Modeling of Chaotic Time Series by Interval Type-2 NEO-Fuzzy Neural Network

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Abstract. This paper describes the development of Interval Type-2 NEO-Fuzzy Neural Network for modeling of complex dynamics. The proposed network represents a parallel set of multiple zero order Sugeno type approximations, related only to their own input argument. The induced gradient based learning procedure, adjusts solely the consequent network parameters. To improve the robustness of the network and the possibilities for handling uncertainties, Type-2 Gaussian fuzzy sets are introduced into the network topology. The potentials of the proposed approach in modeling of Mackey-Glass and Rossler Chaotic time series are studied.

Keywords: neo-fuzzy neuron, neural networks, type-2 fuzzy set, dynamic modeling, chaotic time-series prediction.

1 Introduction

Neural Networks (NN's) [1] and Fuzzy Logic systems (FL's) [2] are well known as universal approximators and they are successfully used for modeling and identification of nonlinear dynamics. Hybrid Neuro-Fuzzy Networks emerged as a synergism of these two major directions in computational intelligence. They possess the learning capabilities similar to those of neural networks, and provide the interpretability and "transparency" of results, inherent to the fuzzy approach. Recently, many applications to solve a wide range of problems such as data mining and processing of complex dynamic signals of different nature under *a priori* uncertainty have been reported [3].

During the last years, many Neuro-Fuzzy Networks have been adopted in the practice as: ANFIS [4], DENFIS [5], NEFCON [6] and e.t.c. The main advantage of these modeling concepts relies on their flexibility to employ data from the process and to adapt quickly the parameters of the network to changing nonlinear process behavior by using fairly standard optimization procedures. A serious drawback for their on-line application for dynamical modeling purposes is the number of parameters under adaptation at each sampling period, since it grows exponentially with the increasing level

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of nonlinearity. Another disadvantage of the classical neuro-fuzzy systems, especially when they operate in on-line mode is the slow convergence of the conventional gradient-based learning procedures and the computational complexity of second-order ones [7]. As well, such classical structures cannot handle major process uncertainties in many complex situations.

To overcome such deficiencies of the classical Neuro-Fuzzy networks, it has been introduced the idea for Neo-Fuzzy Network (NFN), as special tool for modeling of complex dynamical behavior. Usually, the concept of the Neo-Fuzzy Neuron relies on the quite close to the conventional n-inputs artificial neuron. However, instead of usual synaptic weights, it contains the so-called nonlinear synapses. When an input of an NFN is fed by a vector signal, its output is defined by both the input membership functions and the tunable synaptic weights [7]. It is proved that among the most important advantages of the NFN are: the learning rate, the high approximation properties, the computational simplicity and the possibility of finding the global minimum of the learning criterion in real time [8].

During the recent years, many NFN architectures are reported in literature. In [9] are presented different NFN topologies, while in [10,11] are reported respective learning approaches. Applications of modified neo-fuzzy neuron-based approach for economic and environmental optimal power dispatch and approach for bottom parameters estimation in oil wells, are also reported in [12,13]. In [14] authors propose an applied idea for Neo-Fuzzy Neuron model for seasonal rainfall forecast and cascade NFN in the problem of forecasting at the Stock Exchange [15].

Due to its potentials, the NFN approach seems to be a promising solution for modeling of complex dynamical systems, but its application in purpose of process modeling under uncertainties, are not yet well studied.

This paper describes a modified approach for designing of a Neo-Fuzzy Network. The network topology comprises a number of cascade connected Neo-Fuzzy Neurons, whose inputs are fuzzified in terms of Gaussian Type-2 Interval Fuzzy sets with uncertain variance in order to improve the ability of the network for handling occurring uncertainties. As learning procedure for the proposed network structure, a supervised learning scheme, minimizing an error cost term is adopted. The capabilities of the proposed Neo-Fuzzy structure in modeling of different Chaotic Time Series, Mackey-Glass and Rossler are evaluated.

