№ 1 (2), 2020 ISSN: 2682 – 9517 (print) ISSN: 2683 – 0930 (online)

INSTITUTE OF INFORMATICS AND INNOVATIVE TECHNOLOGIES

ИЗЧИСЛИТЕЛНО ЕФЕКТИВНИ НЕВРОННО-РАЗМИТИ ПРЕСКАЗВАЩИ МОДЕЛИ

Маргарита Терзийска Желязко Терзийски

COMPUTATIONALLY EFFICIENT NEURO-FUZZY PREDICTIVE MODELS

Margarita Terziyska
Informatics and Statistics Department
University of Food Technologies
Plovdiv, Bulgaria
m.terziyska@uft-plovdiv.bg

Zhelyazko Terziyski
Faculty of Mathematics and Informatics
University of Plovdiv Paisii Hilendarski,
Plovdiv, Bulgaria
terziyski@engineer.com

Abstract—**Hybrid neuro-fuzzy structures are well known and widely used artificial intelligence techniques. Their computational efficiency is not discussed in any of the existing review articles. In this paper different approaches to reduce the computational burden in these structures will be discussed, it will be presented some ideas of the authors to reduce the number of fuzzy rules and a comparison between them and the classic ANFIS will be made.**

Keywords—neuro-fuzzy systems, ANFIS, DANFA, SFNN, Neo-fuzzy neuron, fuzzy rules reduction

I. INTRODUCTION

Hybrid neuro-fuzzy intelligent architectures is appeared a natural continuation in the development of neural networks and systems with fuzzy logic. They combine the clarity and transparency of fuzzy systems with the learning ability on neural networks. Their fusion has been compared in [1] with the human brain - the neural network is the structure of the brain, i.e. "hardware", while fuzzy logic takes care of "software". Some of the well-known hybrid neuro-fuzzy architectures are ANFIS [2], GARIC [3], NEFCON [4], FALCON [5], FUN [6], SONFIN [7], EFuNN [8], dmEFuNN [9].

A number of overview articles dedicated to the neuro-fuzzy structures, are presented in the scientific literature. All they show the evolution on these intelligent systems. A comparative study of the ANFIS, FALCON, GARIC, SONFIN and EFuNN structures was performed in [10]. Relatively newer in historical terms are the review articles [11-14]. An extremely in-depth analysis of the neuro-fuzzy structures developed in the period 2010-2017 is presented in [15]. The authors made classification the neuron-fuzzy models according to their learning algorithm, according to their structure (static or dynamic), according to the used type of fuzzy logic (Type 1, Type 2, Intuitionistic fuzzy logic), etc. A review of the central theories involved in hybrid models based on fuzzy systems and artificial neural networks, mainly focused on supervised methods for training hybrid models is given in [16].

However, none of these review papers discusses the problem of the computational efficiency of neuron-fuzzy models. It is well known that all these structures are composed of a set of if-then rules. In principle, the number of fuzzy rules depends exponentially on the number of inputs and membership functions. If **p** is the number of inputs in a fuzzy-neural system and **m** is the number of the membership functions, then the number of the generated fuzzy rules is m^p. Thus, the huge number of generated rules requires determination of a large number of parameters during the learning procedure. For instance, for a fuzzy inference system with 8 inputs, each one with three membership functions, the grid partitioning leads to 6561(=3^8) rules, which is an extremely large number of rules for any practical applications. In this paper different approaches to reduce the computational burden in these structures will be discussed, it will be presented some ideas of the authors to reduce the number of fuzzy rules and a comparison between them and the classic ANFIS will be made.

II. METHODS FOR FUZZY RULES REDUCTION

One significant drawback of the fuzzy models that they carry into the neuro-fuzzy structures is the large number of fuzzy rules they work with. In order to reduce the number of generated rules without loss the accuracy of modeling, different methods have been proposed in the scientific literature. One of them is the use of hierarchical neuro-fuzzy structures [17]. Hierarchical fuzzy/neuro-fuzzy systems have also been shown to be universal approximators [18-19]. However, in [17] was proven that the learning algorithm is too complicated.

In [20] the use of the so-called sensory fusion was proposed. In this method, one of several input signals is obtained. The new signal represents a linear function of its components. In this way, the size of the base rule decreases as the number of inputs decreases. The author also proposes the combination of hierarchical structures with sensory fusion. The disadvantage of this idea is that its implementation depends mainly on the experience of the human operator. He is the one who has to determine what the structure of the hierarchical system should be, as well as the respective parameters. In an attempt to overcome this disadvantage, in [her dissertation [21] she] it was proposed an automatic determination of these parameters by using genetic algorithm.

