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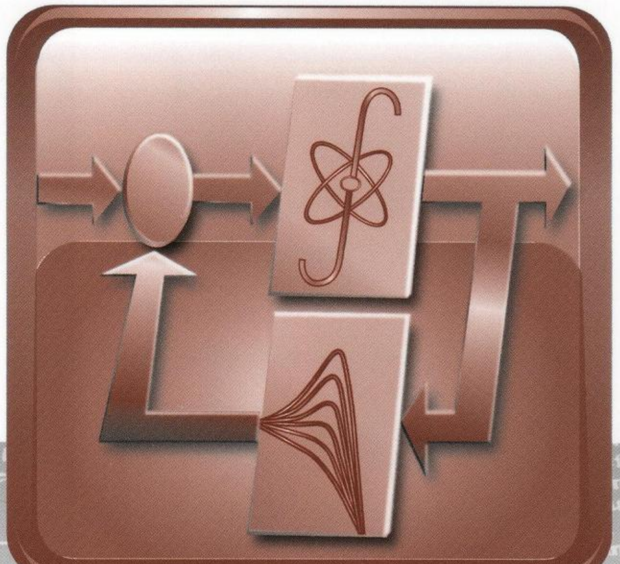

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Modeling of Dynamic Systems Using Orthogonal Endocrine Adaptive Neuro-Fuzzy Inference Systems

This paper presents a new method for designing adaptive neuro-fuzzy inference systems (ANFIS). Improvements are made by introducing specially developed orthogonal functions into the very structure of ANFIS, specifically, into the layer that imitates Sugeno stile defuzzification. These functions are specially tailored for analysis and synthesis of dynamic systems and they also contain an adaptive measure of the variability of the systems operating in a real environment, which can be implemented inside the ANFIS as hormonal effect. [DOI: 10.1115/1.4030758]

Keywords: ANFIS, orthogonal functions, endocrine networks, modeling of dynamic systems

1 Introduction

Hybrid intelligent systems have been the subject of intense study in the recent years [1,2]. They combine various intelligent technologies in order to outline their individual strengths and suppress drawbacks. Among the hybrid intelligent systems, important place belongs to the hybrid neuro-fuzzy systems, which are based on the natural synergy of neural networks and fuzzy logic [3]. The neural networks, on one side, have the ability to learn and adapt to the environmental conditions, and fuzzy logic, on the other, offers an understandable way of knowledge representation to the humans. The most popular systems of such are ANFIS, developed at end of the last century [4]. These systems are basically one type of neural networks, based on Takagi-Sugeno fuzzy inference, corresponding to a set of fuzzy IF-THEN rules.

The main idea behind this paper is to try with improving the classical, well-known ANFIS, by introducing a specially designed basis of quasi-orthogonal functions into the last layer of the neural network, instead of the usual Sugeno-style outputs of fuzzy rules (constant-singleton or linear). To this end, authors have developed generalized quasi-orthogonal functions specifically tailored to the purpose of the analysis and synthesis of dynamic systems, based on previous work in the field of orthogonal functions [5]. One more important advantage of these functions is that they can take

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into account the variations of the components of the real systems due to the changes in environmental conditions, which can conveniently be introduced in ANFIS as the hormonal effect. That effect is motivated by several up-to-date papers where appear so-called endocrine neural networks that have the ability to adapt to the environmental conditions [6]. These networks mimic the biological process of regulating the behavior of the system through hormone secretion from the gland cell associated to the artificial neural network. This principle of adding hormones can be applied to all kinds of regular neural networks [7,8] as well as ANFIS, as in this paper. The advantage of the method presented in this paper is that the system after completion of the training has the ability to adapt to ever changing conditions in which the system operates, based on the information obtained from the external sensors.

Designed improved ANFIS—orthogonal endocrine ANFIS (OEANFIS) was tested by a series of experiments on a laboratory modular servo drive, as a good candidate due to its built-in nonlinearities and dependence on working condition variations. New network has demonstrated improvement in the accuracy of the obtained model and the modeling time compared to the existing AutoRegressive model with eXogenous input (ARX) and classical ANFIS, of course, at the cost of more complex structure. Improved results originate from the very nature of orthogonal systems to approximate the real signals in optimal manner as well as from introduced measure of variations as result of changing conditions of the environment in which the system operates.

