Dynamic Non-Singleton Fuzzy Logic Systems for Nonlinear Modeling

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***Abstract*—We investigate dynamic versions of fuzzy logic systems (FLS's) and, specifically, their non-Singleton generalizations (NSFLS's), and derive a dynamic learning algorithm to train the system parameters. The history-sensitive output of the dynamic systems gives them a significant advantage over static systems in modeling processes of unknown order. This is illustrated through an example in nonlinear dynamic system identification. Since dynamic NSFLS's can be considered to belong to the family of general nonlinear autoregressive moving average (NARMA) models, they are capable of parsimoniously modeling NARMA processes. We study the performance of both dynamic and static FLS's in the predictive modeling of a NARMA process.**

***Index Terms*—Dynamic NSFLS, NARMA, nonlinear modeling.**

I. Introduction

PROMPTED BY the desire to bridge the gap between traditional mathematical models of physical processes and the often abstract, or imprecise information associated with such processes, researchers in recent years have started paying particular attention to fuzzy set theory [29], a mathematical tool for translating abstract concepts into computable entities [4]. In this paper, we present computational systems capable of processing such entities.

In Section II, we give a brief overview of non-Singleton fuzzy logic systems (NSFLS's) [14], [15] that are an extension of the well-known Singleton fuzzy logic systems [9], [25]. These systems implement static nonlinear mappings between their input and output spaces. Here, we extend these systems to their dynamic feedback counterparts. The output of dynamic systems at time $t+1$ depends on exogenous inputs as well as previous outputs at time t so these systems exhibit rich and complex dynamical behavior and can be used to parsimoneously represent dynamic processes of unknown order and structure. Unlike static fuzzy logic systems (FLS's), processing of input patterns by dynamic FLS's depends upon the order of presentation during training or recall; therefore, dynamic FLS's are well suited for the representation and processing of temporal information.

In Section III we derive a dynamic backpropagation type of learning algorithm to update the parameters of a dynamic non-Singleton fuzzy logic system. Although it was a long time after its inception (see [26]) that attention was drawn to backpropagation learning, its utility as a universal learning paradigm for smooth parameterized models (including FLS's) [8], [15], [23] became evident with its successful application to artificial neural networks [17]. Being able to utilize a learning algorithm such as backpropagation implies that a FLS with linguistic information in its rulebase can be updated or adapted using numerical information to gain an even greater advantage over a neural network that cannot make direct use of linguistic information. The collection of modifiable IF-THEN rules comprising the rulebase, constitute an adaptive FLS, i.e., a system whose input–output behavior is defined by a set of modifiable parameters. The systems we describe in this paper belong to the family of adaptive FLS's.

In Section IV we give examples in system identification and the predictive modeling of a nonlinear autoregressive moving average process. These examples illustrate the power of both the dynamic FLS's, and the dynamic learning algorithm.

Section V concludes this paper.

II. Overview of Non-Singleton Fuzzy Logic Systems

The large variety of possible available information, together with the need for modeling all such information to determine a particular solution, necessitate the use of a very flexible information modeling technique. With this in mind, the formulation that provides the highest degree of latitude is a list of statements (rules) where each statement indicates the acceptability of a proposed solution based on some piece of information. The fuzzy formalism can provide a general framework to model certain or uncertain information in which an action is combined with a statement in an antecedent/consequent format and the individual statement solutions are aggregated to provide the overall solution. The set of statements comprise the *fuzzy rule base*, which is a vital part of a FLS (Fig. 1). The *fuzzy inference engine* combines the statements in the rule base according to approximate reasoning theory to produce a mapping from fuzzy sets in the input space U to fuzzy sets in the output space V. The *fuzzifier* maps crisp inputs to fuzzy sets defined on the input space and the *defuzzifier* maps the aggregated output fuzzy sets to a single crisp point in the output space.

A fuzzy logic system processes crisp data at the input and produces crisp data at the output; therefore, a fuzzifier is used at the front of the system to convert crisp data to fuzzy data and a defuzzifier is used at the output of the system to convert fuzzy data into crisp data. The most widely used fuzzifier is the Singleton fuzzifier [9], [10], [25], mainly because of its simplicity and lower computational requirements; however,

Manuscript received December 20, 1995; revised September 5, 1996. This work was supported by the University of Southern California, Los Angeles, National Science Foundation under Grant MIP-9 122 018.

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Publisher Item Identifier S 1063-6706(97)02843-9.

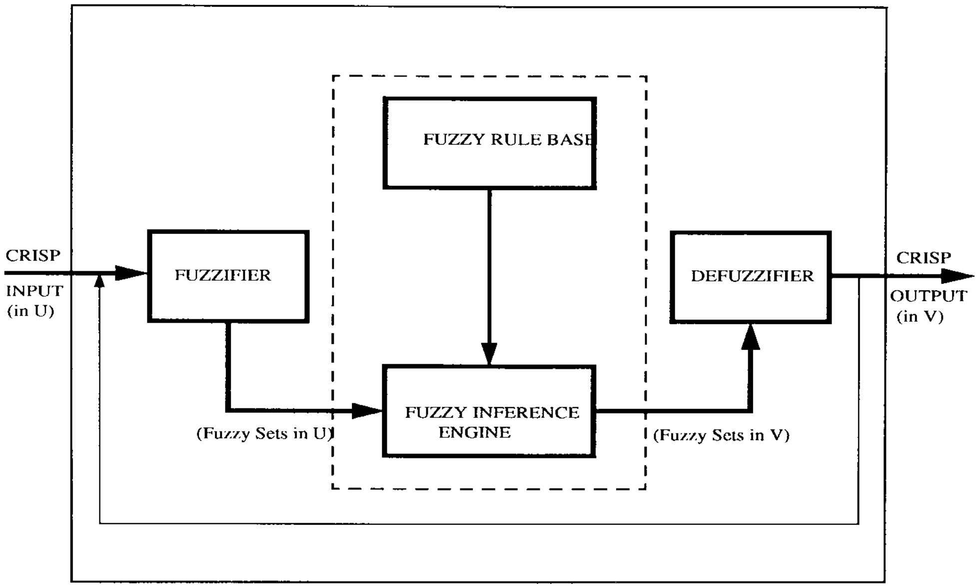


Fig. 1. Structure of a fuzzy logic system.

this kind of fuzzifier may not always be adequate, especially in cases where noise is present in the training data or in the data which is later processed by the system. A different approach is necessary to account for uncertainty in the data, which is why we direct our attention at NSFLS's. NSFLS's are a family of systems that have *non-Singleton* fuzzy sets as inputs. The structure of the rulebase is identical as in the Singleton FLS case, except that input linguistic variables are allowed to take set values (instead of single-point values). NSFLS's are a powerful generalization of Singleton FLS's and provide a mathematically tractable method to treat input uncertainty.

