Neurofuzzy Approaches to Anticipation: A New Paradigm for Intelligent Systems

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***Abstract*—Anticipatory systems are systems whose change of state is based on predictions about the future of the system and/or its environment. Planning and acting on the basis of anticipations of the future is an omnipresent feature of human control strategies, deeply permeating our daily experience; the human attribute of foresight may be considered as the hallmark of natural intelligence. Yet, as the eminent mathematical biologist Robert Rosen has pointed out, such control strategies are curiously absent from existing formal approaches to automatic control and decision-making processes. Recent developments in biology, ethology and cognitive sciences, however, as well as advancements in the technology of computer-based predictive models, compel us to reconsider the role of anticipation in intelligent systems and to the extent possible incorporate predictions about the future in our formal approaches to control. Significant improvements in neural predictive computing when combined with the flexibility of fuzzy systems, supports the development of neurofuzzy anticipatory control architectures that integrate planning and control sequencing functions with feedback control algorithms. In this paper the role of anticipation in intelligent systems is reviewed and a new approach is presented for anticipatory control algorithms which use the predictive capabilities of neural models in conjunction with the descriptive power of fuzzy *if/then* rules.**

***Index Terms*—Anticipatory systems, fuzzy systems, intelligent control, neural computing, neurofuzzy.**

I. Introduction

ANTICIPATORY systems (AS) are systems where change of state is based on information pertaining to present as well as future states. Cellular organisms, industrial processes, global markets, certainly the central nervous system provide many examples of behavior where output is the result of future not only present state. Yet, as the eminent mathematical biologist Robert Rosen very eloquently pointed out in his book *Anticipatory Systems* [7], explicit information about the future remains curiously absent from conventional system descriptions. Rosen's pioneering work provides a profound and lucid critique of the mechanistic epistemology implicit in our dominant system paradigms which are largely grown out of 17th century Newtonian mechanics. Although Rosen's epistemological investigations are of a fundamental nature they provide an important inspiration and a point of departure for advancing new technologies for anticipatory systems. Such systems would be of great interest for developing user-adaptive and context-sensitive technologies in a great number of applications ranging from consumer electronics, intelligent assistants, telecommunications, robotics and improved man-machine interfaces for the management of large complex systems. In the present paper we present a neurofuzzy approach to anticipation where the synergistic utilization of fuzzy logic and neural computing is brought to bear in modeling the uncertainty of predictions and controlling the complexity of anticipatory formalisms.

Research on anticipatory systems draws heavily upon advancements in artificial as well as biological neural computing and learning theories [2], [3], [7] and there is growing interest in anticipatory systems, ranging from plant and traffic control to intelligent agents in the Internet. Although anticipatory systems have been studied by a number of researches in the context of mathematical biology [7], [8], automata theory [11], preview control [10], and, as Rosen points out, their epistemological roots may be traced back to Aristotle's views on causality, it is only recently that the advent of modern computing technologies makes it possible to employ them for complex system regulation and management [1], [12]–[15], [17], [20].

As a transparent example of what is involved in anticipatory systems, consider a car driven on a busy highway. The driver and the car (taken together) comprise an anticipatory system; a good driver makes decisions on the basis of anticipating what may be happening in the future, not simply reacting to what happens at the present. Driving requires awareness of future system inputs by observing the curvature and grade of the road ahead, road conditions and the behavior of other drivers. Perceptual information received at the present may be thought of as input to internal predictive models. The driver–car system, however, is very difficult to model using conventional approaches. In part the difficulty relates to the fact that conventional predictive models are unduly constrained by excessive precision. Generally, in situations like the driver-car system, it is important for a decision-maker (the driver) to use a *parsimonious description* of the overall situation, that is, a model at the appropriate level of precision. Predictions about the future are not very precise and of course may be wrong. Yet, their efficacy does not rest on *precision* as much as on the more general issue of *accuracy*, that is the overall correctness of anticipation within a given situation. High levels of precision may not only be unnecessary for problems utilizing predicted values, they may indeed be counterproductive. A fastidious, or "over-precise driver" may actually be a dangerous driver.

