# 52. IWK

Internationales Wissenschaftliches Kolloquium

International Scientific Colloquium

PROCCEDINGS | 10 - 13 September 2007

## FACULTY OF
## COMPUTER SCIENCE AND AUTOMATION

## COMPUTER SCIENCE MEETS AUTOMATION

## VOLUME I

Session 1 - Systems Engineering and Intelligent Systems

Session 2 - Advances in Control Theory and Control Engineering

Session 3 - Optimisation and Management of Complex Systems and Networked Systems

Session 4 - Intelligent Vehicles and Mobile Systems

Session 5 - Robotics and Motion Systems

TECHNISCHE UNIVERSITÄT
ILMENAU

**Bibliografische Information der Deutschen Bibliothek**
Die Deutsche Bibliothek verzeichnet diese Publikation in der deutschen Nationalbiografie; detaillierte bibliografische Daten sind im Internet über **http://dnb.ddb.de** abrufbar.

**ISBN 978-3-939473-17-6**

## Impressum

| | |
|---|---|
| Herausgeber: | Der Rektor der Technischen Universität Ilmenau<br>Univ.-Prof. Dr. rer. nat. habil. Peter Scharff |
| Redaktion: | Referat Marketing und Studentische Angelegenheiten<br>Kongressorganisation<br>Andrea Schneider<br>Tel.: +49 3677 69-2520<br>Fax: +49 3677 69-1743<br>e-mail: kongressorganisation@tu-ilmenau.de |
| Redaktionsschluss: | Juli 2007 |
| Verlag: | Technische Universität Ilmenau/Universitätsbibliothek<br>Universitätsverlag Ilmenau<br>Postfach 10 05 65<br>98684 Ilmenau<br>www.tu-ilmenau.de/universitaetsverlag |
| Herstellung und Auslieferung: | Verlagshaus Monsenstein und Vannerdat OHG<br>Am Hawerkamp 31<br>48155 Münster<br>www.mv-verlag.de |
| Layout Cover: | www.cey-x.de |
| Bezugsmöglichkeiten: | Universitätsbibliothek der TU Ilmenau<br>Tel.: +49 3677 69-4615<br>Fax: +49 3677 69-4602 |

## Preface

Dear Participants,

Confronted with the ever-increasing complexity of technical processes and the growing demands on their efficiency, security and flexibility, the scientific world needs to establish new methods of engineering design and new methods of systems operation. The factors likely to affect the design of the smart systems of the future will doubtless include the following:

- As computational costs decrease, it will be possible to apply more complex algorithms, even in real time. These algorithms will take into account system nonlinearities or provide online optimisation of the system's performance.
- New fields of application will be addressed. Interest is now being expressed, beyond that in "classical" technical systems and processes, in environmental systems or medical and bioengineering applications.
- The boundaries between software and hardware design are being eroded. New design methods will include co-design of software and hardware and even of sensor and actuator components.
- Automation will not only replace human operators but will assist, support and supervise humans so that their work is safe and even more effective.
- Networked systems or swarms will be crucial, requiring improvement of the communication within them and study of how their behaviour can be made globally consistent.
- The issues of security and safety, not only during the operation of systems but also in the course of their design, will continue to increase in importance.

The title "Computer Science meets Automation", borne by the 52nd International Scientific Colloquium (IWK) at the Technische Universität Ilmenau, Germany, expresses the desire of scientists and engineers to rise to these challenges, cooperating closely on innovative methods in the two disciplines of computer science and automation.

The IWK has a long tradition going back as far as 1953. In the years before 1989, a major function of the colloquium was to bring together scientists from both sides of the Iron Curtain. Naturally, bonds were also deepened between the countries from the East. Today, the objective of the colloquium is still to bring researchers together. They come from the eastern and western member states of the European Union, and, indeed, from all over the world. All who wish to share their ideas on the points where "Computer Science meets Automation" are addressed by this colloquium at the Technische Universität Ilmenau.