Non-Singleton fuzzifiers have been used successfully in a variety of applications [1], [5], [16], [19], [20], [22]. In neural-fuzzy systems [1], [5], vectors of fuzzy sets are used both to train a fuzzy neural network and as inputs during processing. In [16], an optimizing control method for optimizing the fuel consumption rate of a marine diesel engine utilizes empirical rules that are expressed by fuzzy numbers. Non-Singleton input has also been used in turning process automation [20] to represent a human operator's actions in the fuzzy rule base, in the design of fuzzy control algorithms [19], and in fuzzy information and decision-making [22]. These methods are largely heuristic and provide no closed-form expressions for fuzzy logic systems; hence, their generalizations are very difficult.

A. The Non-Singleton Fuzzifier

Fuzzy sets have been interpreted as membership functions μ_X [29] that associate with each element x of the universe of discourse, U, a number $\mu_X(x)$ in the interval [0, 1]:

$$\mu_X : U \to [0,1]. \tag{1}$$

A fuzzifier maps a crisp point $x \in U$ into a fuzzy set $X \in U$.

1) In the case of a *Singleton fuzzifier*, the crisp point $x \in U$ is mapped into a fuzzy set X with support x_i where $\mu_X(x_i) = 1$ for $x_i = x$ and $\mu_X(x_i) = 0$ for $x_i \neq x$, i.e., the *single* point in the support of X with nonzero membership function value is $x_i = x$.

2) In the case of a *non-Singleton fuzzifier*, the point $x \in U$ is mapped into a fuzzy set X with support x_i where μ_X achieves maximum value at $x_i = x$ and decreases while moving away from $x_i = x$. We assume that fuzzy set X is normalized so that $\mu_X(x) = 1$.

Non-Singleton fuzzification is especially useful in cases where the available training data or the input data to the fuzzy logic system are corrupted by noise. Conceptually, the non-Singleton fuzzifier implies that the given input value x is the most likely value to be the correct one from all the values in its immediate neighborhood; however, because the input is corrupted by noise, neighboring points are also likely to be the correct values, but to a lesser degree.

It is up to the system designer to determine the shape of the membership function μ_X based on an estimate of the kind and quantity of noise or uncertainty present. It would be the logical choice, though, for the membership function to be symmetric about x since the effect of noise is most likely to be equivalent on all points. Examples of such membership functions are: 1) the Gaussian

$$\mu_X(x_i) = \exp\left[-\frac{(x - x_i)^2}{2\sigma^2}\right]$$

where the variance σ^2 reflects the width (spread) of $\mu_X(x_i)$; 2) triangular

$$\mu_X(x_i) = \max\left(0, 1 - \left|\frac{x - x_i}{c}\right|\right)$$

and 3)

$$\mu_X(x_i) = \frac{1}{\left(1 + \left|\frac{x - x_i}{c}\right|^p\right)}$$

where x and c are, respectively, the mean and spread of the fuzzy sets. Note that larger values of the spread of the above membership functions imply that more noise is anticipated to exist in the given data.

B. Dynamic Non-Singleton Fuzzy Logic System Formulation

Consider a fuzzy logic system with a rulebase of M rules, and let the lth rule be denoted by R^l. Let each rule have n antecedents and one consequent (as is well known, a rule with q consequents can be decomposed into q rules, each having the same antecedents and one different consequent); also, let $F_r^l, r = 1, 2, \cdots, n - n_f$ and $H_j^l, j = 1, 2, \cdots, n_f$ denote the antecedent membership functions corresponding to $n - n_f$ exogenous inputs and n_f feedback inputs, respectively. For example, in the case of a single-feedback input, $n_f = 1$ and the feedback input linguistic variable takes system output values delayed by one unit. The lth rule is of the general form

R^l: IF u_1 is F_1^l and $\cdots$ and u_{n-n_f} is $F_{n-n_f}^l$ and u_{n-n_f+1} is H_1^l and $\cdots$ and u_n is $H_{n_f}^l$

THEN v is G^l

where $u_k, k = 1, \cdots, n$, and v are the input and output linguistic variables, respectively. Each F_r^l, H_j^l, and G^l are subsets of possibly different universes of discourse. Let

$$
\begin{aligned}
&F_r^l \subset U_r, \qquad r = 1, 2, \cdots, n - n_f \\
&H_j^l \subset U_{n-n_f+j}, \qquad j = 1, 2, \cdots, n_f \quad \text{and} \\
&G^l \subset V.
\end{aligned}
$$

Since $u_{n-n_f+j}, j = 1, 2, \cdots, n_f$, are feedback input linguistic variables, they take values from universe of discourse V; thus, $U_{n-n_f+j} \equiv V, j = 1, 2, \cdots, n_f$ (to maintain consistent notation with the antecedent linguistic variables, we will use $U_k, k = 1, 2, \cdots, n$, to denote universes of discourse of both exogenous and feedback linguistic variables). Each rule can be viewed as a fuzzy relation R^l [30] from a set U to a set V, where U is the Cartesian product space $U = U_1 \times \cdots \times U_n$.$R^l$ itself is a subset of the Cartesian product $U \times V = \{(\boldsymbol{x}, y): \boldsymbol{x} \in U, y \in V\}$, where $\boldsymbol{x} \equiv (x_1, x_2, \cdots, x_n)$ and x_k and y are the points in the universes of discourse, U_k and V of u_k and v. R^l is characterized by a continuous multivariate membership function $\mu_{R^l}(\boldsymbol{x}, y)$, and can be described by the following:

$$
\begin{aligned}
R^l &\equiv \int_{U\times V} \mu_{R^l}(\boldsymbol{x}, y)/(\boldsymbol{x}, y) \\
&= \int_{U_1} \cdots \int_{U_{n-n_f}} \int_{U_{n-n_f+1}} \cdots \int_{U_n} \int_V \mu_{F_1^l}(x_1) \\
&\quad * \cdots * \mu_{F_{n-n_f}^l}(x_{n-n_f}) * \mu_{H_1^l}(x_{n-n_f+1}) \\
&\quad * \cdots * \mu_{H_{n_f}^l}(x_n) * \mu_{G^l}(y)/(\boldsymbol{x}, y) \qquad (2)
\end{aligned}
$$

where $*$ denotes a t-norm, and $\int$ denotes the union of individual points of each set in the continuum.

Let the input to R^l be denoted by A, where A is a subset of an n-dimensional Cartesian product space and is given by

$$
\begin{aligned}
A = &\int_{U_1} \cdots \int_{U_{n-n_f}} \int_{U_{n-n_f+1}} \cdots \int_{U_n} \mu_{X_1}(x_1) \\
&* \cdots * \mu_{X_{n-n_f}}(x_{n-n_f}) \\
&* \mu_{X_{n-n_f+1}}(x_{n-n_f+1}) * \cdots * \mu_{X_n}(x_n)/(\boldsymbol{x}) \qquad (3)
\end{aligned}
$$

where

$$
\begin{aligned}
&X_r \subset U_r, \qquad r = 1, \cdots, n - n_f, \quad \text{and} \\
&X_{n-n_f+j} \subset U_{n-n_f+j}, \qquad j = 1, 2, \cdots, n_f
\end{aligned}
$$

are the fuzzy sets describing the exogenous and feedback inputs, respectively.