Another possibility to simplify the fuzzy/neuro-fuzzy models is the use of orthogonal transformations. In fact, they are a way to determine the most significant rules. In [22] several different methods of orthogonal transformations were compared, namely: Orthogonal Least Squares (OLS) method; Eigenvalue Decomposition (ED); Total Least Squares (TLS) and Direct Singular Value Decomposition (D-SVD). In [23] a modified version of the Gram-Schmidt transformation is presented. In [24] some comments are given concerning the use of orthogonal transformations.

Various ways to reduce the fuzzy rules by removing the redundant ones have been proposed in [25-26]. The conditions for reducing the rule from the point of view of linear matrix inequalities (LMIs) are presented in [27]. A method based on the concept of similarity and vague interpolation is described in [28]. In it, the similarity between the rules is first measured in order to determine the "best", and then interpolation is performed in order to increase the accuracy after the first. An overview of the methods for reducing the fuzzy rules is given in [29].

Another group of algorithms that have become popular in recent years is the so-called self-constructing and self-organizing neuro-fuzzy structures [30-31]. During the learning process, the inactive rules are removed, which in turn leads to a reduction in the number of learning parameters. A method that compresses a system with an arbitrarily large number of rules to one with a small number of rules is presented in [32]. As a result of this compression, the number of on-line operations during the fuzzy inference process is significantly reduced without compromising the solution.

In order to reduce the number of fuzzy rules without loss of accuracy, different fuzzy clustering approaches, such as fuzzy C-means [33, 34] and K-means [35] can be used. Besides, subtractive clustering and hyperplane clustering are proposed in [36, 37]. Evolving fuzzy systems [38, 39], such as DENFIS, includes evolving clustering and dynamically forms bases of fuzzy rules generated during the past instance of the learning process. The new AnYa neuro-fuzzy structure also belongs to the evolving fuzzy systems. This architecture works with the so-called cloud instead of fuzzy sets. This removes the need for training of the membership functions parameters. However, apriori data is needed to form the clouds [40].

III. Computationally efficient neuro-fuzzy models

A. *Distributed Adaptive Neuro-Fuzzy Architecture*

The structure of the Distributed Adaptive Neuro-Fuzzy Architecture (DANFA) model is shown on Fig. 1.

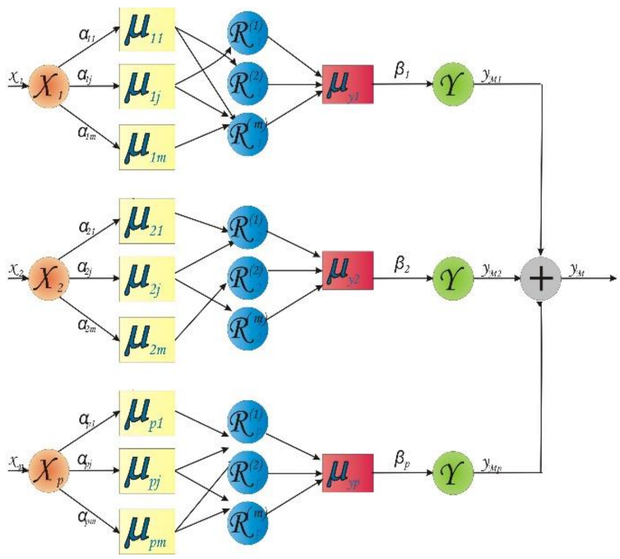

Fig. 1. Structure of the proposed DANFA model

DANFA model is a modification of the well-known Adaptive Neuro-Fuzzy Inference System (ANFIS). The main idea behind it is to "distribute" the input signals to separate ANFIS-type structures. In this way a network of neural fuzzy structures is obtained. Each of these neural-fuzzy structures act as a separate sub-model and global DANFA model is a set of **p** on the number of sub-model. The output signal of a global DANFA model is computed as a sum of the output signals of the **p** ANFIS-type models and is calculated by the following expression:

$$\hat{y}_M(k+j) = \hat{y}_{M1}(k+j) + \ldots + \hat{y}_{Mp}(k+j) \tag{1}$$

where $\hat{y}_{Mr}$ for r=1:p is obtained as follow:

$$\hat{y}_{Mr}(k+j) = \frac{\sum_{i=1}^{q} f_r^{(i)}(k+j)\mu_r^{(i)}(k+j)}{\sum_{i=1}^{q} \mu_r^{(i)}(k+j)} \tag{2}$$

The number of fuzzy rules of the DANFA model is calculated by the following formula:

$$N = m_1^{p_1} + m_2^{p_2} + \ldots + m_q^{p_q} \tag{3}$$

More details about the DANFA model can be found in [41].

