Intelligent Control of Aircraft Dynamic Systems with a New Hybrid Neuro-Fuzzy-Fractal Approach

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We describe in this chapter a hybrid method for adaptive model-based control of nonlinear dynamic systems using Neural Networks, Fuzzy Logic, and Fractal Theory. The new neuro-fuzzy-fractal method combines Soft Computing (SC) techniques with the concept of the fractal dimension for the domain of Nonlinear Dynamic System Control. The new method for adaptive model-based control has been implemented as a computer program to show that our neuro-fuzzy-fractal approach is a good alternative for controlling nonlinear dynamic systems. It is well known that chaotic and unstable behavior may occur for nonlinear systems. Normally, we will need to control this type of behavior to avoid structural problems with the system. We illustrate in this chapter our new methodology in the case of controlling aircraft dynamic systems. For this case, we use mathematical models for the simulation of aircraft dynamics during flight. The goal of constructing these models is to capture the dynamics of the aircraft, so as to have a way of controlling these dynamics to avoid dangerous behavior of the aircraft dynamic system.

1 INTRODUCTION

We describe in this chapter a new method for adaptive control of nonlinear dynamic systems based on the use of Neural Networks, Fuzzy Logic, and Fractal Theory. The dynamics of real-world systems are often highly nonlinear and difficult to control [4]. The problem of controlling them using conventional controllers has been widely studied [1]. Much of the complexity in controlling any process comes from the complexity of the process being controlled. This complexity can be described in several ways. Highly nonlinear systems are difficult to control, particularly when they have complex dynamics (such as instabilities to limit cycles and chaos [12]). Difficulties can often be presented by constraints, either on the control parameters or in the operating regime. Lack of exact knowledge of the process, of course, makes control more difficult. Optimal control of many processes also requires systems that make use of predictions of future behavior. The mathematical models for the dynamic systems are assumed to be differential equations. The goal of having these models is to capture the dynamics of nonlinear processes, so as to have a way of controlling these dynamics for industrial purpose [7].
We need a mathematical model of the nonlinear dynamic system to understand the dynamics of the processes involved in the evolution of the system. For a specific case, this may require testing several models before obtaining the appropriate mathematical model for the process [9]. For real-world systems with complex dynamics, we may even need several models for different sets of parameter values to represent all of the possible behaviors of the system. A general mathematical model of a dynamic system can be expressed as follows:

\[ \frac{dx}{dt} = f_1(x, D, \alpha) - \beta f_2(x, D, \alpha) \]

\[ \frac{dp}{dt} = \beta f_2(x, D, \alpha) \]

where \( x \in \mathbb{R}^n \) is a vector of state variables, \( p \in \mathbb{R}^m \) is a vector of outputs, \( \beta \in \mathbb{R} \) is a constant measuring the efficiency of the conversion process, \( D \in (0, 3) \) is the fractal dimension of the process, and \( \alpha \in \mathbb{R} \) is a selection parameter. The fractal dimension is used to characterize the process, for example, in the case of biochemical reactors \( D \) represents the fractal dimension of the bacteria used for production [2, 9].

For a complex dynamical system it may be necessary to consider a set of mathematical models to represent adequately all possible dynamic behaviors of the system. In this case, we need a decision scheme to select the appropriate model to use according to the linguistic value of a selection parameter \( \alpha \). We use a new fuzzy inference system for differential equations to achieve fuzzy modeling [3]. We have fuzzy rules of the form:

\[ \text{IF } \alpha \text{ is } A_1 \text{ AND } D \text{ is } B_1 \text{ THEN } M_1 \]

\[ \text{...} \]

\[ \text{IF } \alpha \text{ is } A_n \text{ AND } D \text{ is } B_n \text{ THEN } M_n \]

where \( A_1, ..., A_n \) are linguistic values for \( \alpha \), \( B_1, ..., B_n \) are linguistic values for the fractal dimension \( D \), and \( M_1, ..., M_n \) are mathematical models of the form given by Eq. (1). The selection parameter \( \alpha \) can be the temperature for biochemical processes, because temperature changes cause the presence of new bacteria in this case [9]. For the case of aircraft dynamic systems, \( \alpha \) can be related to environment parameters.