Up to this point, the formulation is identical to that of the Singleton case. In the Singleton case, though, it is assumed that each input fuzzy set X_k has nonzero membership value only at a single point, which reduces A to a set with a single point $\boldsymbol{x}' \in U$. In our treatment here, we do not make this assumption. Each input fuzzy set is represented by the more general non-Singleton form in (3), thereby allowing any uncertainty in the input to be represented in the system.

According to the *compositional rule of inference*, the fuzzy subset Y^l of V induced by $A \in U$ is given by the composition of A and R^l

$$
Y^l = A \circ R^l = \sup_{\boldsymbol{x} \in U} (A * R^l). \qquad (4)
$$

Note that all unions (denoted by $\int$) in A and R^l over $U_k, k = 1, \cdots, n$, are over the same spaces; therefore, we can write Y^l as

$$
\begin{aligned}
Y^l = \sup_{\boldsymbol{x}\in U} \Bigg(&\int_{U_1} \cdots \int_{U_{n-n_f}} \int_{U_{n-n_f+1}} \cdots \int_{U_n} \int_V \mu_{X_1}(x_1) \\
&* \cdots * \mu_{X_{n-n_f}}(x_{n-n_f}) * \mu_{X_{n-n_f+1}}(x_{n-n_f+1}) \\
&* \cdots * \mu_{X_n}(x_n) * \mu_{F_1^l}(x_1) * \cdots * \mu_{F_{n-n_f}^l}(x_{n-n_f}) \\
&* \mu_{H_1^l}(x_{n-n_f+1}) * \cdots * \mu_{H_{n_f}^l}(x_n) \\
&* \mu_{G^l}(y)/(\boldsymbol{x}) \Bigg) \Bigg/ (y). \qquad (5)
\end{aligned}
$$

Since the supremum is only over $\boldsymbol{x} \in U$, then by the commutativity and monotonicity properties of a t-norm, we can rewrite Y^l as

$$
\begin{aligned}
Y^l = \int_V \mu_{G^l}(y) * \sup_{\boldsymbol{x}\in U} \Bigg(&\int_{U_1} \cdots \int_{U_{n-n_f}} \int_{U_{n-n_f+1}} \cdots \int_{U_n} \\
&\cdot \mu_{X_1}(x_1) * \cdots * \mu_{X_{n-n_f}}(x_{n-n_f}) * \mu_{X_{n-n_f+1}} \\
&\cdot (x_{n-n_f+1}) * \cdots * \mu_{X_n}(x_n) * \mu_{F_1^l}(x_1) * \cdots \\
&* \mu_{F_{n-n_f}^l}(x_{n-n_f}) * \mu_{H_1^l}(x_{n-n_f+1}) * \cdots \\
&* \mu_{H_{n_f}^l}(x_n)/(\boldsymbol{x}) \Bigg) \Bigg/ (y). \qquad (6)
\end{aligned}
$$

Next, we recall that by definition a t-norm is a two-place function from $[0, 1] \times [0, 1]$ [31]; thus, we can consider every t-norm in (6) to be acting on a pair of membership functions. The calculation of the t-norm over all the points in the corresponding spaces of the two membership functions is easier to visualize if the membership functions are in the same space; therefore, we rewrite (6) in the following manner:

$$\begin{aligned}Y^l = \int_V \mu_{G^l}(y) * \sup_{\boldsymbol{x}\in U} \Bigg(\int_{U_1} \cdots \int_{U_{n-n_f}} \int_{U_{n-n_f+1}} \cdots \int_{U_n} \\ \cdot [\mu_{X_1}(x_1) * \mu_{F_1^l}(x_1)] * \cdots * [\mu_{X_{n-n_f}}(x_{n-n_f}) * \\ * \mu_{F_{n-n_f}^l}(x_{n-n_f})] * [\mu_{X_{n-n_f+1}}(x_{n-n_f+1}) \\ * \mu_{H_1^l}(x_{n-n_f+1})] * \cdots * [\mu_{X_n}(x_n) \\ * \mu_{H_{n_f}^l}(x_n)]/(\boldsymbol{x}) \Bigg) \Bigg/ (y). \end{aligned} \tag{7}$$

Note that the supremum in (7) is over all points $\boldsymbol{x}$ in U (in an n-dimensional Cartesian product space). By the monotonicity property of a t-norm [31], that supremum is attained when each term in brackets attains its supremum. Let

$$\mu_{Q_r^l}(x_r) \equiv \mu_{X_r}(x_r) * \mu_{F_r^l}(x_r) \qquad r = 1, 2, \cdots, n - n_f \tag{8}$$

$$\mu_{S_j^l}(x_{n-n_f+j}) \equiv \mu_{X_{n-n_f+j}}(x_{n-n_f+j}) * \mu_{H_j^l}(x_{n-n_f+j}) \qquad j = 1, 2, \cdots, n_f \tag{9}$$

where $\mu_{Q_r^l}, \mu_{X_r}, \mu_{F_r^l} \in U_r, r = 1, 2, \cdots, n - n_f$, and $\mu_{S_j^l}(x_{n-n_f+j})$, $\mu_{X_{n-n_f+j}}$ (x_{n-n_f+j}), $\mu_{H_j^l}$ (x_{n-n_f+j}) $\in U_{n-n_f+j}$, $j = 1, 2, \cdots, n_f$. Assuming that $\mu_{Q_r^l}$ and $\mu_{S_j^l}(x_{n-n_f+j})$ produced by (8) and (9), respectively, are functions whose suprema can be evaluated, let $x_{r,\mathrm{sup}}$ and $x_{n-n_f+j,\mathrm{sup}}$ denote the points in U_r and U_{n-n_f+j} where those suprema are attained; then (7) becomes

$$\begin{aligned} Y^l = \int_V \mu_{G^l}(y) * \mathcal{T}_{r=1}^{n-n_f} \mu_{Q_r^l}(x_{r,\mathrm{sup}}) \\ * \mathcal{T}_{j=1}^{n_f} \mu_{S_j^l}(x_{n-n_f+j,\mathrm{sup}})/(y) \end{aligned} \tag{10}$$

where $\mathcal{T}_{r=1}^{n-n_f}$ and $\mathcal{T}_{j=1}^{n_f}$ denote sequences of t-norm operations.

Using the modified height defuzzifier [7], [25], the output of our NSFLS can be written as a non-Singleton fuzzy basis function (NSFBF) expansion (11) and (12), shown at the bottom of the page, where the basis functions are given by (13), shown at the bottom of the page, in which M denotes the number of rules, $\overline{y}^l$ denotes the point of maximum membership of the lth consequent fuzzy set, and δ^l is proportional to the uncertainty in the consequent fuzzy sets (e.g., if the consequent membership function is triangular, then δ^l could be chosen as the length of its base).