B. *Semi Fuzzy Neural Network*

The structure of the proposed SFNN model is shown on Fig. 2. It represents five-layered architecture with Takagi-Sugeno inference mechanism. However, in SFNN model a part of input signals are not fuzzyfied, but they come with their real values, weighted by the appropriate coefficient, into the third layer (fuzzy rules layer), i.e. directly into the THEN part of the functions of Sugeno.

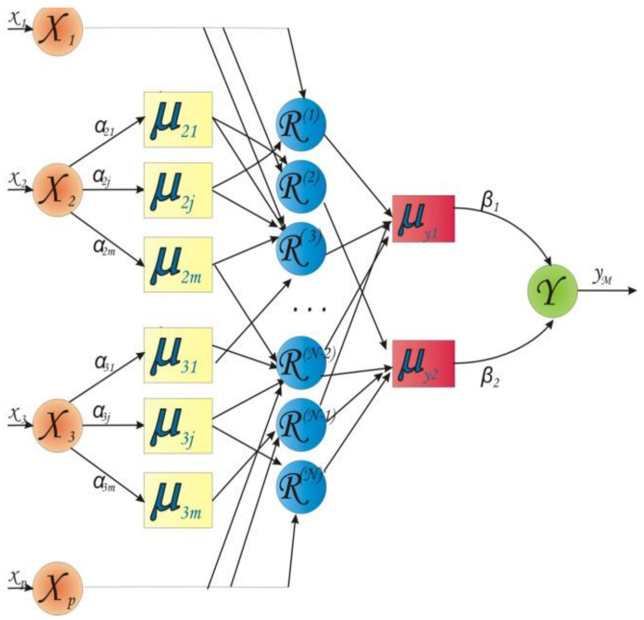

Fig. 2. Structure of the proposed SFNN model

Thus, on the one hand it is reduced the number of fuzzy rules with which the model is working and on the other hand – it is reduced the number of the parameters that must be determined during learning procedure. For example, for implementation of NARX model with 4 inputs, each of which is fuzzyfied with 3 fuzzy sets, then for ANFIS model is needed 81 fuzzy rules while SFNN works with only 9 fuzzy rules. Furthermore, in ANFIS model during the learning procedure it is needed to obtain 405 linear and 648 nonlinear parameters or total 1053 parameters! The number of parameters that must be determined during the training procedure is only 81 (45 linear and 36 nonlinear parameters). More details about the SFNN model can be found in [42, 43].

C. *Modified Neo-Fuzzy Network*

Modified Neo-Fuzzy Network (MNFN) is based on the concept of Neo-fuzzy neuron (NFN), which was initially introduced by T. Yamakawa and E. Uchino [44]. The architecture of the neo-fuzzy neuron is shown in Fig.3. The Neo-Fuzzy neuron is similar to a zero order Sugeno fuzzy system where only one input is included in each fuzzy rule, and to a radial basis function network (RBFN) with scalar arguments of basis functions. The neo-fuzzy neuron implements nonlinear mapping using the following equation:

$$f(x) = \sum_{j=1}^{m} \mu_j(x(k))w_j \tag{4}$$

where x(k) is the input, w_j is the weight coefficient and μ_j for j=1:m is a defined set of Gaussian membership functions:

$$\mu_{Xp,m}^{(n)} = \exp\frac{-(x_p - c_{Xp,m})^2}{2\sigma_{Xp,m}^2} \tag{5}$$

where c and σ represent its center (mean) and width (standard deviation).