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Intelligent control refers to complex automatic control systems realizing "intelligent functions" such as comparing different solutions to a problem, selecting the best in accordance with specified criteria, and allowing for variation of external stimuli and consequent variation of the character of the solution and of the criteria [18]. One of the important functions inherent in human thinking is the ability to learn how to predict. No action is performed without forecasting in some form the results of the action. Hence, when investigating the forecasting problem in engineering it is impossible not to investigate how the corresponding functions are carried out in living organisms. Generally, though, the immense problem associated with forecasting mechanisms in the brain, giving mastery over the future (a problem important both to neurophysiology and to engineering) is still far from solution.

The study of cognition is posing a fascinating and challenging question to systems theorists: *How does the anticipation of future events in the brain takes place (through seemingly timeless memory) and what are the implications of such a process to the development of anticipatory control systems capable of learning to perform difficult tasks by automatically enhancing their predictive capabilities in the course of their lifetime?* In brain research, a number of theoretical and clinical studies have emerged in recent years pointing to the importance of *anticipation* in various control functions involving the central nervous system. In kinesiology, the question of how the process of movement specification proceeds with reference to brain structures has occupied a central importance and has been addressed by Goldberg through the *dual premotor systems hypothesis* which identifies two major sources of informational constraints that are used to control motor functions: an intrinsic source related to intentionality and an extrinsic source related to external conditions [3]. The first source enables a human to function in an anticipatory adaptive mode using information that is derived from intrinsic models structured from past experience, while the second source enables motor responses that are reactive to environmental conditions. Similarly, conditional responses can be separated into those that are *anticipatory* or *expectant* (*forward-directed*) versus those that are *reactive* or *backward-directed*. The *dual premotor systems hypothesis* has guided the identification of separate premotor circuitry in the brain particularly in the *supplementary motor area*, where most activity for anticipatory postural adjustments preceding voluntary movement has been observed. Self-initiated voluntary movement involves an *anticipatory* activation of the medial premotor system that enables *prospective* control of behavior (i.e., following a *plan*) and permits the perceptual differentiation of active self-generated activity from passive response to external forces. In the words of Goldberg, "a central message from *efferent* to *afferent* brain regions informs the perceptual centers in advance regarding *forthcoming self-generated activity* and *anticipated consequences*, so that the perceptual products of activity (e.g., re-afferent proprioceptive discharge) can be appropriately determined to be originating either from within or outside the organism."

It is thus clear that the nervous system differentiates in a fundamental way between actions made in relationship to external conditions and actions performed in an *anticipatory, willed* manner through the elaboration of internal goals. Hence, brain phenomena of anticipation appear to provide an important key to the understanding of *intelligence* and *consciousness* as well as novel computational metaphors that can be exploited in the design of intelligent systems. In the next section we examine the connection between prediction and fuzzy arithmetic. In Section III we delineate the overall methodological approach taken, that is, we address how we can describe a system's anticipatory behavior by fuzzy *if/then* rules. In Section IV we describe an approach to identification and prediction via neural networks called *virtual measurement*, and in Section V we present an example where radial basis functions networks are used as predictive models. Finally, we conclude in Section VI with a summary and a description of work ahead.

II. Prediction and Fuzziness

The simplest method of predicting the future is based on the assumption that the future will be like the recent past and present, for example, the statement "*tomorrow will be about the same weather as today*" is of this type. This primitive method of forecasting the weather is correct about 70% of the time, but nonetheless, the likelihood of correct weather forecasting using such a *no-change heuristic* decreases exceedingly rapidly as the anticipation time increases.

Prediction over a longer period of time requires consideration of not only the present state of a system, but also its rate of change. A somewhat better method of forecasting is based on the assumption that the "*rate of increase or decrease is about constant*." Such forecasting heuristics are often used, for example, in demography. Generally, forecasting over a long period calls for increasing the complexity of the model by which future values are predicted. It is possible, for example, to consider not only the state of the process and rate of change, but also acceleration and perhaps the third and higher derivatives. In a number of cases such an increase of complexity gives good results, since it increases the probability of accurate forecasting over longer periods. Nevertheless in such cases as well, the period of accurate forecasting is determined by the properties of the process, as reflected in the constancy of the coefficients in the prediction formula (state, rate of change, acceleration, etc.). In *stationary processes*, these coefficients are constant and for such processes forecasting methods are very effective.