Note that when the input fuzzy set becomes a singleton, then $x_{k,\mathrm{sup}} = x_k, (k = 1, 2, \cdots, n), \mu_{Q_k^l} = \mu_{F_k^l}$, and $\mu_{S_j^l} = \mu_{H_j^l}$ [14], so that the NSFLS becomes a SFLS

$$y_s = f_s(\boldsymbol{x}) = \sum_{l=1}^{M} \overline{y}^l p_s^l(\boldsymbol{x}) \tag{14}$$

where

$$p_s^l(\boldsymbol{x}) = \frac{\mathcal{T}_{r=1}^{n-n_f} \mu_{F_r^l}(x_r) * \mathcal{T}_{j=1}^{n_f} \mu_{H_j^l}(x_{n-n_f+j})/(\delta^l)^2}{\sum_{l=1}^{M} \mathcal{T}_{r=1}^{n-1} \mu_{F_r^l}(x_r) * \mathcal{T}_{j=1}^{n_f} \mu_{H_j^l}(x_{n-n_f+j})/(\delta^l)^2}. \tag{15}$$

Observe that depending on the choice of t-norm operation and membership functions, a NSFLS provides a mapping of the set-valued inputs x_k to produce $x_{k,\mathrm{sup}}$, which can be viewed as a form of nonlinear prefiltering [11]. How this is done will become clear in Sections III and IV.

Equations (11)–(13) define a special case of a NSFLS with arbitrary membership functions, arbitrary t-norms, and modified height defuzzification. Each NSFBF $p_{ns}^l(\boldsymbol{x})$ is associated with either a fuzzy linguistic statement (with uncertain input) or uncertain numerical data; hence, both types of information can be easily combined in a natural framework using NSFBF's.

III. A Learning Algorithm for Dynamic NSFLSS

In this section, we derive an algorithm for the adaptive training of dynamic NSFLS's. Dynamic NSFLS's compared to static NSFLS's (which are static mappings between their input and output spaces) are a richer family of systems, capable of implementing a wide range of dynamic systems. The task of training dynamic NSFLS's is equivalent to finding a particular NSFLS from a parameterized family of such systems that optimizes a specific cost function [27] and achieves a desired mapping defined by a set of input–output pairs of a target system. The dependence of the system output at time $t+1$ on the values of the state variables of the system at time t

$$y_{ns} = f_{ns}(\boldsymbol{x}) = \frac{\sum_{l=1}^{M} \overline{y}^l \mathcal{T}_{r=1}^{n-n_f} \mu_{Q_r^l}(x_{r,\mathrm{sup}}) * \mathcal{T}_{j=1}^{n_f} \mu_{S_j^l}(x_{n-n_f+j,\mathrm{sup}})/(\delta^l)^2}{\sum_{l=1}^{M} \mathcal{T}_{r=1}^{n-n_f} \mu_{Q_r^l}(x_{r,\mathrm{sup}}) * \mathcal{T}_{j=1}^{n_f} \mu_{S_j^l}(x_{n-n_f+j,\mathrm{sup}})/(\delta^l)^2} \tag{11}$$

$$= \sum_{l=1}^{M} \overline{y}^l p_{ns}^l(\boldsymbol{x}) \tag{12}$$

$$p_{ns}^l(\boldsymbol{x}) = \frac{\mathcal{T}_{r=1}^{n-n_f} \mu_{Q_r^l}(x_{r,\mathrm{sup}}) * \mathcal{T}_{j=1}^{n_f} \mu_{S_j^l}(x_{n-n_f+j,\mathrm{sup}})/(\delta^l)^2}{\sum_{l=1}^{M} \mathcal{T}_{r=1}^{n-n_f} \mu_{Q_r^l}(x_{r,\mathrm{sup}}) * \mathcal{T}_{j=1}^{n_f} \mu_{S_j^l}(x_{n-n_f+j,\mathrm{sup}})/(\delta^l)^2} \tag{13}$$

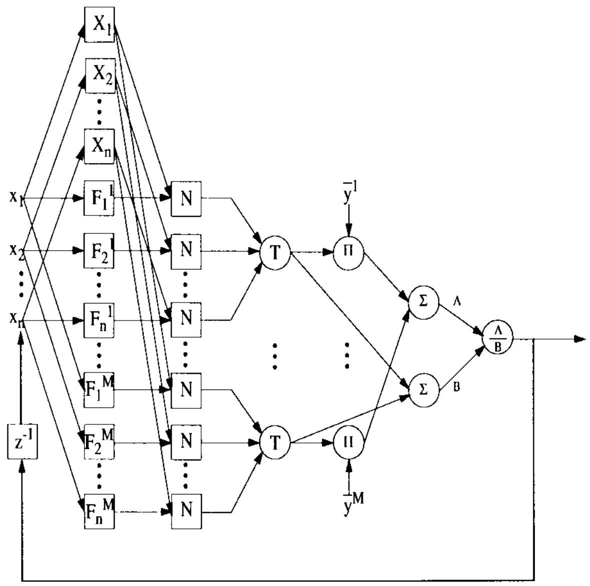


Fig. 2. Network structure of a dynamic non-Singleton fuzzy logic system, with M rules, $n-1$ exogenous inputs, and one feedback input, which is labeled x_n. T denotes a sequence of t-norm operations.

makes this task more complicated than that of training static systems [18]. For the sake of simplicity, we will assume in the derivation of the learning algorithm that the NSFLS has only one feedback input and uses product t-norm. Fig. 2 depicts the network structure of a dynamic NSFLS with M rules, $n-1$ exogenous inputs and one feedback input. The nodes labeled N denote the nonlinear processing of input information to generate $x_{k,\sup}$.

Given a sequence of input–output pairs, we develop a learning algorithm for temporal supervised tasks [28] that allows the adaptation of the parameters of a NSFLS. Assuming a single-feedback input (so that $n_f = 1$) and product t-norm, the NSFLS in (11) [using (8) and (9)] can be re-expressed in terms of the following quantities:

$$w^l(t) = \prod_{r=1}^{n-1} \mu_{F_r^l}(x_{r,\sup}(t))\mu_{X_r}(x_{r,\sup}(t))\mu_{H_1^l}(x_{n,\sup}(t)) \cdot \mu_{X_n}(x_{n,\sup}(t)) \tag{16}$$

$$g(t) = \sum_{l=1}^{M} w^l(t) \tag{17}$$

$$h(t) = \sum_{l=1}^{M} \overline{y}^l w^l(t). \tag{18}$$

At time-step $t+1$, the output of the NSFLS is computed as

$$f_{ns}(t+1) = h(t)/g(t). \tag{19}$$

Note that the exogenous inputs at time t do not affect the output of the system until time $t+1$.