All the University's Faculties have joined forces to ensure that nothing is left out. Control engineering, information science, cybernetics, communication technology and systems engineering – for all of these and their applications (ranging from biological systems to heavy engineering), the issues are being covered.

Together with all the organizers I should like to thank you for your contributions to the conference, ensuring, as they do, a most interesting colloquium programme of an interdisciplinary nature.
I am looking forward to an inspiring colloquium. It promises to be a fine platform for you to present your research, to address new concepts and to meet colleagues in Ilmenau.

Professor Peter Scharff
Rector, TU Ilmenau

Professor Christoph Ament
Head of Organisation

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Ye. Bodyanskiy / P. Otto / I. Pliss / N. Teslenko

# Nonlinear process identification and modeling using general regression neuro-fuzzy network

## INTRODUCTION

At present time, artificial neural networks are widely used for solving the problems of identification, prediction and modeling of nonlinear processes and systems. However, when the data are fed in real time and their processing must be simultaneous with functioning of the plant, in the case of nonstationary plant the problem becomes difficult. The so-called "optimization-based networks" such as Multilayer Perceptron, Radial Basis Functions Networks (RBFN) or Normalized Radial Basis Functions Networks (NRBFN) can be ineffective to solve such a problem thorough their slow convergence rate, curse of dimensionality, appearance of regions where all neurons of the network are inactive and possibility of getting to the local minima.

"Memory-based networks", such as General Regression Neural Network (GRNN), proposed by D. F Specht [1], can be referred to, so-called, just-in-time models [2], which are learned by one-pass learning algorithm by the principle "neurons at data points" [3]. These properties are the cause of GRNN high learning rate.

For the solving of nonlinear plant identification problem

$$y(x) = F(x(k)),$$

where $y(x)$, $x(k)$– scalar and $(nx1)$-vector of output and input signals correspondingly in the instant time $k=1,2,\ldots,$ $F(\bullet)$ – unknown nonlinear operator of the plant, it is necessary to form learning sample $\left\{x^*(k), y^*(k)\right\}$, $k=1,2,\ldots,l,$ whereupon it is possible to get the estimate $\hat{y}(x)$ of the plant response $y(x)$ to arbitrary input signal $x$ in the form

$$\hat{y}(x) = \sum_{k=1}^{l} y^*(k)\varphi(D(k))\left(\sum_{k=1}^{l}\varphi(D(k))\right)^{-1} \qquad (1)$$

where $D(k)$ – distance measure in accepted metrics between $x$ and $x^*(k)$, $\varphi(\bullet)$ – some kernel function, usually, Gaussian. GRNN converges asymptotically to optimal nonlinear regression surface with the growing of learning sample size [4] and its learning process can be organized easily in real time. But the main problems connected with GRNN using are defined by possible curse of dimensionality, when the number of data $l$ is large.

Neuro-Fuzzy Systems (NFS) [5-6] combine the neural networks learning abilities with transparence and interpretability of the Fuzzy Inference Systems (FIS). Having approximating abilities of RBFN [6-7], NFS subject to curse of dimensionality with less degree, that provides them advantage in comparison with neural networks because of using univariate Fuzzy Basis Functions (FBF) instead of multidimansional RBF.

Among NFS Adaptive Network-based Fuzzy Inference System (ANFIS) have got wide spread [8]. ANFIS has five-layer architecture and is typical representative of the optimization-based networks family, which are characterized by insufficient learning rate. Lattice-based Associative Memory Networks (LAMN) [9-10] are the representatives of memory-based networks, whose output signal is formed on basis of univariate bell-shaped functions uniformly distributed on axes of $n$-dimensional input space. As a result of aggregation operation multidimensional FBFs are formed, whose centers are also uniformly distributed in multidimensional space, and their layout doesn't depend on characteristics of learning sample.