2 Generalized Orthogonal Polynomials

The authors of this paper have already explored some new types of orthogonal functions and their generalizations [5], suitable for the application in practical engineering [9], especially in the areas of modeling [10], and control of dynamic systems [11]. The advantage of orthogonal functions described in the earlier papers is that they were developed by using certain transformations in the complex domain, which makes them suitable for use in the analysis and synthesis of continuous systems. In this paper, we are taking a next step and demonstrate the process of generating generalized orthogonal polynomials specially designed for use in endocrine ANFIS. They contain an adaptive measure of the variability of the system while operating in a real environment, suitable for modeling by the hormonal effect. The extensive math behind these orthogonal functions and the logic of using these functions in analysis and synthesis of dynamical systems is given in cited papers, and here we will present only a short extract, necessary for building our own ANFIS.

Let us start with the classical definition of orthogonal polynomials with the form of $P_n(x)=\sum_{k=0}^{n} a_k x^k$ [12]. If we define the inner product of two polynomials of this set as

$$(P_m(x),P_n(x))=\int_a^b w(x)P_m(x)P_n(x)dx \qquad (1)$$

where $w(x)$ represents the weight function and a and b are the limits of orthogonality interval, then, polynomials are orthogonal if

$$(P_m(x),P_n(x))=\begin{cases}0, & m\neq n\\ N_n\neq 0, & m=n\end{cases} \qquad (2)$$

On the other side, if the following is valid:

$$(P_m(x),P_n(x))=\begin{cases}\varepsilon\approx 0, & m\neq n\\ N_n\neq 0, & m=n\end{cases} \qquad (3)$$

where ε is a constant very close to zero (but not equal to it), then we can talk about: "almost" or "near" orthogonal polynomials [10].

The relationship between classical and almost orthogonal polynomials [13] is given by the relation

$$P_n^{(\varepsilon)}(x)=P_n(x)+\sum_{k=1}^{n-1}\frac{b_k(\varepsilon)}{\|P_k\|^2}P_k(x) \qquad (4)$$

where $\|P_k\|^2$ is the square of the norm and b_k are polynomials of ε

$$b_{k+1}(\varepsilon)=b_k(\varepsilon)-\frac{b_k^2(\varepsilon)}{\|P_k\|^2},\quad b_0=\varepsilon \qquad (5)$$

If we now switch to more convenient constant for further development $\delta=1+\varepsilon\approx 1$ and apply the definition of almost orthogonality on, for instance, shifted Legendre polynomials (their definition is most convenient for our research because of their specific weight function $w(x)=1$ and interval of orthogonality (0,1) in their explicit form)

$$P_n(x)=\frac{1}{n!}\sum_{j=0}^{n}(-1)^{n-j}\binom{n}{j}\frac{(n+j)!}{j!}x^j \qquad (6)$$

we obtain the sequence of almost orthogonal Legendre polynomials

$$P_n^{(\delta)}(x)=\sum_{i=0}^{n}A_{n,i}^{\delta}x^i \qquad (7)$$

where

$$A_{n,i}^{\delta}=(-1)^{n+i}\frac{\Gamma(n\delta+i+1)}{\Gamma(n\delta+1)i!(n-i)!} \qquad (8)$$

and Γ is the symbol for the gamma function.

Final generalization of the concept of orthogonality can be introduced by the following definition of quasi-orthogonality for the polynomial set $P_n(x)$ [14]:

$$\left(P_n^k(x),P_m^k(x)\right)=\int_a^b w(x)P_n^k(x)P_m^k(x)dx =\begin{cases}0, & 0\le m\le n-k-1\\ N_{n,m}^k\neq 0, & n-k\le m\le n\end{cases} \qquad (9)$$

where k represents the order of quasi-orthogonality, a and b are the limits of quasi-orthogonality interval, and $w(x)$ is the weight function.