In the special case of Gaussian antecedent and input fuzzy sets, the antecedent membership functions are given by

$$\mu_{H_1^l}(x_{n,\sup}(t)) = \exp\left[-\frac{(x_{n,\sup}(t) - m_{H_1^l})^2}{\sigma_{H_1^l}^2}\right] \tag{20}$$

and

$$\mu_{F_r^l}(x_{r,\sup}(t)) = \exp\left[-\frac{(x_{r,\sup}(t) - m_{F_r^l})^2}{\sigma_{F_r^l}^2}\right] \quad r = 1, 2, \cdots, n-1 \tag{21}$$

and the input membership functions by

$$\mu_{X_k}(x_{k,\sup}(t)) = \exp\left[-\frac{(x_{k,\sup}(t) - x_k(t))^2}{\sigma_{X_k}^2}\right] \quad k = 1, 2, \cdots, n \tag{22}$$

where [13]–[15]

$$x_{n,\sup}(t) = \frac{\sigma_{X_n}^2 m_{H_1^l} + \sigma_{H_1^l}^2 x_n(t)}{\sigma_{X_n}^2 + \sigma_{H_1^l}^2} \tag{23}$$

$$x_{r,\sup}(t) = \frac{\sigma_{X_r}^2 m_{F_r^l} + \sigma_{F_r^l}^2 x_r(t)}{\sigma_{X_r}^2 + \sigma_{F_r^l}^2}, \qquad r = 1, 2, \cdots, n-1 \tag{24}$$

and

$$x_n(t) \equiv f_{ns}(t). \tag{25}$$

Next, we define a time-varying error function

$$e(t) = \tfrac{1}{2}\left[f_{ns}(t) - d(t)\right]^2 \tag{26}$$

and the sum of squared errors

$$\mathcal{C}_{\text{total}}(t_0, t_1) = \sum_{t=t_0+1}^{t_1} e(t). \tag{27}$$

The update of a particular system parameter θ (which can be any parameter from the set $\{\overline{y}^l, m_{F_r^l}, \sigma_{F_r^l}, \sigma_{X_r^l}, \delta^l, m_{H_1^l}, \sigma_{H_1^l}, \sigma_{X_n^l}\}$), is obtained by accumulating the values of $\nabla_\theta e(t)$ for each time step along the trajectory, i.e.,

$$\begin{aligned}\Delta\theta &= \kappa \nabla_\theta \mathcal{C}_{\text{total}}(t_0, t_1) = \kappa \sum_{t=t_0+1}^{t_1} \nabla_\theta e(t) \\ &= \kappa \sum_{t=t_0+1}^{t_1} \frac{\partial e(t)}{\partial \theta} = \kappa \sum_{t=t_0+1}^{t_1} [f_{ns}(t) - d(t)] \frac{\partial f_{ns}(t)}{\partial \theta}\end{aligned} \tag{28}$$

where κ is the constant positive learning rate, and parameter θ remains constant in the interval $[t_0, t_1]$.

We show some of the basic steps in the derivation of the update for $\overline{y}^l$, but we omit details of similar steps in the derivations for the remaining parameters. To obtain an expression for the recursive computation of $\partial f_{ns}(t)/\partial \overline{y}^l$, we begin by differentiating the system dynamics using the chain rule

$$\begin{aligned}\frac{\partial f_{ns}(t+1)}{\partial \overline{y}^l} &= \left[\frac{\partial f_{ns}(t+1)}{\partial g(t)} \frac{\partial g(t)}{\partial w^l(t)} + \frac{\partial f_{ns}(t+1)}{\partial h(t)} \frac{\partial h(t)}{\partial w^l(t)}\right] \\ &\quad \cdot \frac{\partial w^l(t)}{\partial f_{ns}(t)} \frac{\partial f_{ns}(t)}{\partial \overline{y}^l} + \frac{\partial f_{ns}(t+1)}{\partial h(t)} \frac{\partial h(t)}{\partial \overline{y}^l}\end{aligned} \tag{29}$$

where, using (16)–(19), we find

$$\frac{\partial f_{ns}(t+1)}{\partial g(t)} = -\frac{h(t)}{g^2(t)} \tag{30}$$

$$\frac{\partial g(t)}{\partial w^l(t)} = 1 \tag{31}$$

$$\frac{\partial f_{ns}(t+1)}{\partial h(t)} = \frac{1}{g(t)} \tag{32}$$

$$\frac{\partial h(t)}{\partial w^l(t)} = \overline{y}^l \tag{33}$$

$$\frac{\partial h(t)}{\partial \overline{y}^l} = w^l(t) \tag{34}$$

and [using (16), (23), and (25)]

$$\frac{\partial w^l(t)}{\partial f_{ns}(t)} = \prod_{r=1}^{n-1} \mu_{X_r}(\sigma_{X_r}, m_{F_r^l}, \sigma^2_{F_r^l})\mu_{F_r^l}(\sigma_{X_r}, m_{F_r^l}, \sigma^2_{F_r^l}) \cdot \left[\frac{\partial \mu_{X_n}(x_{n,\sup}(t))}{\partial f_{ns}(t)}\mu_{H_1^l}(x_{n,\sup}(t)) + \mu_{X_n}(x_{n,\sup}(t))\frac{\partial \mu_{H_1^l}(x_{n,\sup}(t))}{\partial f_{ns}(t)}\right] \tag{35}$$

where [using (22), (23), and (25)]

$$\frac{\partial \mu_{X_n}(x_{n,\sup}(t))}{\partial f_{ns}(t)} = -\frac{\sigma^2_{X_n}}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\left[\frac{f_{ns}(t)-m_{H_1^l}}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\right] \cdot \mu_{X_n}(x_{n,\sup}(t)) \tag{36}$$

and [using (20), (23), and (25)]

$$\frac{\partial \mu_{H_1^l}(x_{n,\sup}(t))}{\partial f_{ns}(t)} = -\frac{\sigma^2_{H_1^l}}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\left[\frac{f_{ns}(t)-m_{H_1^l}}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\right] \cdot \mu_{H_1^l}(x_{n,\sup}(t)). \tag{37}$$

Substituting (36) and (37) into (35), we find

$$\frac{\partial w^l(t)}{\partial f_{ns}(t)} = \left(\frac{m_{H_1^l}-f_{ns}(t)}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\right)w^l(t). \tag{38}$$

Substituting (30)–(34) and (38) into (29), we obtain

$$\begin{aligned}\frac{\partial f_{ns}(t+1)}{\partial \overline{y}^l} &= \left[-\frac{h(t)}{g^2(t)}+\frac{\overline{y}^l}{g(t)}\right]\left(\frac{m_{H_1^l}-f_{ns}(t)}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\right) \cdot w^l(t)\frac{\partial f_{ns}(t)}{\partial \overline{y}^l}+\frac{w^l(t)}{g(t)}\\ &= \frac{w^l(t)}{g(t)}\left[(\overline{y}^l - f_{ns}(t+1))\left(\frac{m_{H_1^l}-f_{ns}(t)}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\right) \cdot \frac{\partial f_{ns}(t)}{\partial \overline{y}^l}+1\right].\end{aligned} \tag{39}$$

Assuming that $\partial f_{ns}(0)/\partial \overline{y}^l = 0$, and letting $\phi_{\overline{y}^l}(t) \equiv \partial f_{ns}(t)/\partial \overline{y}^l$, (39) can be expressed as

$$\phi_{\overline{y}^l}(t+1) = \frac{w^l(t)}{g(t)}\left[(\overline{y}^l - f_{ns}(t+1))\left(\frac{m_{H_1^l}-f_{ns}(t)}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\right) \cdot \phi_{\overline{y}^l}(t)+1\right], \qquad \phi_{\overline{y}^l}(0)=0 \tag{40}$$

which is the desired recursion for $\partial f_{ns}(t)/\partial \overline{y}^l$.