2 Neo-Fuzzy Neural Network Design

The Neo-Fuzzy Network is a nonlinear multi-input, single-output system which can be described in general as:

$$\hat{y}(k) = f(x(k)) \tag{1}$$

where $\mathbf{x(k)}$ is an input vector of the states in terms of different time instants. Each Neo-Fuzzy Neuron comprises a simple fuzzy inference which produces reasoning to singleton weighting consequents:

$$R^{(i)} : if\ x_i\ is\ \tilde{A}_i\ then\ f_i(x_i) \tag{2}$$

Each element of the input vector is being fuzzified using Type-2 Interval Fuzzy set:

$$\mu_{ij}(x_i) = -\exp\left(\frac{x_i - c_{ij}}{2\sigma_{ij}}\right)^2 = \begin{cases} \overline{\mu}_{ij} \text{ as } \sigma_{ij} = \overline{\sigma}_{ij} \\ \underline{\mu}_{ij} \text{ as } \sigma_{ij} = \underline{\sigma}_{ij} \end{cases} \tag{3}$$

where μ is the membership degree defined by a Gaussian membership function with uncertain variance and c and σ represent the center (mean) and the width (standard deviation) depending on the defined footprint of uncertainty. Graphically the fuzzification procedure is demonstrated on Fig. 1.

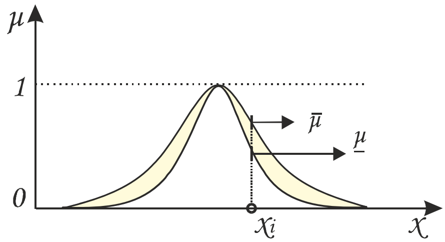

Fig. 1. Gaussian Membership Function with uncertain upper and lower membership functions

The fuzzy inference should match the output of the fuzzifier with fuzzy logic rules performing fuzzy implication and approximation reasoning in the following way:

$$\mu_{ij}{}^{*} = \begin{cases} \overline{\mu}_{ij}{}^{*} = \prod_{i=1}^{n} \overline{\mu}_{ij} \\ \underline{\mu}_{ij}{}^{*} = \prod_{i=1}^{n} \underline{\mu}_{ij} \end{cases} \tag{4}$$

The output of the network is produced by implementing consequence matching, type reduction and linear combination as follows:

$$\hat{y}(k) = \frac{1}{2}\sum_{j=1}^{l}(\overline{\mu}_{ij}{}^{*} + \underline{\mu}_{ij}{}^{*}) f_i(x_i) = \frac{1}{2}\sum_{i=1}^{l}(\overline{\mu}_{ij}{}^{*} + \underline{\mu}_{ij}{}^{*}) w_{ij} \tag{5}$$

which in fact represents a weighted product composition of the $i^{\text{-}th}$ input to $j^{\text{-}th}$ synaptic weight, as presented in Fig. 2.

2.1 Learning Algorithm for the Proposed Neo-Fuzzy Neural Network

To train the proposed modeling structure a supervised learning scheme has been used. For that purpose, a defined error cost term is being minimized at each sampling period in order to update the weights in the consequent part of the fuzzy rules:

$$E = {\varepsilon^2}/{2} \text{ and } \varepsilon(k) = y_d(k) - \hat{y}(k) \tag{6}$$

where y_d is the reference output measured form the process and $\hat{y}$ is the output being estimated by the model. As learning approach is used the well known back propagation approach:

$$\beta(k+1) = \beta(k) + \Delta\beta = \beta(k) + \eta\left(\frac{\partial E(k)}{\partial \beta(k)}\right) \tag{7}$$

where η is the learning rate and β is a vector of the trained parameters: the synaptic links in the consequent part of the rules. Form (6) and (7) it can be derived using the chain rule notation:

$$\Delta\beta = -\eta\frac{\partial E}{\partial \beta} = -\eta\frac{\partial E}{\partial \hat{y}}\frac{\partial \hat{y}}{\partial \beta} = -\eta(y_d - \hat{y})\frac{\partial \hat{y}}{\partial \beta} \tag{8}$$