If we apply (9) on the almost orthogonal Legendre polynomials defined by Eqs. (7) and (8), we can obtain generalized quasi-orthogonal Legendre polynomials over interval (0, 1) with weight function $w(x)=1$

$$P_n^{(k,\delta)}(x)=\sum_{i=0}^{n}A_{n,i}^{k,\delta}x^i \qquad (10)$$

where

$$A_{n,i}^{(k,\delta)}=(-1)^{n+i+k}\frac{\prod_{j=1}^{n-k}(i+j\delta)}{i!(n-i)!} \qquad (11)$$

In Eq. (5), k is the order of quasi-orthogonality and δ is a constant very close to one ($\delta\approx 1$) [5].

For example, the first few first-order ($k=1$) generalized quasi-orthogonal Legendre polynomials of this sequence are

$$
\begin{aligned}
P_1^{(1,\delta)}(x) &= -x+1 \\
P_2^{(1,\delta)}(x) &= -\frac{(\delta+2)}{2}x^2+(\delta+1)x-\frac{\delta}{2} \\
P_3^{(1,\delta)}(x) &= -\frac{(\delta+3)(2\delta+3)}{6}x^3+(\delta+1)(\delta+2)x^2-\frac{(\delta+1)(2\delta+1)}{2}x+\frac{\delta^2}{3} \\
P_4^{(1,\delta)}(x) &= -\frac{(\delta+2)(\delta+4)(3\delta+4)}{12}x^4+\frac{(\delta+1)(\delta+3)(2\delta+3)}{2}x^3 \\
&\quad -\frac{(\delta+1)(\delta+2)(3\delta+2)}{2}x^2+\frac{(\delta+1)(2\delta+1)(3\delta+4)}{6}x-\frac{\delta^3}{4} \\
&\cdots
\end{aligned} \tag{12}
$$

After introducing substitution $x=e^{-t}$ to Eq. (4) and applying Laplace transform, we obtain kth order rational function in the form of transfer function, suitable for modeling continuous dynamical systems [15]

$$
W_n^{(k,\delta)}(s) = \frac{\prod_{i=1}^{n-k}(s-i\delta)}{\prod_{i=0}^{n}(s+i)} = \frac{(s-\delta)(s-2\delta)\cdots(s-(n-k)\delta)}{s(s+1)(s+2)\cdots(s+n)} \tag{13}
$$

Now, let us define the quasi-orthogonality via the following inner product:

$$
N_{nm}^{(k,\delta)} = \oint_C W_n^{(k,\delta)}(s)\bar{W}_m^{(k,\delta)}(s)w(s)ds \tag{14}
$$

with weight function $w(s)=1$, where $m>n$. By using transformation $\bar{s}=f(s)$ and the property of symmetry applied on Eq. (13)

$$
\bar{W}_m^{(k,\delta)}(s) = \frac{\prod_{i=1}^{m-k}(s+i\delta)}{\prod_{i=0}^{m}(s-i)} = \frac{(s+\delta)(s+2\delta)\cdots(s+(m-k)\delta)}{s(s-1)(s-2)\cdots(s-m)} \tag{15}
$$

After applying Cauchy theorem for solving contour integral in Eq. (14)

$$
N_{nm}^{(k,\delta)} = 2\pi j\sum_{r=1}^{m-k}\mathrm{Res}\left[W_n^{(k,\delta)}(s)\bar{W}_m^{(k,\delta)}(s)\right] \tag{16}
$$

With inclusion of regulation factor δ, we can get a better representation of the real systems model. This factor can define measure of the variability of the given system in working conditions of a real environment suitable for the modeling via the introduced hormonal effect into ANFIS.

3 OEANFIS

Classic ANFIS is basically a neural network that mimics Sugeno fuzzy model where the set of fuzzy rules is being generated based on a given set of inputs and outputs of the system. Typically, Sugeno fuzzy rule has the following form:

$$
\begin{aligned}
&\text{IF } x_1 \text{ is } A_1 \\
&\text{AND } x_2 \text{ is } A_2 \\
&\vdots \\
&\text{AND } x_n \text{ is } A_n \\
&\text{THEN } y = f(x_1, x_2, \ldots, x_n)
\end{aligned} \tag{17}
$$

where x_1, x_2,..., x_n are input variables, A_1, A_2,..., A_n are fuzzy sets, and y is either a constant or linear function of input variables. In the case of y being constant, we have a zero-order Sugeno fuzzy model in which the effects of fuzzy rules are defined by singletons—fuzzy sets with a membership function equal to unity at one point of the universe of discourse and zero everywhere else.