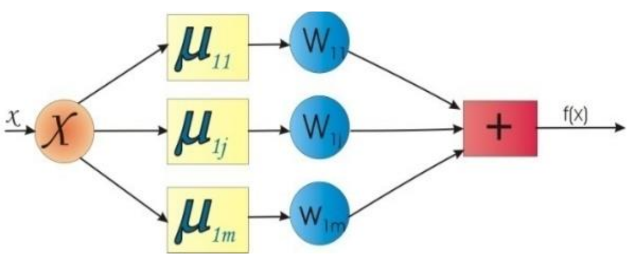

Fig. 3. Single Neo-Fuzzy neuron

Using the basic concept of the neo-fuzzy neuron, it is easy to obtain a network containing a larger number of such neurons. Such a structure is shown in Fig. 4. More details about the MNFN model can be found in [45, 46].

The MNFN model represents a six-layered architecture as each layer perform following:

Layer 1: The neurons in this layer receive the input signals and transmit them to the next layer.

Layer 2: Each node in this layer does fuzzification via a Gaussian membership function (5).

Layer 3: This layer is a kind of a fuzzy rules generator. All rules have the following form:

$$f_{ij}(k) = \mu_{ij}(k) * w_{ij}(k) \qquad (6)$$

Layer 4: Summation of the values calculated in layer 3 using the expression (4) is realized.

Layer 5: Multiplication on the output of each neo-fuzzy neuron by he input signal for it is performed.

Layer 6: The output of the MNFN model is obtained as follows:

$$\begin{aligned} y_m(k) &= \sum_{i=1}^{p} x_i(k) f_i(x_i(k)) = \\ &= \sum_{i=1}^{p} x_i(k) \sum_{j=1}^{m} \mu_{ij}(x_i(k)) w_{ij}(k) \end{aligned} \qquad (7)$$

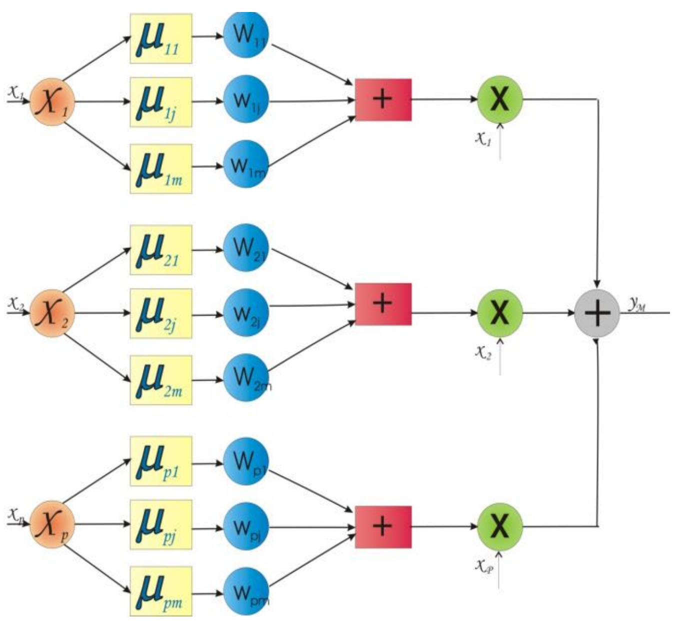

Fig. 4. Structure of the proposed MNFN model

IV. Comparative Study of the Presented Computationally Efficient Neuro-Fuzzy Models

In this section, a comparison between the models presented above and ANFIS have been made. To test the prediction ability of all these models, Mackey-Glass chaotic systems have been chosen. The used time series will not converge or diverge, and the trajectory is highly sensitive to initial conditions. The MG time series is described by time-delay differential equation:

TABLE I. COMPARATIVE STUDY OF THE STUDIED NEURO-FUZZY MODELS

Model	Steps	MSE
ANFIS *Rules=81 Parameteres=1053 t[ms]=2,82*	50	9,2 e-2
	100	7,7 e-2
	150	7,9 e-2
	200	7,8 e-2
	250	7,6 e-2
	300	7,65 e-2
	350	7,62 e-2
	400	0,96 e-2
	450	0,85 e-2
	500	0,76 e-2
DANFA *Rules=18 Parameteres=126 t[ms]=1,83*	50	5,3 e-2
	100	2,7 e-2
	150	1,9 e-2
	200	1,4 e-2
	250	1,2 e-2
	300	1,03 e-2
	350	0,91 e-2
	400	0,82 e-2
	450	0,74 e-2
	500	0,69 e-2
SFNN *Rules=9 Parameteres=63 t[ms]=1,58*	50	16 e-5
	100	8,7 e-5
	150	6,04 e-5
	200	4,8 e-5
	250	3,97 e-5
	300	3,5 e-5
	350	3,1 e-5
	400	2,8 e-5
	450	2,6 e-5
	500	2,3 e-5
MNFN *Rules=12 Parameteres=36 t[ms]=1,67*	50	9,35 e-5
	100	7,06 e-5
	150	5,6 e-5
	200	4,5 e-5
	250	3,9 e-5
	300	3,4 e-5
	350	3,12 e-5
	400	2,92 e-5
	450	2,33 e-5
	500	2,17 e-5