The goal of this work is solving the problem of nonlinear process identification and modeling using General Regression Neuro-Fuzzy Network (GRNFN), which represents by itself NFS and learns as GRNN that provides approximating properties of ANFIS with learning rate of memory-based networks.

## THE GENERAL REGRESSION NEURO-FUZZY NETWORK ARCHITECTURE

The architecture of General Regression Neuro-Fuzzy Network is illustrated on Fig. 1 and consists of five sequentially connected layers. First hidden layer is composed of $l$ blocks with $n$ FBF in each and realizes fuzzification of the input variables vector. Second hidden layer implements aggregation of membership levels that are computed in first layer, and consists of $l$ multiplication blocks. Third hidden layer – the layer of synaptic weights that are defined in special way. Fourth layer is formed by two summation units and computes the sums of output signals from the second and third layers. Finally, normalization takes place in fifth (output) layer, where the output signal is computed.

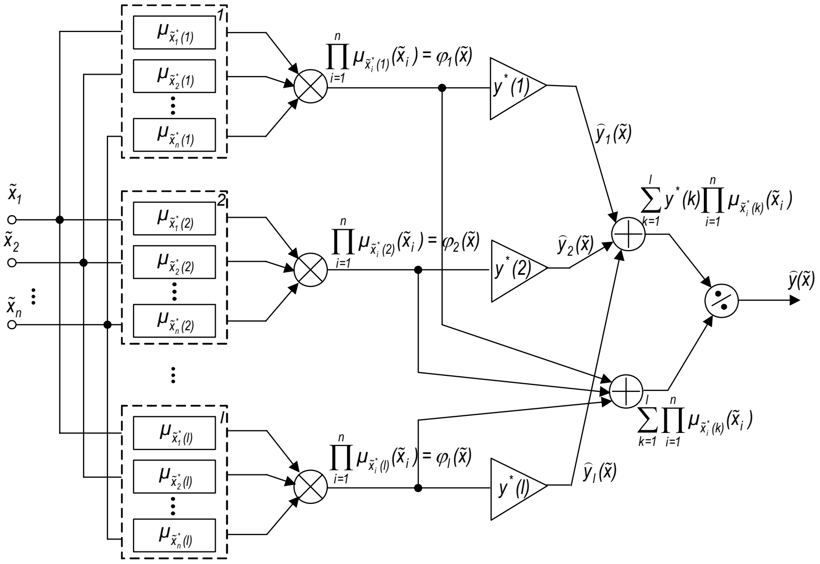


Fig.1 – General Regression Neuro-Fuzzy Network.

## GENERAL REGRESSION NEURO-FUZZY NETWORK LEARNING

Since GRNFN belongs to memory-based networks, its learning is based on principle “neurons at data points” that makes it extremely easy and fast. Learning sample vectors $x^*(1),...,x^*(k),...,x^*(l)$ are normalized in advance on unit centered hypercube so, that $x_i^{*min} \le x_i^*(k) \le x_i^{*max}$, $-0,5 \le \tilde{x}_i^*(k) \le 0,5$, $i=1,2,...,n$. For each vector from the learning sample $\tilde{x}^*(k)=(\tilde{x}_1^*(k),\tilde{x}_2^*(k),...,\tilde{x}_n^*(k))^T$ in the first hidden layer own set of fuzzy-basis membership functions $\mu_{\tilde{x}_1^*(k)},\mu_{\tilde{x}_2^*(k)},...,\mu_{\tilde{x}_n^*(k)}$ is formed, so that centers of $\mu_{\tilde{x}_i^*(k)}$ coincide with $\tilde{x}_i^*(k)$, $k=1,2,\ldots,l$. The process of FBF formation is illustrated on Fig. 2. Note that GRNFN contains *nl* fuzzy-basis functions, that can’t lead to the curse of dimensionality.