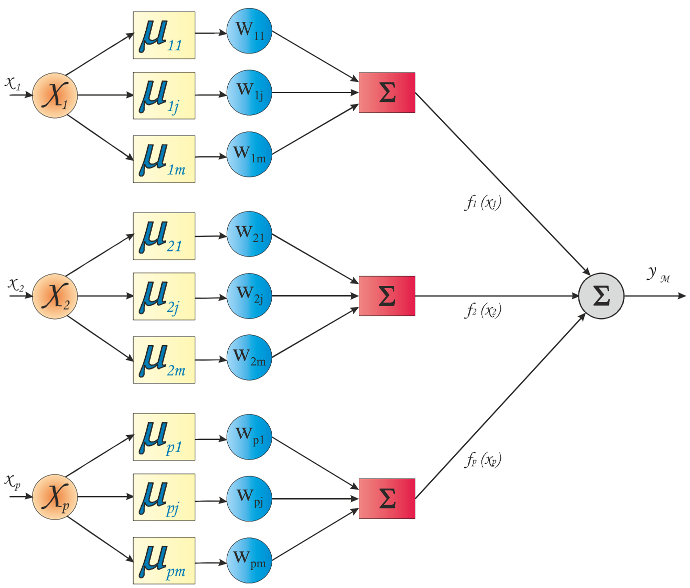

Fig. 2. Structure of the proposed Neo-Fuzzy Neural Network

3 Results and Discussion

Chaos is a common dynamical phenomenon in various fields [16] and different definitions as series representations exist. Chaotic time series are inherently nonlinear, sensitive to initial conditions and difficult to be predicted. Therefore, the chaotic time series prediction based on measurement is a practical technique for studying characteristics of complicated dynamics [17] and evaluation of the accuracy of different types of nonlinear models. In this section the proposed interval Type-2 NEO-Fuzzy Network is tested to model two chaotic time series - Mackey-Glass [18] and Rossler [19] for 200 time steps. The Mackey-Glass chaotic series is defined by the following parameters: a=0.2; b=0.1; C=10; initial conditions x(0)=0.1 and s= 17s. and on Fig. 3 is demonstrated performance of the proposed network using η=0.05. For greater clarity, the results are given in linear and logarithmic scales. As it can be seen, the proposed model structure estimate accurately the generated time series, with minimum MSE and RMSE and fast transient response of the RMSE, reaching values closer to zero.

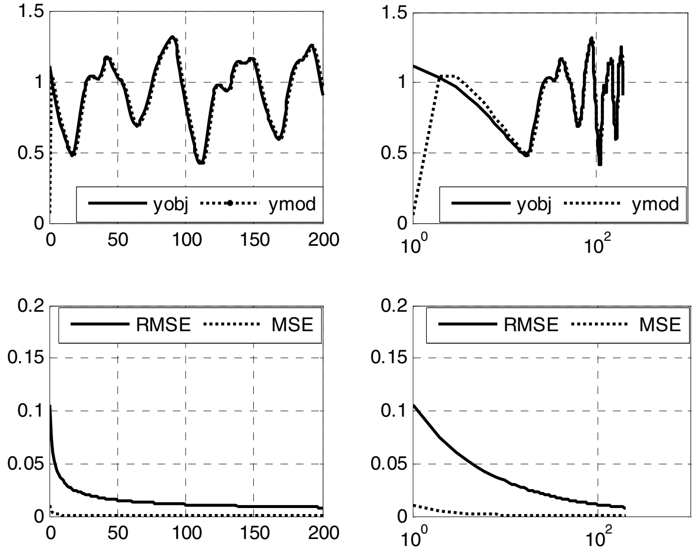

Fig. 3. Model validation by using Mackey-Glass chaotic time series – left column in linear scale and right column in logarithmic scale

On Fig.4 is presented the same case when is added uniformly distributed disturbance to the Mackey-Glass chaotic system of about 10% of the nominal input signal. The aim is to investigate the model behavior when an uncertain condition occurs. It can be seen that the interval Type-2 Neo-Fuzzy network model follows again the Mackey-Glass signal with minimum error and a slight increase of the RMSE.

Another test of the proposed model is made with Rossler chaotic time series with the following conditions: a=0.2; b=0.4; c=5.7; initial conditions x0=0.1; y0=0.1; z0=0.1. The results with the above presented cases are given respectively on Fig.5 and Fig.6. As it can be seen the model behavior is similar to the studied above. An increased value of the RMSE is observed again in the case of additive uniformly distributed disturbance, but the model performance is still stable.