ANFIS is usually feed-forward neural network consisting of five layers (Fig. 1) [16]. External input signals are passed first to the fuzzification layer, and, in experiments in this paper, we used simple bell activation functions specified as

$$
y_i = \frac{1}{1+\left(\frac{x_i-a_i}{c_i}\right)^{2b_i}} \tag{18}
$$

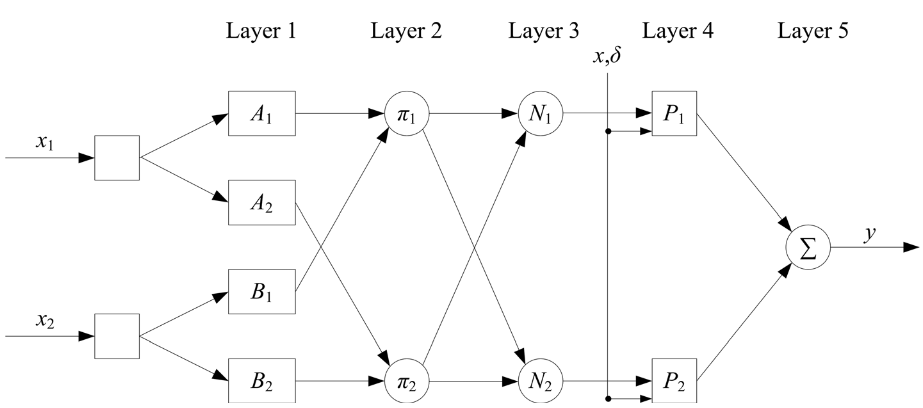

Fig. 1 The structure of OEANFIS with two inputs

where x_i is the input and y_i the output of neuron i in layer 1, and a_i, b_i, and c_i are the parameters of the bell-shaped activation function for that neuron.

Each neuron in the second (rule) layer corresponds to the single Sugeno-type fuzzy rule and has the function to calculate the firing strength of the rule it represents, based on inputs from corresponding fuzzification neurons. Conjunction of rule antecedents is usually performed by product operator. Normalized firing strength of a given rule (representing the contribution of a given rule to the final result) is calculated by the neurons in third (normalization) layer, based on the inputs from all the neurons in the rule layer.

Next layer is defuzzification layer where each neuron calculates the weighted consequent value of a given rule as constant or linear combination of system inputs. This layer is the focal point of this paper. Main idea is to replace singleton functions in neurons of this layer by orthogonal functions described by Eqs. (10) and (11), as the orthogonal basis specially designed for modeling dynamical systems should provide better approximation with lower training time (only one parameter to be trained instead of several). The second change in the regular ANFIS structure is the introduction of adaptive factor to the neurons of the fourth layer. As already mentioned, there are several papers published in last few years dealing with introduction of endocrine component to the neural systems. Idea is to mimic the process from the nature where the behavior of the neurons is regulated by hormones secreted by glands of endocrine system. In contrast to these papers [6–8] where hormones are usually used to modify weights of neurons in artificial neural networks, based on external conditions, idea of this paper is to introduce these stimuli directly to the neurons of fourth layer, via parameter δ in Eq. (11), as reaction to the variations of nominal components of dynamical system under effect of changed working conditions, determined by sensors.

Fifth and the final layer has a single summation neuron that calculates the sum of outputs of all defuzzification neurons in order to produce the overall ANFIS output. So, the whole neural network structure actually mimics the functionality of Sugeno fuzzy model with one important advantage—ANFIS has the ability to learn the parameters and tune membership functions by itself during the training process. Suggested default learning algorithm for training FIS membership function parameters to emulate a given training data set is a combination of least-squares estimator and gradient descent method [4]. In the training algorithm, each epoch has a forward pass and a backward pass. During the forward pass, input vector is presented to the ANFIS and neuron outputs are calculated layer-by-layer. During backward pass, the backpropagation algorithm is applied. Errors are being propagated back and antecedent parameters are updated according to training rules. Default training algorithm [17] implies optimization of both sets of parameters, consequent in forward and antecedent in backward pass. The ability of ANFIS to generalize and converge rapidly is very important in online learning and numerous applications, especially in adaptive control [18].

