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Neural network model with fuzzy activation functions for time series predictions

This study develops neural models using fuzzy activation functions to solve the problems of time series predictions. Several fuzzy neural networks with different types of activation function are created. The paper shows the comparison result between the feasibilities of these networks for solving time series prediction problems.

Keywords: fuzzy neural network, fuzzy activation function, membership function, time series predictions.
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In recent years, methods based on artificial intelligence have been widely used to solve prediction problems for data provided in the time series form. Several neural network models have been developed, such as the feed-forward network and the Elman network models [1]. In this paper, we propose fuzzy neural networks that utilize membership functions as activation functions (AFs) to obtain time series solutions.

Modeling of membership functions as the activation functions

According to literature [2], the fuzzy number is a convex, normalized fuzzy set, whose membership function $\mu(x)$ is at least segmentally continuous. Moreover, $\mu(x)$ must have a functional value at only one value of *x*. This value of *x* is regarded as the mean of the fuzzy number.

There are various different types of AF used in neural networks. In this paper, we propose a new form of membership function using the triangular fuzzy number $\tilde{N} = (A, B, C)$, where *A*, *B* and *C* are three specific points.

The support of fuzzy number $\tilde{N}$ is defined as follow [2]:

$$\operatorname{supp}(\tilde{N})=[A,C]:\ \mu_N(x)>0,\ \forall x\in[A,C].$$

The LR-type membership function, which is defined by expression (1), is used in our paper [3].

$$\mu_N(x,A,B,C)=\begin{cases} f_L(x), & x\in[A,B); \\ 1, & x=B; \\ f_R(x), & x\in(B,C]; \\ 0, & x\notin[A,C]. \end{cases} \qquad (1)$$

where $f_L(x)$, $f_R(x)$, which have the form of second-order polynomial, denote the left and right parts of the membership function.

If $f_L(x)$, $f_R(x)$ are second-order polynomials and their derivatives, equal zero at specific points, the membership function given by equation (1) could be given by one of these expressions [3]:

$$\begin{cases} f_L'(A)=0; \\ f_R'(C)=0. \end{cases} \qquad (2)$$

$$\begin{cases} f_L'(A)=0; \\ f_R'(C)=0. \end{cases} \qquad (3)$$

$$\begin{cases} f_L'(A)=0; \\ f_R'(C)=0. \end{cases} \qquad (4)$$

$$\begin{cases} f_L'(A)=0; \\ f_R'(C)=0. \end{cases} \qquad (5)$$

The shapes of membership functions utilizing triangular fuzzy numbers with the conditions (2)–(5) are shown in Fig. 1.

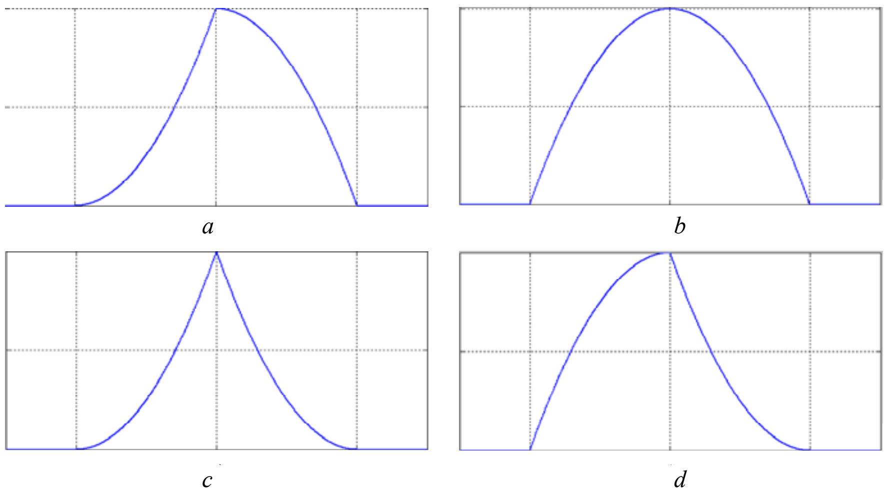

Fig. 1. Membership functions with additional conditions: *a* – conditions by equation (2); *b* – conditions by equation (3); *c* – conditions by equation (4); *d* – condition by equation (5)

A fuzzy neural network is represented in a multilayer feed-forward network with AND – OR neurons [4]. More details about the definitions of AND – OR neurons can be found in [5]. The AND and OR fuzzy neurons realize pure logic operations on the membership values. The role of the connections is to differentiate between particular levels of impact that the individual inputs might have on the result of aggregation.

The fuzzy neural network, which is mentioned above, is termed the first-type fuzzy neural networks. The present paper proposes the second-type fuzzy neural network model, whose AFs are given by Fig. 1. The first-type fuzzy neural networks utilize fuzzy inference systems by neural network methods. For the second-type fuzzy neural network model, fuzziness is an attribute of neurons. Moreover, it is necessary to study the third type of fuzzy neural network, which is formed by combining the first and second types.

Application of the second-type fuzzy neural network to solve the problem of time series predictions

Time series are sequences of numbers having time-dependent characteristics. A time series is usually represented by a vector $x(t)$, t = 0,1,….., where t – elapsed time.