Following a similar procedure, we obtain

$$\phi_{m_{F_r^l}}(t+1) = \mathcal{A}(t)\left[\mathcal{B}(t)\cdot\phi_{m_{F_r^l}}(t)+\left(\frac{x_r-m_{F_r^l}}{\sigma^2_{F_r^l}+\sigma^2_{X_r^l}}\right)\right] \tag{41}$$

$$\phi_{\sigma_{F_r^l}}(t+1) = \mathcal{A}(t)\left[\mathcal{B}(t)\cdot\phi_{\sigma_{F_r^l}}(t)+\frac{\sigma_{F_r^l}(x_r-m_{F_r^l})^2}{(\sigma^2_{F_r^l}+\sigma^2_{X_r^l})^2}\right] \tag{42}$$

$$\phi_{\sigma_{X_r^l}}(t+1) = \mathcal{A}(t)\left[\mathcal{B}(t)\cdot\phi_{\sigma_{X_r^l}}(t)+\frac{\sigma_{X_r^l}(m_{F^l}-x_r)^2}{(\sigma^2_{F_r^l}+\sigma^2_{X_r^l})^2}\right] \tag{43}$$

$$\phi_{\delta^l}(t+1) = \mathcal{A}(t)\left[\mathcal{B}(t)\cdot\phi_{\delta^l}(t)-\frac{2}{\delta^l}\right] \tag{44}$$

where

$$\mathcal{A}(t) = \left[\frac{\overline{y}^l - f_{ns}(t+1)}{g(t)}\right]w^l(t) \tag{45}$$

$$\mathcal{B}(t) = \left(\frac{m_{H_1^l}-f_{ns}(t)}{\sigma^2_{H_1^l}+\sigma^2_{X_n}}\right) \tag{46}$$

and all of the above recursions are initialized to zero at $t=0$.

To obtain recursions suitable for real-time training of the NSFLS, we can relax the assumption that the parameters remain fixed in $[t_0, t_1]$. We can make the parameter changes at each time point while the system is running (see [28]), i.e., update each parameter with

$$\Delta\theta' = \kappa\nabla_\theta e(t) = \kappa[f_{ns}(t)-d(t)]\phi_\theta(t) \tag{47}$$

instead of $\Delta\theta$. This implies that the real-time algorithm will not follow the exact negative gradient of the total error surface. The difference, however, usually becomes very small as the learning rate κ becomes small [28]. (Note that this is equivalent to the familiar static backpropagation type of algorithms which also modify each parameter at every time point [6].) Then, the recursions for the NSFLS parameters are given by

$$\overline{y}^l(t+1) = \overline{y}^l(t) - \kappa_1[f_{ns}(t)-d(t)]\phi_{\overline{y}^l}(t) \tag{48}$$

$$m_{F_r^l}(t+1) = m_{F_r^l}(t) - \kappa_2[f_{ns}(t)-d(t)]\phi_{m_{F_r^l}}(t) \tag{49}$$

$$\sigma_{F_r^l}(t+1) = \sigma_{F_r^l}(t) - \kappa_3[f_{ns}(t)-d(t)]\phi_{\sigma_{F_r^l}}(t) \tag{50}$$

$$\sigma_{X_r^l}(t+1) = \sigma_{X_r^l}(t) - \kappa_4[f_{ns}(t)-d(t)]\phi_{\sigma_{X_r^l}}(t) \tag{51}$$

$$\delta^l(t+1) = \delta^l(t) - \kappa_5[f_{ns}(t)-d(t)]\phi_{\delta^l}(t). \tag{52}$$

The recursions for $m_{H_1^l}$ and $\sigma_{H_1^l}$ are identical to those of $m_{F_r^l}$ and $\sigma_{F_r^l}$, respectively, when we replace input x_r with $f_{ns}(t), m_{F_r^l}$ with $m_{H_1^l}$, and $\sigma_{F_r^l}$ with $\sigma_{H_1^l}$.

The sequence of computations for the dynamic learning algorithm is as follows: we initialize the system using the one-pass (OP) method [24], and use (11) with Gaussian membership functions, product inference, and $n_f = 1$ to obtain the system output. The exogenous inputs together with the feedback input comprise the entire set of inputs. At time $t = 0$, we initialize all variables ϕ to zero and, subsequently, use (40)–(44) to compute their updates over all $r = 1, 2, \cdots, n-1$, and $l = 1, 2, \cdots, M$. The initial value of the feedback input is chosen to be in the range of the desired response, i.e., it should lie in the interval $[\inf d(t), \sup d(t)]$. Using the computed values of ϕ together with the instantaneous error $f_{ns}(t) - d(t)$ we calculate the correction $\kappa \nabla_\theta e(t)$ in (47) and, subsequently, use (48)–(52) to compute the system parameter updates. The procedure is repeated for each time-step t.

It should be noted that no convergence analysis exists yet for this kind of dynamic learning algorithm, therefore, caution should be exercised so that the system does not become unstable. To minimize this risk, it is recommended that the time scale of parameter changes be much slower than the time scale of the system operation, i.e., the learning rate be kept sufficiently small [6], [28].

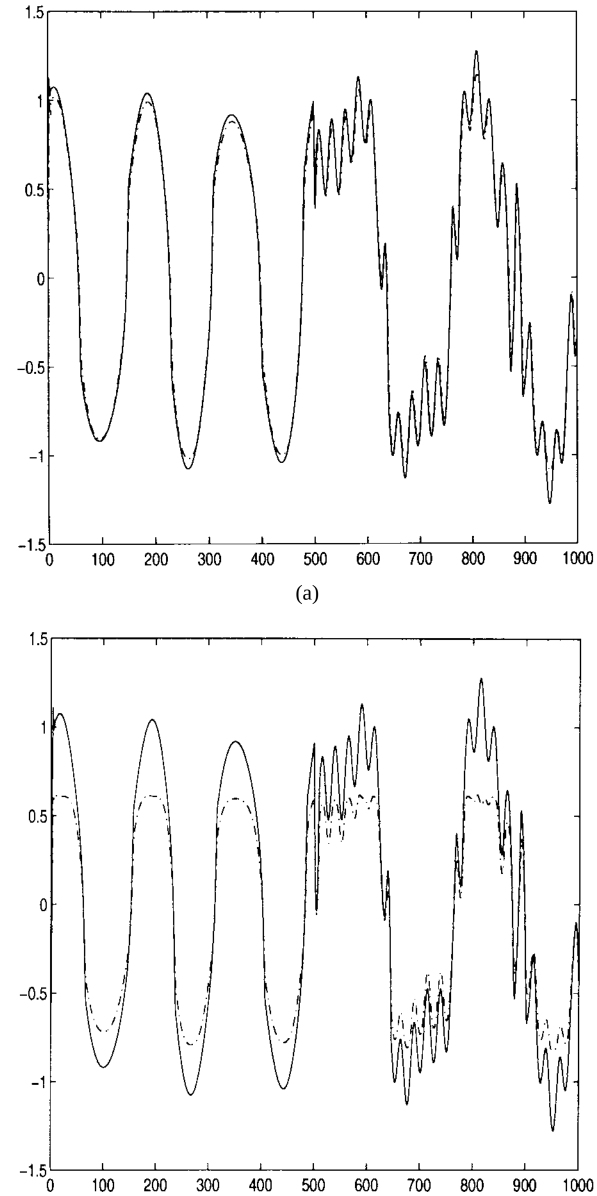
In the absence of feedback, the dynamic learning algorithm (40)–(52) reduces to the static backpropagation algorithm for NSFLS's [15]. If, in addition, the input becomes a Singleton, $\sigma_{X_k}^2 = 0, k = 1, 2, \cdots, n,$ (48)–(52) reduce to the Singleton back-propagation scheme proposed in [23]. Note that unlike a Singleton FLS, a NSFLS can be trained to account for uncertainty at the input by training for σ_{X_k}.