We combine adaptive model-based control using neural networks with the method for modeling using fuzzy logic and fractal theory, to obtain a new hybrid neuro-fuzzy-fractal method for control of nonlinear dynamic systems. This general method combines the advantages of neural networks (ability for identification and control) with the advantages of fuzzy logic (ability for decision and use of expert knowledge) to achieve the goal of robust adaptive control of nonlinear dynamic systems. We also use the fractal dimension to characterize the processes in modeling these dynamical systems. We have developed intelligent control systems using this new method for adaptive control for several applications, to validate our new approach for control. We have obtained very good results in controlling biochemical reactors and chemical reactors with the hybrid approach for control [8]. In this chapter, we describe the application of our new method to the case of controlling aircraft dynamic systems.

2 FUZZY MODELING OF DYNAMICAL SYSTEMS

For a real-world dynamical system it may be necessary to consider a set of mathematical models to represent adequately all of the possible dynamic behaviors of the system [8, 9].

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In this case, we need a fuzzy [15] decision procedure to select the appropriate model to use according to the value of a selection parameter vector \( \alpha \). To implement this decision procedure, we need a fuzzy inference system that can use differential equations as consequents. For this purpose, we have developed a new fuzzy inference system that can be considered as a generalization of Sugeno’s inference system [13, 14], in which we are now using differential equations as consequents of the fuzzy rules, instead of simple polynomials like in the original Sugeno’s method. Using this method, a fuzzy model for a general dynamical system can be expressed as follows:

\[
\text{IF } \alpha_1 \text{ is } A_{11} \text{ AND } \alpha_2 \text{ is } A_{12} \ldots \text{ AND } \alpha_m \text{ is } A_{1m} \text{ THEN } \frac{dy}{dt} = f_1(y, \alpha) \\
\text{IF } \alpha_1 \text{ is } A_{21} \text{ AND } \alpha_2 \text{ is } A_{22} \ldots \text{ AND } \alpha_m \text{ is } A_{2m} \text{ THEN } \frac{dy}{dt} = f_2(y, \alpha) \\
\ldots \\
\text{IF } \alpha_1 \text{ is } A_{n1} \text{ AND } \alpha_2 \text{ is } A_{n2} \ldots \text{ AND } \alpha_m \text{ is } A_{nm} \text{ THEN } \frac{dy}{dt} = f_n(y, \alpha)
\]

(3)

where \( A_{ij} \) is the linguistic value of \( \alpha_j \) for rule \( i \)th, \( \alpha \in R^m \) and is defined by \( \alpha = [\alpha_1, \ldots, \alpha_m] \), and \( y \in R^p \) is the output obtained by the numerical solution of the corresponding differential equation. Of course, it is assumed that each differential equation in (3) locally approximates the real dynamical system over a neighborhood (or region) of \( R^m \).

The numerical solution of the differential equations can be achieved by the standard Runge–Kutta type method:

\[
y_{n+1} = RK(y_n) + 1/2(k_1 + k_2) \\
k_1 = hf(y_n, t_n) \\
k_2 = hf(y_n + k_1, t_n+1),
\]

where \( h \) is the step size of the method and \( RK \) can be considered as the Runge–Kutta operator that transforms numerical solutions from time \( n \) to time \( n+1 \). Numerical solutions are then aggregated by weighted average with weights obtained by the minimum of the firing strengths of the inputs:

\[
y = \frac{w_1y_1 + w_2y_2 + \ldots + w_ny_n}{w_1 + w_2 + \ldots + w_n}
\]

(5)

where: \( y_1 = RK(f_1(y, \alpha)) \), \( y_2 = RK(f_2(y, \alpha)) \), \ldots, \( y_n = RK(f_n(y, \alpha)) \).

The new fuzzy inference system for differential equations can be illustrated as in Fig. 1, where a complex dynamical system is modeled by using four different mathematical models (\( M_1, M_2, M_3, \) and \( M_4 \)). The decision scheme can be expressed as a single-input fuzzy model as follows:

\[
\text{IF } \alpha \text{ is small THEN } \frac{dy}{dt} = f_1(y, \alpha) \\
\text{IF } \alpha \text{ is regular THEN } \frac{dy}{dt} = f_1(y, \alpha) \\
\text{IF } \alpha \text{ is medium THEN } \frac{dy}{dt} = f_1(y, \alpha) \\
\text{IF } \alpha \text{ is large THEN } \frac{dy}{dt} = f_1(y, \alpha)
\]

(6)

where the output \( y \) is obtained by the numerical solution of the corresponding differential equation.

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Figure 1 Modeling a complex dynamical system with the new fuzzy system.

3 NEURAL NETWORKS FOR CONTROL

Parametric Adaptive Control is the problem of controlling the output of a system with a known structure but unknown parameters. These parameters can be considered as the elements of a vector $p$. If $p$ is known, the parameter vector $\theta$ of a controller can be chosen as $\theta^*$ so that the plant together with the fixed controller behaves like a reference model described by a difference (or differential) equation with constant coefficients [11]. If $p$ is unknown, the vector $\theta(t)$ has to be adjusted on-line using all the available information concerning the system.