Theoretically, the value of x changes continuously with time t. However, for numerical analyses, signals of physical systems are represented by series of discrete data. The windowing method [6] is used to divide time series into segments (windows), and then a training data set is obtained. After using the windowing method with the segments of size d, we can create the mapping set of input-output data. The methods of so-called «theory of experiment» [7] are used to process the data of the experiment.

In this paper, we investigate the feasibility of the second-type fuzzy neural network model for the problem of time series predictions.

The experiment uses the set of time series data, which provides daily measured pollution for the last one and half years. The fuzzy neural network is built based on a NAR network [8]. The hidden layer comprises 200 neurons with fuzzy AFs. A linear AF is employed for the output layer.

Table 1

Input-output data set

Input	Output
$x(1), x(2), x(3)\ldots\ldots x(d)$	$x(d+1)$
$x(2), x(3), x(4), \ldots, x(d+1)$	$x(d+2)$
.	.
.	.
$x(n–d–1), x(n–d), x(n–d+1), \ldots, x(n–1)$	$x(n)$

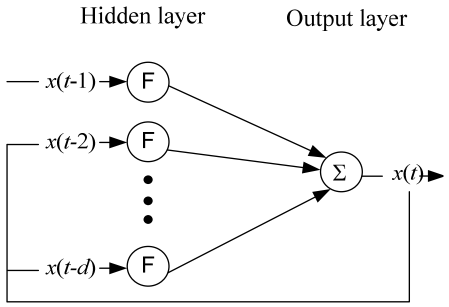

Fig. 2. Network structure

The training process is based on Levenberg-Marquardt backpropagation procedure [8]. This training function is the fastest backpropagation-type algorithm. The Levenberg-Marquardt backpropagation algorithm was designed to approximate the second-order derivative with no need to compute the Hessian matrix, therefore increasing the training speed. For the training process, data are randomly divided with 70% used for training and 30% for testing.

Figure 3 shows the time-series response after training with our neural network when using ordinary.

By showing mean squared errors, Table 2 can confirms the accuracy of the prediction by each neural network model.

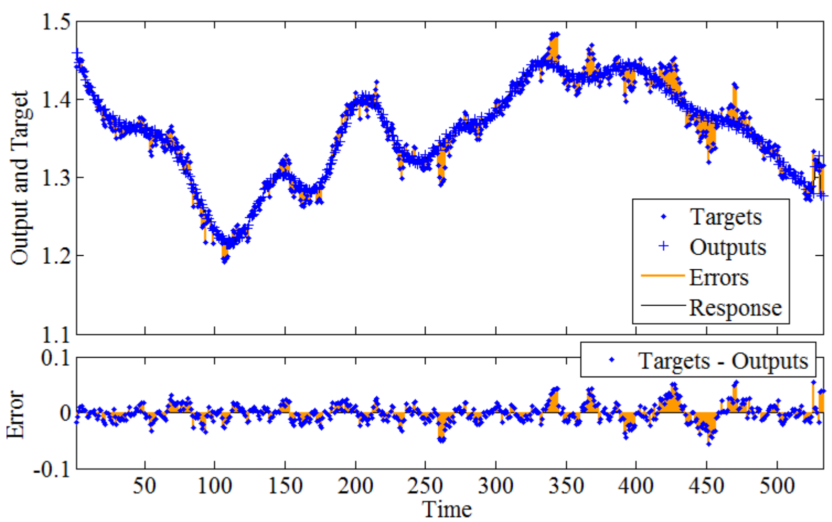

Fig. 3. Time-series response by neural networks using ordinary AF

Table 2

Mean squared errors by neural networks using ordinary and fuzzy AFs

Ordinary AF	AF type *a*	AF type *b*	AF type *c*	AF type *d*
26×10^{-5}	28×10^{-5}	19×10^{-5}	27×10^{-5}	25×10^{-5}

From the test results it follows that the mean squared errors of predicted data are less than 5%. Therefore, the neural networks with fuzzy activation functions can be used for the problems of time series predictions with an acceptable level of accuracy.

The results also showed that neural networks with the fuzzy activation functions type b and type d can provide more precise results than those by neural network models with an ordinary activation function.

Conclusions

The paper shows that the model of second- type fuzzy neural neuron and fuzzy neural network can well solve the problems of time series predictions. Therefore, neural networks with fuzzy impulse activation functions may be commonly used in various fields, such as business, medicine, science, etc. for some problems of classification, prediction, approximation, etc. For the next studies, we will analyze the advantages of each fuzzy activation function and when to use them.

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Нгуен А.Т., Кориков А.М.

Модель нейронной сети с нечеткими функциями активации для прогнозирования временного ряда

Разрабатываются модели нейронов с нечеткими функциями активации для решения проблемы прогнозирования временных рядов. На основе моделей нейронов с нечеткими функциями активации создаются модели нечетких нейронных сетей (ННС) и проводится анализ возможностей ННС для решения задач прогнозирования временных рядов.

Ключевые слова: модель нейрона, функция принадлежности, функция активации, прогнозирование временных рядов.