Theoretically, any kernel function with non-strictly local support can be used as FBF that allows to avoiding of appearance of “gaps” [4]. As such a function one can recommend generalized Gaussian

$$\mu_{\tilde{x}_i^*(k)}(\tilde{x}_i)=\left(1+\left|\frac{\tilde{x}_i^*(k)-\tilde{x}_i}{\sigma_i(k)}\right|^{2b}\right)^{-1},\ b\ge 0,5\ , \qquad (2)$$

that is the bell-shaped function, whose shape is defined by the scalar parameter *b* [6]. As for choosing of the width parameter $\sigma_i(k)$, standard recommendation leads to the idea [11], that it must ensure small overlapping of FBFs neighboring. At the same time with FBFs forming in first hidden layer, the synaptic weights are formed in the third hidden layer and they are supposed to be equal to the signals of learning sample $y^*(k)$.

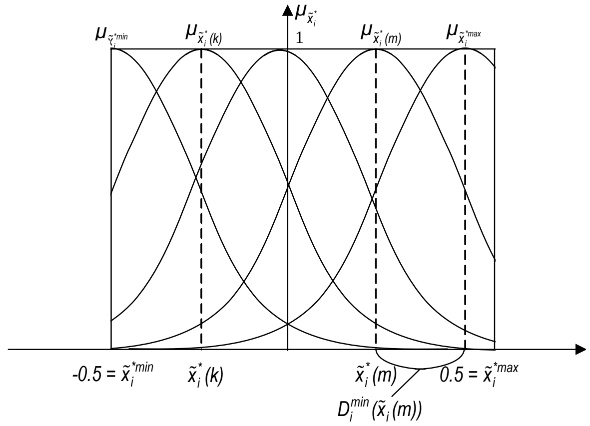


Fig.2 – Fuzzy-basis membership functions.

Thus, when arbitrary signal $\tilde{x}$ is fed to the input of GRNFN in the first hidden layer membership levels $\mu_{\tilde{x}_i^*(k)}(\tilde{x}_i)$, $i=1,2,\ldots,n,\ k=1,2,\ldots,l$ are computed, in the second layer their aggregation is realized by forming multidimensional FBFs

$$\varphi_k(\tilde{x}) = \prod_{i=1}^{n}\left(1+\left|\frac{\tilde{x}_i^*(k)-\tilde{x}_i}{\sigma_i(k)}\right|^{2b}\right)^{-1},\ k=1,2,\ldots,l, \tag{3}$$

in the third layer products $\hat{y}(\tilde{x}) = y^*(k)\varphi_k(\tilde{x})$ are determined, fourth layer computes the values of signals $\sum_{k=1}^{l} y^*(k)\varphi_k(\tilde{x})$ and $\sum_{k=1}^{l}\varphi_k(\tilde{x})$, and, finally, in the output layer the estimate

$$\hat{y}(\tilde{x}) = \frac{\sum_{k=1}^{l} y^*(k)\varphi_k(\tilde{x})}{\sum_{k=1}^{l}\varphi_k(\tilde{x})} = \frac{\sum_{k=1}^{l} y^*(k)\prod_{i=1}^{n}\mu_{\tilde{x}_i^*(k)}(\tilde{x}_i)}{\sum_{k=1}^{l}\prod_{i=1}^{n}\mu_{\tilde{x}_i^*(k)}(\tilde{x}_i)}, \tag{4}$$

is forming, which coincides with (1) with the only difference, that instead of radial-basis functions multidimensional fuzzy-basis functions are used, that were formed of univariate FBF.