Two distinct approaches to the adaptive control of an unknown system are (i) direct control and (ii) indirect control. In direct control, the parameters of the controller are directly adjusted to reduce some norm of the output error. In indirect control, the parameters of the system are estimated as $p(t)$ at any time instant and the parameter vector $\theta(t)$ of the controller is chosen assuming that $p(t)$ represents the true value of the system parameter vector.

When indirect control is used to control a nonlinear system, the plant is parameterized using a mathematical model of the general form described in Section 1 and the parameters of the model are updated using the identification error. The controller parameters in turn are adjusted by backpropagating the error (between the identified model and the reference model outputs) through the identified model. A block diagram of such an adaptive system is shown in Fig. 2.

The overall structure of the adaptive system proposed in this paper to control a nonlinear dynamical system is the same as shown in Fig. 2 and is independent of the specific model used to identify the system. The delayed values of the system input and system output form the inputs to the neural network $N_c$, which generates the feedback control signal to the system. The parameters of the Neural Network $N_i$ are adjusted by backpropagating the identification error $e_i$ while those of the Neural Network $N_c$ are adjusted by backpropagating the control error (between the output of the reference model and the identification model) through the identification model.

The mathematical model for the nonlinear dynamic system in the time domain is generated by the method of modeling (described in Section 2) using the real data that is measured on-line in the system. On the other hand, the fractal module is used to charac-
General architecture for adaptive neuro-fuzzy-fractal control.

Figure 2 General architecture for adaptive neuro-fuzzy-fractal control.

terize the process and this information is used to specify the mathematical model in the
time and space domain. This scheme enables dynamic changes of models according to the
changes of on-line process identification. Our new method for adaptive model-based con-
trol combining Neural Networks, Fuzzy Logic and Fractal Theory differs from our previous
approach of considering only the use of neural networks and models [5, 6].

4 ADAPTIVE CONTROL OF AIRCRAFT SYSTEMS

The mathematical models of aircraft systems can be represented as coupled nonlinear dif-
fferential equations [10]. In this case, we can develop a fuzzy rule base for modeling that
enables the use of the appropriate mathematical model according to the changing condi-
tions of the aircraft and its environment. For example, we can use the following model of
an airplane when wind velocity is relatively small:

\[
p' = I_1(-q + l), \quad q' = I_2(p + m),
\]

where \( I_1 \) and \( I_2 \) are the inertia moments of the airplane with respect to axis \( x \) and \( y \), re-
spectively, \( l \) and \( m \) are physical constants specific to the airplane, and \( p, q \) are the positions
with respect to axis \( x \) and \( y \), respectively. However, a more realistic model of an airplane
in three-dimensional space is as follows:

\[
p' = I_1(-qr + l), \quad q' = I_2(pr + m), \quad r' = I_3(-pq + n),
\]

where now \( I_3 \) is the inertia moment of the airplane with respect to the \( z \) axis, \( n \) is a physical
constant specific to the airplane, and \( r \) is the position along the \( z \) axis. Now considering
wind disturbances in the model, we have the following equation:

\[
p' = I_1(-qr + l) - u_g, \quad q' = I_2(pr + m), \quad r' = I_3(-pq + n),
\]

where \( u_g \) is the wind velocity. The magnitude of wind velocity is dependent on the altitude
of the airplane in the following form:

\[
u_g = u_{wind510} \left(1 + \frac{\ln(h/510)}{\ln(51)}\right),
\]

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Table 1 Fuzzy rule base for modeling aircraft dynamic systems

<table>
<thead>
<tr>
<th>Wind velocity</th>
<th>Inertia moment</th>
<th>Fractal dimension</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small</td>
<td>Small</td>
<td>Low</td>
<td>$M_1$</td>
</tr>
<tr>
<td>Small</td>
<td>Small</td>
<td>Medium</td>
<td>$M_2$</td>
</tr>
<tr>
<td>Small</td>
<td>Large</td>
<td>Low</td>
<td>$M_2$</td>
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<tr>
<td>Small</td>
<td>Large</td>
<td>Medium</td>
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<tr>
<td>Large</td>
<td>Small</td>
<td>Medium</td>
<td>$M_3$</td>
</tr>
<tr>
<td>Large</td>
<td>Large</td>
<td>Medium</td>
<td>$M_3$</td>
</tr>
<tr>
<td>Large</td>
<td>Large</td>
<td>High</td>
<td>$M_3$</td>
</tr>
</tbody>
</table>

where $u_{wind510}$ is the wind speed at 510 ft altitude (typical value = 20 ft/sec).