$$x(i+1) = \frac{x(i) + ax(i-s)}{(1 + x^c(i-s)) - bx(i)} \tag{8}$$

where a=0.2; b=0.1; C=10; initial conditions x(0)=0.1 and s= 17s.

It have also been chosen that all these models to have four inputs, each of which is fuzzyfied by three Gaussian membership functions.

To determine which is the best model, several criteria are defined:

- number of fuzzy rules;
- number of parameters, updated of each iteration of the learning procedure;
- accuracy;
- time for one iteration of the learning process.

The results are shown in Table I. In accordance to the defined criteria, MNFN has been chosen as the best model. It has been realized in a variant with Type 2 and with Intuitionist fuzzy logic. The obtained results are presented in Table 2.

TABLE II. COMPARATIVE STUDY OF TYPE 2 NEO-FUZZY NETWORK AND INTUITIONISTIC NEO-FUZZY NETWORK

Steps	Type 2 Neo-Fuzzy Network		Intuitionistic Neo-Fuzzy Network	
	Without disturbance	With disturbance	Without disturbance	With disturbance
	MSE	MSE	MSE	MSE
50	2.38e-4	2.98e-4	1.26e-6	3.42e-6
100	1.26e-4	1.69e-4	7.05e-7	2.25e-6
150	8.85e-5	1.31e-4	5.19e-7	1.87e-6
200	7.01e-5	1.07e-4	4.32e-7	1.61e-6
250	5.89e-5	8.4e-5	3.75e-7	1.48e-6
300	5.19e-5	7.22e-5	3.41e-7	1.37e-6
350	4.63e-5	6.72e-5	3.13e-7	1.26e-6
400	4.26e-5	5.91e-5	2.96e-7	1.19e-6
450	3.92e-5	5.33e-5	2.78e-7	1.13e-6
500	3.69e-5	4.76e-5	2.67e-7	1.09e-6

Time to perform the necessary calculations for one iteration of the learning procedure is as follows:

- **Intuitionistic Neo-fuzzy network:** 1.48 ms for the case without disturbance and 1.50 ms for the case with disturbance and.
- **Type 2 Neo-fuzzy network:** 1.93 ms for the case without disturbance and 1.96 ms for the case with disturbance and.

V. CONCLUSIONS

In this paper different approaches to reduce the computational burden in intelligent hybrid neuro-fuzzy structures was summarized, some ideas of the authors to reduce the number of fuzzy rules was presented and comparison between them and the classic ANFIS was made. The Mackey-Glass chaotic systems was chosen to test prediction ability of these models. The proposed DANFA, SFNN and MNFN models predict accurately the generated chaotic time series, with minimum prediction error and fast transient response of the MSE, reaching values closer to zero. Their main advantage is that operates by a small number of rules and respectively has a smaller number of parameters for learning. This makes the models suitable for real-time applications. The MNFM has been chosen as the best in terms of the set criteria (number of rules, number of parameters, speed and accuracy). After that, MNFN has been realized in a variant with Type 2 and with Intuitionist fuzzy logic. The results show that the Intuitionistic Neo-fuzzy network is more accurate and faster than Type 2 Neo-fuzzy network in the studied two cases –in the presence of disturbance and without disturbance.

REFERENCES

[1] Chennakesava R. Alavala, Fuzzy logic and neural networks: basic concepts & application, New Age International, 2008.

[2] J-SR. Jang, "ANFIS: adaptive-network-based fuzzy inference system", IEEE transactions on systems, man, and cybernetics, 23(3),1993, pp. 665-685.

[3] H. R. Bherenji and P. Khedkar, Learning and Tuning Fuzzy Logic Controllers through Reinforcements, *IEEE Trans. on Neural Networks*, Vol (3), pp. 724-740, 1992.