The scheme of fuzzy inference, which is realized by GRNFN can be presented as a logic equations system

$$IF(\tilde{x}_1.IS.A_1(1)).AND.(\tilde{x}_2.IS.A_2(1)).AND.....AND.(\tilde{x}_n.IS.A_n(1)),\quad THEN\quad \hat{y}_1(\tilde{x}) = y^*(1)$$

$$\vdots$$

$$IF(\tilde{x}_1.IS.A_1(k)).AND.(\tilde{x}_2.IS.A_2(k)).AND.....AND.(\tilde{x}_n.IS.A_n(k)), \quad THEN \quad \hat{y}_k(\tilde{x}) = y^*(k)$$
$$\vdots$$
$$IF(\tilde{x}_1.IS.A_1(l)).AND.(\tilde{x}_2.IS.A_2(l)).AND.....AND.(\tilde{x}_n.IS.A_n(l)), \quad THEN \quad \hat{y}_l(\tilde{x}) = y^*(l)$$

where the operator $A_i(k)$ is represented by the membership function (2). Hence, using of neuro-fuzzy approach allows to ensure the interpretation of obtained results.

The GRNFN learning process can proceed both in batch mode, when learning sample $\left\{x^*(k), y^*(k)\right\}$ is given apriori and in real time, when pairs $x^*(k)$, $y^*(k)$ are fed sequentially, forming multidimensional FBFs $\varphi_k$. It is sufficiently easy to organize the slight information pairs exclusion process. If for some observation $\tilde{x}^*(m)$ the condition

$$\max_i D_i^{min}(\tilde{x}_i(m)) < r < (l-1)^{-1} \quad (5)$$

is held (here $D_i^{min}(\tilde{x}_i(m))$ – the least distance between $\tilde{x}_i(m)$ and earlier formed neighboring centers of FBFs), then $\tilde{x}^*(m)$ doesn't form function $\varphi_m$ and is removed from the consideration. Note, that for univariate situation the threshold parameter $r$ and the distance $D_i^{max}$ are significantly easier to define, then in multidimensional case of GRNN.

Operation of GRNFN can be organized simply in the online adaptation mode that is essentially important for nonstationary processes identification and control. In this situation it is possible to use two approaches. The first one – on the sliding window of $l$ observations, when new learning pairs $x^*(l+1)$, $y^*(l+1)$ are being fed to the input of the network, in the first and third layers the pair of $\mu_{\tilde{x}_i^*(1)}$ and $y^*(1)$ is removed, and instead of it the membership function $\mu_{\tilde{x}_i^*(l+1)}$ and weight $y^*(l+1)$ are formed. The second approach is based on inequality (5). In this case newly received pair $x^*(m)$, $y^*(m)$ isn't removed, but replaces the nearest to it in the "old" data. As far as the learning process operates almost immediately, there is no problem with following properties of tuning algorithm at all.

## NUMERICAL EXPERIMENT

The plant to be identified has the form [12]

$$y(k+1)=y(k)/(1+y^2(k))+u^3(k),$$

where the input to the plant $u(k)=sin(2\pi k/25)+sin(2\pi k/10)$ for $k$=100.

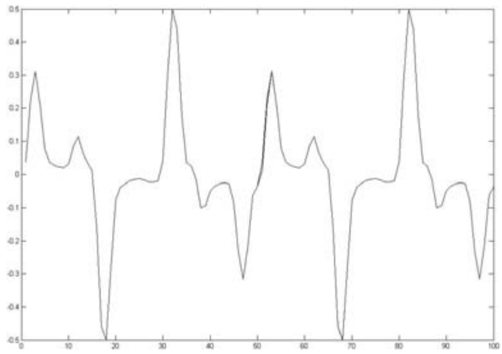

Fig.3 – Outputs of the original plant, GRNN and GRNFN for 50 signals in learning sample.

Numerical results of the experiment show that if learning sample consists of 50 signals, then both networks operates equally and have no mistakes. Fig.3 shows the plant and the outputs of GRNN and GRNFN and the differences between them are undistinguished. But if the number of signals which form the learning sample less then a half of all number of signals, GRNFN has the accuracy higher by 3-5% then GRNN.

## CONCLUSIONS

General Regression Neuro-Fuzzy Network, that is generalization of conventional GRNN and adaptive fuzzy inference systems, is proposed in this work. This network is characterized by computational simplicity, interpretability of the results and ensures high accuracy in the nonlinear nonstationary processes identification and modeling problems.

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