4 Modeling Servo System Using OEANFIS

Modular servo drive shown in Fig. 2 was considered as case study for modeling of dynamic systems using OEANFIS. This servo system [19,20], beside hardware, includes open-architecture software that extends the MATLAB environment for real-time control experiments. The servo system setup consists of several modules (direct current motor, brass inertia, backlash, encoder, magnetic brake, gearbox with the output disk, tachogenerator, and potentiometer) arranged in the chain, mounted at the metal rail and coupled with the small clutches. The rotation angle of the shaft is measured via incremental encoder. RTDAC/USB acquisition board with A/D converters is used for all the measurements whereby all the functions of the board can be accessed from the Modular Servo Toolbox, part of the MATLAB/SIMULINK environment. There are a few incorporated nonlinearities (saturation, hysteresis) inside the servo drive, emerging from elements like

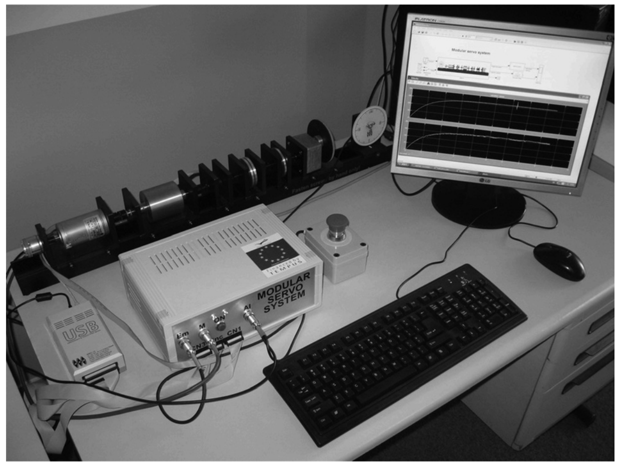

Fig. 2 The modular servo system setup

backlash, amplifiers, and actuators. It should be also considered that parameters of the servo drive, while operating in the real-world conditions, depend on the various environment factors like temperature, moisture, presence of the nearby fields. In this paper, we will consider only variations in nominal value of components based on changes in temperature, detected by temperature sensors.

In order to validate the proposed structure of OEANFIS, we conducted a series of experiments of modeling described servo drive and compared the results with those obtained by using default ARX and ANFIS neural network. As training sets, we used data for input (applied voltage) and output (angular velocity) for 180 s given in Fig. 3. Applied input voltage was changed randomly every 4 s, between −1.5 V and 1.5 V. Input and output signals were sampled every 10 ms, so resulting vectors had 18,000 samples each. First half was used as training and second as checking data.

ARX [21] assumes a linear system model of the form

$$y(k) + a_1 y(k-1) + \cdots + a_m y(k-m) = b_1 u(k-d) + \cdots + b_n u(k-d-n+1) \tag{19}$$

where ARX structure is specified by three preset parameters [m, n, d] and, on the other side, a_i ($i = 1$ to m) and b_j ($j = 1$ to n), as the parameters to be determined. In order not to make to complex and computationally demanding models, we have chosen for all our models to use the last three samples of input signal and two last samples of output signal, meaning [m, n, d] = [2, 3, 0]. Best set of parameters a_i and b_j was obtained by using MATLAB built in function "arx" that automatically determines best parameters a_i and b_j based on least-squares method.

The ARX model, as a basically linear model, has important advantage that it can perform fast identification of the model structure and parameter values. However, if a better modeling accuracy is desired, we should use some nonlinear model like ANFIS.

