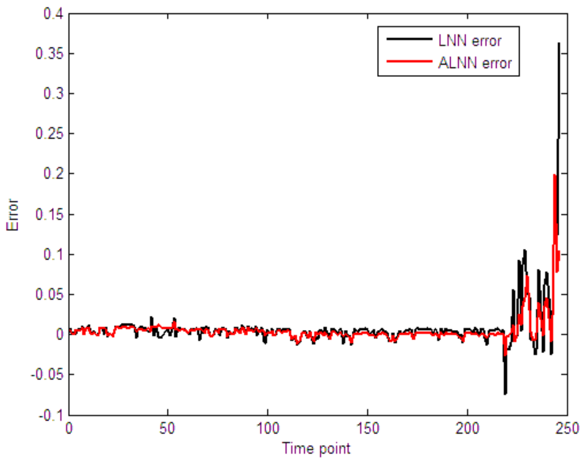

Figure 3. Predicted error by LNN and ALNN

4 Conclusion

In order to resolve the disadvantages of LNN, this paper propose a novel Legendre neural network model, namely additive Legendre neural network (ALNN). ALNN utlizes binary particle swarm optimization algorithm to select proper input Legendre polynomials in order to determine the struture of ALNN. Firefly algorithm is used to optimize the parameters of ALNN model. Shanghai stock exchange composite index is used to test the performance of ALNN. Results reveal that ALNN predicts more accurately than LNN model.

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