[4] D. Nauk and R. Kruse, A Neuro Fuzzy Controller Learning by Fuzzy Error Propagation, In *Proceedings of the North American Fuzzy Information Processing Society NAFIPS'92, Mexico*, pp. 388-397, 1992.

[5] C. T. Lin and C. S. G. Lee, Neural Network based Fuzzy Logic Control and Decision System, *IEEE Trans. on Comput.*, Vol. 40, Issue 12, pp. 1320-1336, 1991.

[6] S. M Sulzberger, N. N. Tschicholg-Gurman and S. J. Vestli, FUN: Optimization of Fuzzy Rule Based Systems Using Neural Networks, In *Proceedings of IEEE Conference on Neural Networks, San Francisco*, pp. 312-316, 1993.

[7] J. Ch. Feng and L. Ch. Teng, An Online Self Constructing Neural Fuzzy Inference Network and its Applications, *IEEE Transactions on Fuzzy Systems*, Vol. 6, No. 1, pp. 12-32, 1998.

[8] N. Kasabov, Evolving Fuzzy Neural Networks for Supervised/Unsupervised On-line Knowledge-Based

Learning, IEEE Trans of Systems, Man and Cybernetics, Part B – Cybernetics, Vol. 31, No. 6, pp. 902-918, 2001.

[9] N. Kasabov and Q. Song, Dynamic Evolving Fuzzy Neural Networks with ‘m-out-of-n‘ Activation Nodes for On-line Adaptive Systems, Technical Report TR99/04, Department of information science, University of Otagoq 1999.

[10] J. Vieira, F. M. Dias and A. Mota, Neuro-fuzzy systems: a survey, 5th WSEAS NNA International Conference on Neural Networks and Applications, Udine, Italia, 2004.

[11] S. Sahin, M. R. Tolun, & R. Hassanpour, Hybrid expert systems: A survey of current approaches and applications, Expert Systems with Applications, 39(4), 4609-4617, 2012.

[12] S. Kar, S. Das and P. K. Ghosh, Applications of neuro fuzzy systems: A brief review and future outline, Applied Soft Computing Vol.15 pp. 243-259, 2014.

[13] G. Bosque, I. del Campo & J. Echanobe, Fuzzy systems, neural networks and neuro-fuzzy systems: A vision on their hardware implementation and platforms over two decades, Engineering Applications of Artificial Intelligence, 32, 283-331, 2014.

[14] Z. J. Viharos, & K. B. Kis, Survey on Neuro-Fuzzy systems and their applications in technical diagnostics and measurement, Measurement, 67, 126-136, 2015.

[15] K. V. Shihabudheen & G. N. Pillai, Recent advances in neuro-fuzzy system: A survey, Knowledge-Based Systems, 152, pp. 136-162, 2018.

[16] Paulo Vitor de Campos Souza, "Fuzzy neural networks and neuro-fuzzy networks: A review the main techniques and applications used in the literature", Applied Soft Computing 106275, 2020.

[17] Wen Yu, Marco Moreno-Armendariz, and Floriberto Ortiz Rodriguez, "System identification using hierarchical fuzzy neural networks with stable learning algorithm", Journal of Intelligent & Fuzzy Systems, pp. 171-183, 2007.

[18] Chen Wei, and Li-Xin Wang, "A note on universal approximation by hierarchical fuzzy systems." Information sciences, pp. 241-248, 2000.

[19] Xiao-Jun Zeng, et al., "Approximation Capabilities of Hierarchical Neural Fuzzy Systems for Function Approximation on Discrete Spaces", International Journal of Computational Intelligence Research pp. 29-41, 2005.

[20] Mohammad Jamshidi. "Fuzzy control of complex systems", Soft computing pp. 42-56, 1997.

[21] Y. Ledeneva, "Automatic estimation of parameters to reduce rule base of fuzzy control complex systems." a master thesis in august, 2006.

[22] John Yen and Liang Wang, "Simplifying fuzzy rule-based models using orthogonal transformation methods", IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 29.1, pp. 13-24, 1999.

[23] Faisal Alturki and Russell Mersereau, "An oblivious robust digital watermark technique for still images using DCT phase modulation", 2000 IEEE International Conference on Acoustics, Speech, and Signal Processing. Proceedings (Cat. No. 00CH37100). Vol. 4. IEEE, 2000.

[24] Magne Setnes and Robert Babuska, "Rule base reduction: some comments on the use of orthogonal transforms", IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 31.2, pp. 199-206, 2001.