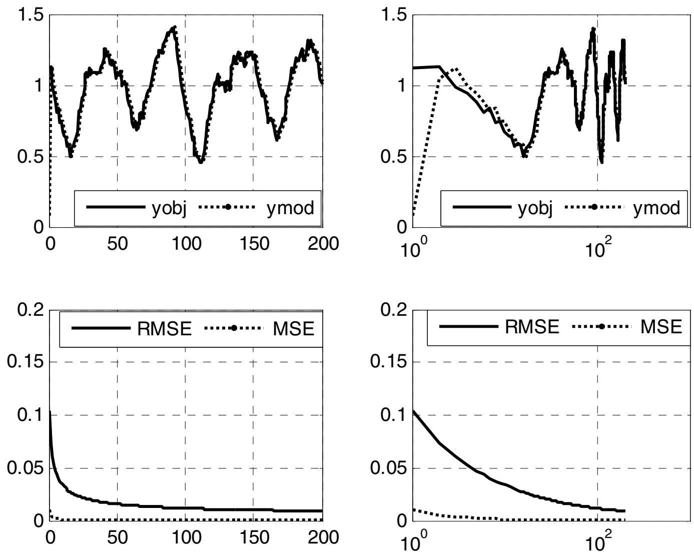

Fig. 4. Model validation by using Mackey-Glass chaotic time series with uniformly distributed disturbance – left column in linear scale and right column in logarithmic scale

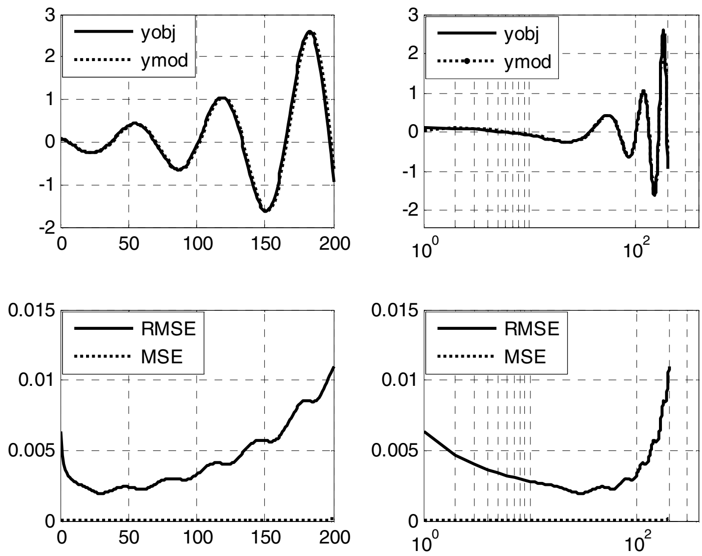

Fig. 5. Model validation by using Rossler chaotic time series – left column in linear scale and right column in logarithmic scale

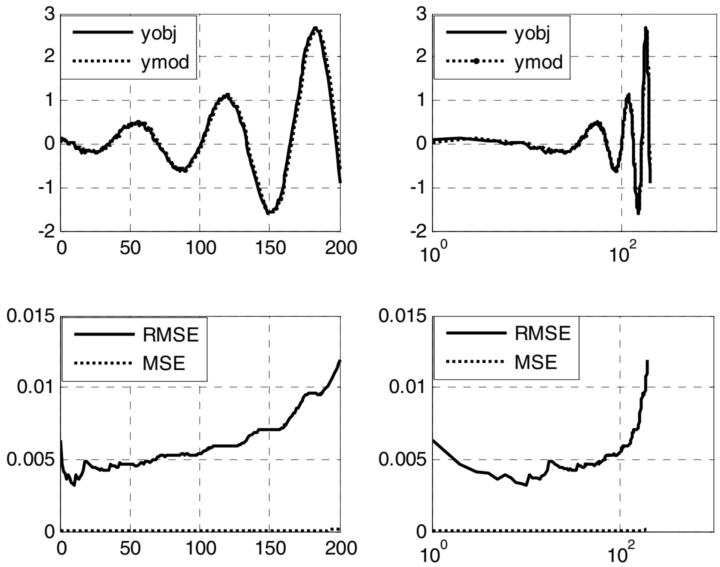

Fig. 6. Model validation by using Rossler chaotic time series – left column in linear scale and right column in logarithmic scale

Conclusions: It was presented in this paper an approach for designing a Neural Network, using the concept of NFN. For each input neuron is defined an Interval Type-2 Gaussian Fuzzy set in order to improve the ability of the network to handle uncertainties. The model output is produced by simple consequence matching, type reduction and linear combination. The achieved results in modeling of two common benchmark chaotic time series: Rossler and Mackey-Glass, have shown a stable model performance and slight error increase in the case of occurring uniformly distributed disturbance. A major benefit of the proposed approach is the relatively simple model structure with less number of parameters under adaptation and fuzzy mechanism dealing with input uncertainties. This opens new horizons to be studied in the future the potentials of the proposed approach in purpose of model based control strategies, where the computational accuracy of the model is crucial issue.

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