IV. Examples and Applications

In this section, we present examples to investigate the utility of the proposed dynamic system and dynamic learning algorithm that demonstrate they can offer significant advantages in different scenarios.

A. System Identification

To illustrate the superiority of our dynamic FLS over a corresponding static FLS in modeling processes of unknown order and structure, we give an example for the identification of a nonlinear dynamic system. System identification requires selecting one of a parameterized family of functions so as to approximate the input–output behavior of a target function in an optimum manner, as defined by a given cost function. When the identification problem involves a dynamic system whose output depends both on past inputs and past outputs, it would be preferable to construct a dynamic identification model that can exhibit similar behavior. Despite the fact that the output of a static FLS is a function of its current inputs only, static FLS's have been used in the past (see [25]) for the identification and control of dynamical systems. If the order of the system (or an upper bound of it) is known, then the appropriate number of past inputs and outputs can be explicitly used as inputs to the static FLS. This could be unrealistic if inadequate information is available about the unknown plant and impractical if a large number of inputs is needed [21]. Here, we compare the performance of static and dynamic FLS's when minimal information is available about the plant.



(a)

(b)

Fig. 3. (a) Output of plant (53) with input (54) (solid line) and output of the dynamic FLS identification model (dash-dotted line). (b) Output of plant (53) with input (54) (solid line) and output of the static FLS identification model (dash-dotted line).

The output of the plant is given by

$$y(t+1) = \frac{y(t)}{1 + y(t-1)^2 + y(t-2)^2} + 0.3u(t) + 0.7u(t-1) \tag{53}$$

i.e, it depends on two previous inputs and three previous outputs. Both static FLS's and feedforward neural networks used in the past to identify systems similar to (53), required five inputs of the appropriate past values of u and y [21] [i.e., $x_1 = u(t), x_2 = u(t-1), x_3 = y(t), x_4 = y(t-1), x_5 =$

$y(t-2)]$. This restrictive limitation, which makes such systems hard to use when the order of the plant is unknown, is removed (at least in this example) by using dynamic FLS's. For our example, we only used x_1 and x_3 as inputs. The dynamic FLS we used is of the form of (11) with Gaussian membership functions, product inference, $M = 30$, and $n_f = 1$. We trained our system with a random input uniformly distributed in the interval $[-2, 2]$, using the learning algorithm (40)–(52) for 5000 time steps and a learning rate of 0.3. For the testing phase, we used the following inputs:

$$\begin{aligned} u(t) &= 0.4\sin(3\pi t/250)\cos(\pi t/50) + 0.6\cos(3\pi t/250) \\ &\qquad t \le 500 \\ &= 0.6\sin(\pi t/125) + 0.2\sin 2(\pi t/25) + 0.2\cos(\pi t/50) \\ &\qquad 500 < t \le 1000. \end{aligned} \tag{54}$$

We compared the performance of the dynamic FLS with a static FLS that had the same structure, type of membership functions, and inference as the dynamic FLS (11). The only difference between the two systems is the presence of the additional feedback input in the case of the dynamic system. The static FLS was trained using the static backpropagation algorithm given in [15] for 5000 iterations and a learning rate of 0.5. Both systems were identically initialized using the OP method. Fig. 3(a) and (b) shows the output of the plant (solid line) and the outputs of the dynamic and static identification models (dash-dotted lines), respectively. We see that the dynamic FLS has evolved through the dynamic learning algorithm to be able to reproduce the behavior of (53), but the corresponding static system failed to do so.

B. Predictive Modeling of a NARMA Process

Here, we examine the predictive ability of our dynamic FLS for a nonlinear autoregressive moving average (NARMA) process and compare its performance with static FLS's of different orders. Static FLS's essentially belong to the general family of nonlinear autoregressive [NAR(n)] models given by

$$x_t = h(x_{t-1}, x_{t-2}, \cdots, x_{t-n}) + e_t \tag{55}$$

where h is an unknown smooth function [2]. Then, assuming that $E[e_t | x_{t-1}, x_{t-2}, \cdots] = 0$, and the error variance σ_e^2 is finite, the optimal mean-squared error predictor of x_t, given $x_{t-1}, x_{t-2}, \cdots, x_{t-n}$ is the conditional mean, i.e.,

$$\begin{aligned} \hat{x} &= E[x_t | x_{t-1}, x_{t-2}, \cdots, x_{t-n}] \\ &= h(x_{t-1}, x_{t-2}, \cdots, x_{t-n}), \qquad t \ge n+1. \end{aligned}$$

A dynamic FLS belongs to the family of $\mathrm{NARMA}\,(n, m)$ [2] models

$$x_t = h(x_{t-1}, x_{t-2}, \cdots, x_{t-n}, e_{t-1}, e_{t-2}, \cdots, e_{t-m}) + e_t \tag{56}$$

where, again, h is an unknown smooth function, the same assumptions hold for e_t as in the NAR case, and the optimum predictor is

$$\hat{x} = h(x_{t-1}, x_{t-2}, \cdots, x_{t-n}, e_{t-1}, e_{t-2}, \cdots, e_{t-m}).$$

In our example, we approximated the optimum predictor by

$$\hat{x}_t = h(x_{t-1}, x_{t-2}, \cdots, x_{t-n}, \hat{e}_{t-1}, \hat{e}_{t-2}, \cdots, \hat{e}_{t-m}) \tag{57}$$

$$\hat{e}_{t-k} = x_{t-k} - \hat{x}_{t-k}, \qquad j = 1, 2, \cdots, m. \tag{58}$$

We trained the dynamic system (11) as a one-step predictive model of

$$\begin{aligned} x_t = {} & \nu_t + 1.2 x_{t-1} \exp\left(-\frac{x_{t-1}^2}{6}\right) + 0.8\nu_{t-1} \\ & \cdot \exp\left(-\frac{\nu_{t-1}^2}{3}\right) \end{aligned} \tag{59}$$

where ν_t is a zero-mean uniform white noise process with standard deviation σ_ν (see Fig. 4). The system had one exogenous input (x_{t-1}) and one feedback input $f_{ns}(t-1) = \hat{x}_{t-1}$. The FLS was trained for 1500 samples, after 1000 points were allowed for the transients to die out. The model was then tested on the 500 points following the training segment, for 100 Monte Carlo iterations. We similarly trained and tested static FLS's of different orders [NAR(1)–NAR(6)], with the static backpropagation algorithm in [15]. All FLS's employed Gaussian membership functions and product inference and contained 50 rules in their rulebase. The results are given in Table I for both dynamic and static FLS's for different values of σ_ν. It is obvious that the NARMA(1, 1) dynamic FLS outperforms all static FLS's. The NAR(1) FLS outperforms all other static systems in both in-sample and out-of-sample performance. The mean-suared error (MSE) for the NAR model increases dramatically when increasing the number of inputs from one to two, but it decreases gradually as the number of inputs continues to inrease. The learning rate κ was set conservatively to 0.1 for the $\sigma_\nu = 0.3$ and $\sigma_\nu = 0.5$ cases, and to 0.07 for the $\sigma_\nu = 0.7$ case. When κ starts becoming too large (i.e., $\kappa > 1$), the dynamic system starts to exhibit oscillatory behavior and, finally, becomes unstable.