ANFIS model was made by using MATLAB embedded function "genfis1" with effect of generating an initial Sugeno-type fuzzy inference system for ANFIS training using a grid partition. This function has the following syntax with four input arguments: genfis1 (data, nummfs, inputmf, outputmf), where "data" represents set of input and output vectors, "nummfs" is the number of membership functions per neural network input (we kept the default value of two membership functions per each of five inputs), "inputmf" represents the type of membership function for each input (we kept the default value—bell activation function described with (18)), and "outputmf"—output membership function type (we used constant functions). Training of the neural network was performed by using MATLAB function "anfis." That function uses a hybrid learning algorithm (combination of least-squares and backpropagation gradient descent methods) to

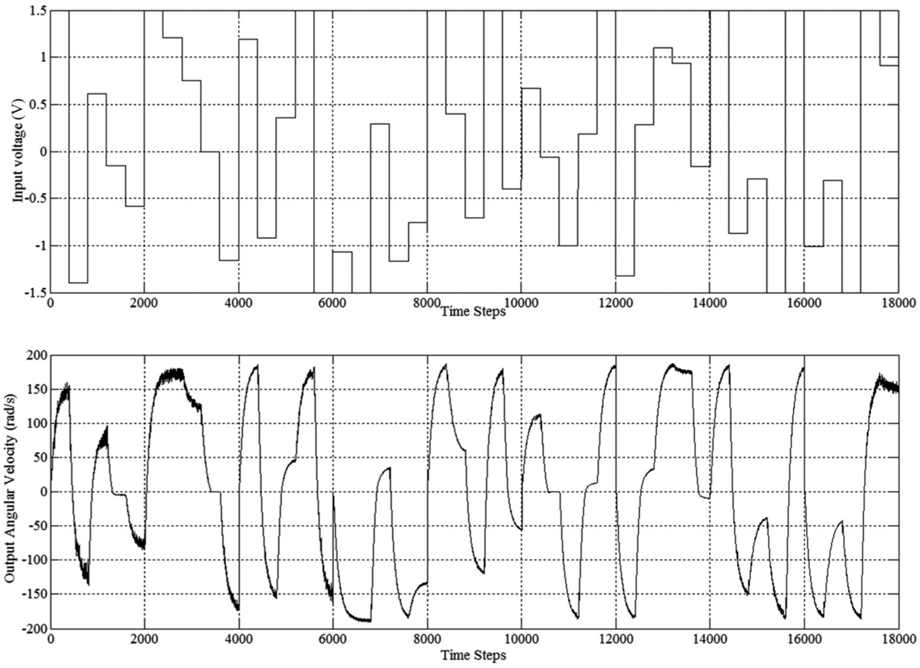

Fig. 3 Input and output training sets

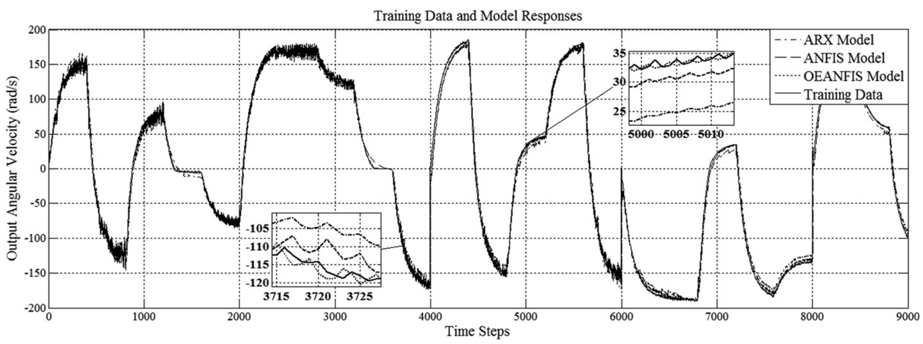

Fig. 4 Training data and model responses

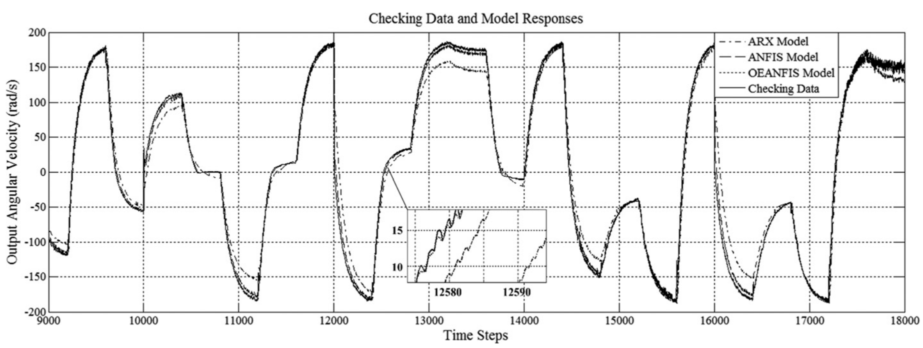

Fig. 5 Checking data and model responses

identify (train) the membership function parameters to model a given set of input/output data (first 9000 samples for our experiment).