Predictions about the future of a system have been taken into account in *preview control*, an approach that was developed by Tomizuka during his doctoral dissertation at MIT in the early 1970's. In preview control future information is considered as probabilistic in kind and the control problem seen as a problem of time-delay [10]. The situation is illustrated in Fig. 1 where a discrete control problem that lasts n time steps is considered. The system's present time is denoted as $t = i$. Tomizuka postulated that up to certain time n_{la} past i, reliable predictions about the future can be made and utilized by the controller at i. This part of the future is considered "deterministic." Further away into the more distant future we have a time zone, called "probabilistic," where predictions are generally not reliable enough to be successfully used by a controller. Thus, the future is divided into *deterministic* and *probabilistic*

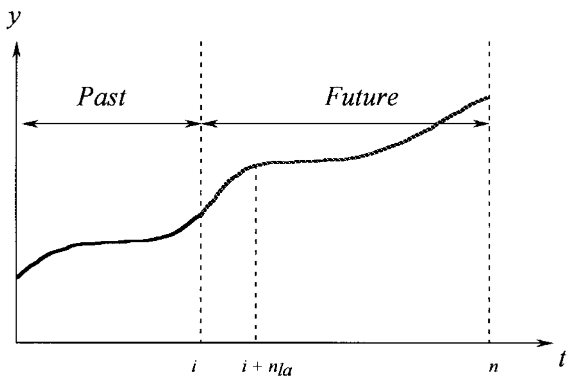

Fig. 1. Predictions in finite preview control.

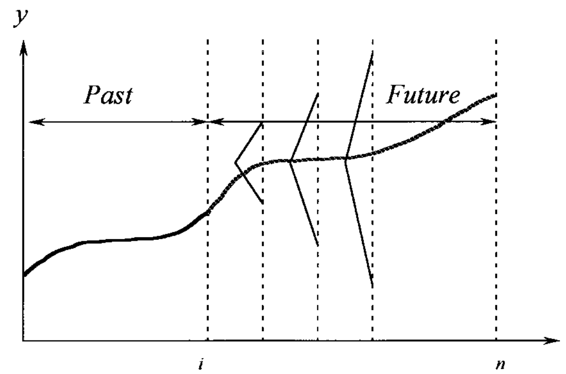

Fig. 2. Predictions as fuzzy numbers.

parts as seen in the Fig. 1. The controller is assumed to make use of preview information with respect to a command signal (desired trajectory) from the present time i up to n_{la} time units into deterministic future. The quantity, n_{la} is the *preview time* (or *length of anticipation*) and is usually shorter than n, the problem duration, often one or two time steps. To make the solution applicable to a broader class of problems, measurement time delay, observation noise and driving noise were included in formulating the problem. The solution shows how to utilize the local future information obtained by finite preview (n_{la}) in order to minimize an optimality criterion evaluated over the problem duration n. It was found that preview dramatically improved the performance of a system relative to nonpreview optimal performance, and a heuristic criterion about the preview time, n_{la}, was suggested, i.e.,

$$n_{la} \approx 3 \times \text{(longest closed loop plant time constant)}.$$

Extending Tomizuka's work, we consider future information to be essentially *fuzzy* in nature, that is, predicted values are not imbued with stochastic or probabilistic type of uncertainty but fuzzy uncertainty. Whereas probabilistic uncertainty pertains primarily to uncertainty in measurement or observation, fuzzy uncertainty pertains to linguistic categorization or labeling, that is the way we group objects in the milieu of symbols. Since whatever may be said about the future, if anything, does not come from measurements but models, predictions ought to be modeled as fuzzy numbers, that is, linguistic categorizations of information pertaining to the future of the system [16]. Generally, fuzziness is a property of language, whereas randomness is a property of observation and since there is no physical measurement pertaining to the future the mathematics of fuzzy sets may be more appropriate for modeling predicted values. Consider, for example, the process depicted in Fig. 2. At any time i we have available information from the present as well as information from the output of some predictive model, which is model as a fuzzy number (a fuzzy subset of the reals whose membership function is normal and convex (see [16]). Therefore, the mathematical tools for utilizing the prediction at present time i ought to be fuzzy as well. The time Δt into the future, the anticipatory time step, depends on the nature of the problem and the predictive model used, and generally, need not be restricted to one or two time steps as is often the case in preview control. As is suggested in Fig. 2 the fuzziness of a prediction is postulated to depend on Δt in the sense that for greater Δt's we get fuzzier predictions.