V. Conclusion

We have presented a formulation for dynamic NSFLS's, with two main distinguishing features: 1) they generalize static NSFLS's and 2) they generalize Singleton FLS's. Extensive comparisons between singleton and non-Singleton FLS's are given in [13]–[15]. In this paper, through several examples, we have demonstrated that dynamic NSFLS's can significantly outperform static NSFLS's in different applications. We have also derived a dynamic learning algorithm to train the system parameters given a sequence of input–output pairs. The dynamic learning algorithm (40)–(52) has characteristics similar to the static backpropagation algorithm for Singleton [23] and non-Singleton [15] FLS's. It can be initialized based on linguistic information, or using a simple procedure like the one-pass method. This kind of initialization, as opposed to random initialization as in the neural network case, can constrain the search space during optimization, thus resulting in much faster convergence. Since the parameters being updated with the learning algorithm are directly associated with the information in the rule base, the linguistic meaning of the rules is preserved throughout the training process. The learning algorithm for dynamic NSFLS's also includes training

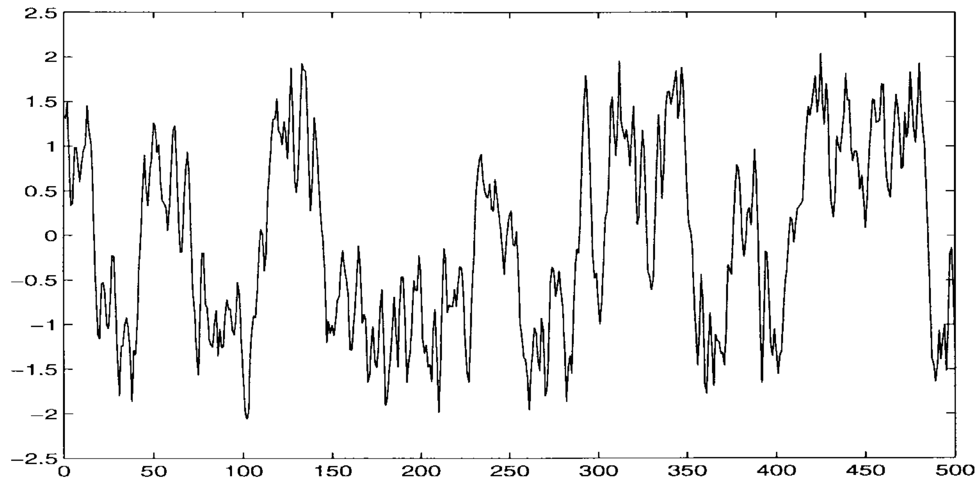


Fig. 4. Nonlinear autoregressive moving average process (59) with $\sigma_\nu = 0.3$.

TABLE I
PREDICTIVE MODELING RESULTS FOR THE NARMA(1, 1) PROCESS (59). ALL SYSTEMS WERE TRAINED FOR 1500 SAMPLES, AFTER 1000 POINTS WERE ALLOWED FOR THE TRANSIENTS TO DIE OUT. ALL RESULTS WERE AVERAGED OVER 100 MONTE CARLO ITERATIONS

Noise std = 0.3	Training mse	Testing mse	Training std	Testing std
Dynamic FLS (NARMA(1,1))	0.14959	0.15169	0.41549	0.42040
Static FLS (NAR(1))	0.23637	0.23970	0.51883	0.52295
Static FLS (NAR(2))	0.98778	0.99921	1.30617	1.33570
Static FLS (NAR(3))	0.70791	0.72730	1.00326	1.02114
Static FLS (NAR(4))	0.59357	0.60698	0.90215	0.92933
Static FLS (NAR(5))	0.51702	0.53835	0.83927	0.86847
Static FLS (NAR(6))	0.41993	0.44609	0.72982	0.75021

Noise std = 0.5	Training mse	Testing mse	Training std	Testing std
Dynamic FLS (NARMA(1,1))	0.41020	0.41172	0.74687	0.75178
Static FLS (NAR(1))	0.47017	0.48763	0.83915	0.84420
Static FLS (NAR(2))	1.48926	1.51058	1.87004	1.90084
Static FLS (NAR(3))	1.38008	1.38263	1.78067	1.79702
Static FLS (NAR(4))	1.30205	1.32557	1.70006	1.73300
Static FLS (NAR(5))	1.20256	1.23846	1.60474	1.64985
Static FLS (NAR(6))	1.13150	1.16789	1.52302	1.56824

Noise std = 0.7	Training mse	Testing mse	Training std	Testing std
Dynamic FLS (NARMA(1,1))	0.62818	0.63217	1.00943	1.01618
Static FLS (NAR(1))	0.91287	0.92454	1.33465	1.36060
Static FLS (NAR(2))	1.83255	1.85864	2.26543	2.29705
Static FLS (NAR(3))	1.73073	1.75982	2.17637	2.21373
Static FLS (NAR(4))	1.63573	1.66323	2.05391	2.09283
Static FLS (NAR(5))	1.62831	1.66999	2.05332	2.09996
Static FLS (NAR(6))	1.41556	1.45758	1.85065	1.90050

to include the right amount of input uncertainty. Furthermore, if the feedback input is removed, then (40)–(52) reduce to a static backpropagation algorithm [15].

In Section IV-A, we compared the performance of a dynamic FLS trained with the dynamic learning algorithm with that of a corresponding static FLS trained with static backpropagation. Both systems were trained as identification models for a nonlinear dynamic system whose order was not known. The failure of the static system to successfully identify the unknown plant has demonstrated that using static FLS's to model dynamical systems may be unsatisfactory [21]. On the other hand, the dynamic FLS was able to capture the behavior of the plant without being explicitly fed all inputs and outputs, $x_1, \cdots, x_5$.

Viewing dynamic NSFLS's as belonging to the general family of nonlinear autoregressive moving average models and static NSFLS's as general nonlinear autoregressive models, we have examined their performance in the predictive modeling of a NARMA process. For time series that possess moving average components, dynamic NSFLS's have proven to produce models that not only have a lower mean-square error, but also are more parsimonious and have better generalization capabilities.

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