If we use the models of Eqs. (7)–(9) for describing aircraft dynamics, we can formulate a set of rules that relate the models to the conditions of the aircraft and its environment. Let us assume that $M_1$ is given by Eq. (7), $M_2$ is given by Eq. (8), and $M_3$ is given by Eq. (9). Now using the wind velocity $u_g$ and inertia moment $I_1$ as parameters, we can establish the fuzzy rule base for modeling as in Table 1.

In Table 1, we are assuming that the wind velocity $u_g$ can have only two possible fuzzy values (small and large). This is sufficient to know if we have to use the mathematical model that takes into account the effect of wind ($M_3$) for $u_g$ large or if we don’t need to use it and simply the model $M_2$ is sufficient (for $u_g$ small). Also, the inertia moment ($I_1$) helps in deciding between models $M_1$ and $M_2$ (or $M_3$).

5 EXPERIMENTAL RESULTS

To give an idea of the performance of our neuro-fuzzy-fractal approach for adaptive control, we show below simulation results for aircraft dynamic systems. First, we show in Fig. 3(a) the fuzzy rule base for a prototype intelligent system developed in the fuzzy logic toolbox of the MATLAB programming language. We show in Fig. 3(b) the nonlinear surface for the problem of aircraft dynamics using fractal dimension and wind velocity as input variables.

We show simulation results for an aircraft system obtained using our new method for modeling dynamical systems. In Figs. 4(a) and 4(b) we show results for an airplane with inertia moments: $I_1 = 1$, $I_2 = 0.4$, $I_3 = 0.05$ and the constants are: $l = m = n = 1$. The initial conditions are: $p(0) = 0$, $q(0) = 0$, $r(0) = 0$.

To give an idea of the performance of our neuro-fuzzy approach for adaptive model-based control of aircraft dynamics, we show below (Fig. 5) simulation results obtained for the case of controlling the altitude of an airplane for a flight of 6 hours. We assume that the airplane takes about one hour to achieve the cruising altitude 30,000 ft, then cruises along for about three hours at this altitude (with minor fluctuations), and finally descends for about two hours to its final landing point. We will consider the desired trajectory as
follows:

\[ h_d = \begin{cases} 
30t + \sin 2t & \text{for } 0 \leq t \leq 1 \\
30 + 2\sin 10t & \text{for } 1 < t \leq 4 \\
90 - 15t & \text{for } 4 < t \leq 6.
\end{cases} \]

Of course, a complete desired trajectory for the airplane would have to include the positions for the airplane in the \( x \) and \( y \) directions. However we think that here for illustration purposes it is sufficient to show the control of the altitude \( h \) for the airplane.

We used three-layer neural networks (with 10 hidden neurons) with the Levenberg–Marquardt algorithm and hyperbolic tangent sigmoidal functions as the activation functions for the neurons. We show in Fig. 5 the function approximation achieved by the neural network for control after 800 epochs of training with a variable learning rate. The identification achieved by the neural network (after 800 epochs) can be considered very good because the error has been decreased to the order of \( 10^{-1} \). Still, we can obtain a better approximation by using more hidden neurons or more layers. In any case, we can see clearly (from Fig. 5) how the neural network learns to control the aircraft, because it is able to
follow the arbitrary desired trajectory.

We have to mention here that these simulation experiments for the case of a specific flight for a given airplane show very good results. We have also tried our approach for control with other types of flights and airplanes with good results.

6 CONCLUSIONS

We have developed a general method for adaptive model-based control of nonlinear dynamic systems using Neural Networks, Fuzzy Logic, and Fractal Theory. We illustrated our method for control by the case of controlling aircraft dynamics. In this case the models represent the aircraft dynamics during flight. We also described in this chapter an adaptive controller based on the use of neural networks and mathematical models for the system. The proposed adaptive controller performs rather well considering the complexity of the domain being considered in this research work. We have shown that our method can be used to control chaotic and unstable behavior in aircraft systems. Chaotic behavior has been associated with the “flutter” effect in real airplanes, and for this reason it is very important to avoid this kind of behavior. We can say that combining Neural Networks, Fuzzy Logic, and Fractal Theory, using the advantages that each of these methodologies has, can give good results for this kind of application. Also, we believe that our neuro-fuzzy-fractal approach is a good alternative for solving similar problems.

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