[25] M. Ciliz, "Rule base reduction for knowledge-based fuzzy controllers with application to a vacuum cleaner", Expert Systems with Applications 28.1, pp. 175-184, 2005.

[26] Yaochu Jin, "Fuzzy modeling of high-dimensional systems: complexity reduction and interpretability improvement", IEEE Transactions on Fuzzy Systems 8.2, pp. 212-221, 2000.

[27] Tadanari Taniguchi and Kazuo Tanaka, "Rule Reduction and Robust Control of Generalized Takagi-Sugeno Fuzzy Systems", JACIII 4.5, pp. 373-379, 2000.

[28] Hatem Bellaaj, Rouf Ketata and Mohamed Chtourou, "A new method for fuzzy rule base reduction", Journal of Intelligent & Fuzzy Systems 25.3, pp. 605-613, 2013.

[29] Okyay Kaynak, Karel Jezernik and Agnes Szeghegyi, "Complexity reduction of rule based models: a survey", 2002 IEEE World Congress on Computational Intelligence, 2002 IEEE International Conference on Fuzzy Systems, FUZZ-IEEE'02. Proceedings (Cat. No. 02CH37291), Vol. 2, IEEE, 2002.

[30] Hector Allende-Cid, et al., "Self-organizing neuro-fuzzy inference system", Iberoamerican Congress on Pattern Recognition, Springer, Berlin, Heidelberg, 2008.

[31] Andres Ferreyra and Jose de Jesus Rubio, "A new on-line self-constructing neural fuzzy network", Proceedings of the 45th IEEE Conference on Decision and Control, IEEE, 2006.

[32] Alexander Gegov, Complexity management in fuzzy systems, Vol. 711, Berlin, Germany, Springer, 2007.

[33] Keh-Shih Chuang et al., Fuzzy c-means clustering with spatial information for image segmentation, Computerized Medical Imaging and Graphics, 30 (2006) 9–15.

[34] K. R. Žalik, Fuzzy C-Means Clustering and Facility Location Problems, Artificial Intelligence and Soft Computing, 2006.

[35] Laurent Gallucc et al., Graph based k-means clustering, Signal Processing, Vol. 92, Issue 9, September 2012, pp. 1970-1984.

[36] Mehrabian, A. R. et al., Neuro-Fuzzy Modeling of Superheating System of a Steam Power Plant, Artificial Intelligence and Applications, February 13 – 16, 2006.

[37] M. Panella, A Hierarchical Procedure for the Synthesis of ANFIS Networks, Advances in Fuzzy Systems,Volume 2012.

[38] N. Kasabov, Qun Song. DENFIS: Dynamic Evolving Neural-Fuzzy Inference System and Its Application for Time-Series Prediction, IEEE Transactions on Fuzzy Systems, 10(2), April 2002.

[39] N. Kasabov, D. Filev. Evolving Intelligent Systems: Methods, Learning & Applications, International Symposium of Evolving Fuzzy Systems, September 2006.

[40] P. Angelov, Autonomous Learning Systems, Wiley, 2013.

[41] M. Terziyska, "A distributed adaptive neuro-fuzzy network for chaotic time series prediction." Cybernetics and Information technologies 15.1 (2015): 24-33.

[42] M. Terziyska, and Lyubka Doukovska, "Semi Fuzzy Neural Network. Part 1: Nonlinear System Identification", Advanced Control and Optimisation: Step Ahead (2014): 18.

[43] M. Terziyska, Y. Todorov and M. Olteanu, "Input space selective fuzzification in intuitionistic semi fuzzy-neural network", 2016 8th International Conference on Electronics, Computers and Artificial Intelligence (ECAI). IEEE, 2016.

[44] E. Uchino and T. Yamakawa, "System modeling by a neo-fuzzy-neuron with applications to acoustic and chaotic systems", International Journal on Artificial Intelligence Tools 4.01n02 (1995): 73-91.

[45] M. Terziyska, et al. "Multi-input Multi-output Neo-Fuzzy Neural Network for PM 10 and PM 2.5 Daily Concentrations Forecasting", 2019 Big Data, Knowledge and Control Systems Engineering (BdKCSE). IEEE, 2019.

[46] Y. Todorov, and M. Terziyska, "Modeling of chaotic time series by interval type-2 neo-fuzzy neural network", International Conference on Artificial Neural Networks. Springer, Cham, 2014.