OEANFIS used in experiment had a completely equal structure to the default ANFIS, except implemented orthogonal membership functions in the neurons of the fourth layer instead of singletons, and introduced δ obtained from the sensors (in this case, temperature sensor) as the measure of environmental changes. δ was calculated in the real-time based on difference between normal (nominal) operating environmental conditions and real conditions, as parameter close to one (equal to one, for nominal values). We used four neurons in the fourth layer (i.e., first four orthogonal functions given in Eq. (12)) because we wanted to have the same conditions as in second experiment with regular ANFIS, and the training of ANFIS resulted in exactly four neurons of the output layer.

Sensed output signals and approximations obtained from three different models: ARX, ANFIS, and OEANFIS are given in Figs. 4 and 5. We can see that all three models follow training

Table 1 Comparative results for different models

Models	ARX	ANFIS	OEANFIS
Training RMSE	12.9092	4.1669	3.4272
Checking RMSE	18.6473	7.4531	4.7119
Computation time (s) (Intel—3.30 GHz, 8 GB RAM)	2.6668	17.1208	12.9306

data well (Fig. 4) but difference becomes noticeable with checking data set (Fig. 5). While OEANFIS response is practically overlapping with systems output, other two models fall behind in terms of modeling precision. Difference between three models can be best noticed from comparative results for all three modeling methods in terms of root-mean-squared error (RMSE) and needed computational time, given in Table 1.

The ARX modeling spends the least amount of time to reach the worst precision, and two models based on ANFIS take more time to reach the better precision. In other words, if fast modeling is the goal, then ARX model or some simple neural network is the right choice. But if precision is the utmost concern, then ANFIS is the right answer, because it is structurally designed for modeling dynamic systems and higher precision. By comparing two ANFIS models we can see improvement in precision when dealing with OEANFIS, coming from the natural property of orthogonal basis to approximate signals in optimal manner, opposed to the random distributed singleton functions. On the other hand, improvement in computational time comes from the need to train and adjust only one parameter to feed the orthogonal basis in fourth layer, off course, at the cost of higher model complexity. Another important advantage of using orthogonal functions described in this paper is that, knowing the coefficients (weights) of the orthogonal basis, we can easily obtain systems' model in the form of transfer function [10].

5 Conclusion

This paper presented a new method of modeling dynamic systems, based on the modification of existing, well-known ANFIS. ANFIS was chosen because, as a hybrid technique, it provides excellent synergy of fuzzy logic and neural networks. Fuzzy logic provides to this combination the possibility of representing knowledge in a way understandable to the humans, and neural network an opportunity for learning and adapting to the environmental conditions. The paper describes in detail the structure of ANFIS, layer by layer.

The main proposed modification of ANFIS consists in replacing the existing singleton or linear functions characteristic for the Sugeno-type fuzzy inference, implemented as a fourth layer of ANFIS, by orthogonal functions specifically tailored and adapted for the analysis and synthesis of continuous dynamic systems. Another advantage of these orthogonal functions is also reflected in the fact that they contain a built-in measure of imperfections of real systems that can be introduced into neural network by the mechanism of hormonal action that enables adaptability to ever changing environmental conditions in which the system operates.

The proposed new method of modeling dynamic systems has been tested through experiments with servo system. Modeling of the system was performed with the randomly generated input signal and sensed response of the system. Half of the obtained data was used as training set for the neural network, and half as verification data. The system was then modeled by three different methods: ARX, ANFIS, and modified ANFIS (OEANFIS), then the results were compared in terms of mean square error and the time required for the modeling process. The results confirmed the quality of the designed OEANFIS modeling method and showed that OEANFIS can be effectively used for modeling dynamic systems due to the better approximation power of orthogonal functions and introduced adaptive hormonal effect.

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