Consider, for example, a situation where temperature is observed and during the entire observation period it remains fairly constant, for example at $x = 50$ °C. Suppose that our present time is $t = 0$. Using the *no-change heuristic* we can predict that in the near future the temperature will also be "*about* 50 °C," where "*about* 50 °C" can be modeled as a membership function having its normal point at $x = 50$ °C and a spread which depends on the prediction horizon as seen in Fig. 3. The more distant into the future is the prediction horizon the fuzzier the prediction becomes. For example, a Δt after $t = 0$ (the present) we can predict that temperature will be *about* 50 °C where this fuzzy number has membership function

$$\mu_{\text{about 50 °C}}(x; \Delta t) = \frac{1}{1 + 0.0005(|x - 50|)^6}. \tag{1}$$

At $t = 2\Delta t$ the prediction *about* 50 °C may be modeled by a wider membership function

$$\mu_{\text{about 50°C}}(x; 2\Delta t) = \frac{1}{1 + 0.0005(|x - 50|)^5}. \tag{2}$$

At $t = 3\Delta t$ the prediction *about* 50°C may be modeled by an even wider membership function

$$\mu_{\text{about 50 °C}}(x; 3\Delta t) = \frac{1}{1 + 0.0005(|x - 50|)^4}. \tag{3}$$

More generally then the prediction that temperature will be *about* 50 °C at some time $t = n\Delta t$ into the future can be modeled by a membership function of the form

$$\mu_{\text{about 50 °C}}(x; n\Delta t) = \frac{1}{1 + a(|x - d|)^b} \tag{4}$$

where the parameters a, b, c are used to adjust the overall shape of the predicted value. Parameter a adjusts the width of the membership function, b determines the extent of fuzziness, and c describes the location of the "peak" or normal point of the membership function. This is the point in the universe of discourse where $\mu(x) = 1$. In Fig. 3, we see that $c =$ 50 °C, $a = 0.0005$ and b varies inversely with the length of the prediction horizon. In other words as n gets larger b becomes smaller thus making the prediction fuzzier. In the extreme case where $n \rightarrow \infty, b \rightarrow 0$, the predicted value becomes

$$\mu_{\text{about 50 °C}}(x; n\Delta t)|_{n\rightarrow\infty} = 1. \tag{5}$$

In other words, at the distant future our prediction becomes very fuzzy and therefore possibly useless. Of course other

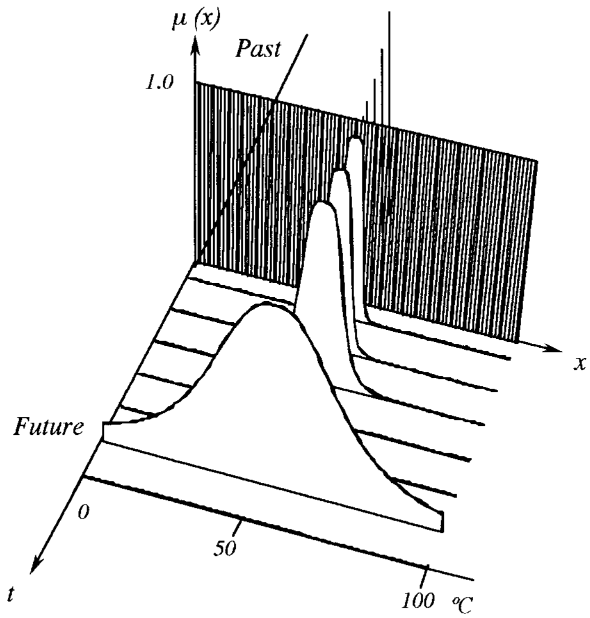

Fig. 3. Past and present observations are crisp numbers while predictions are fuzzy numbers.

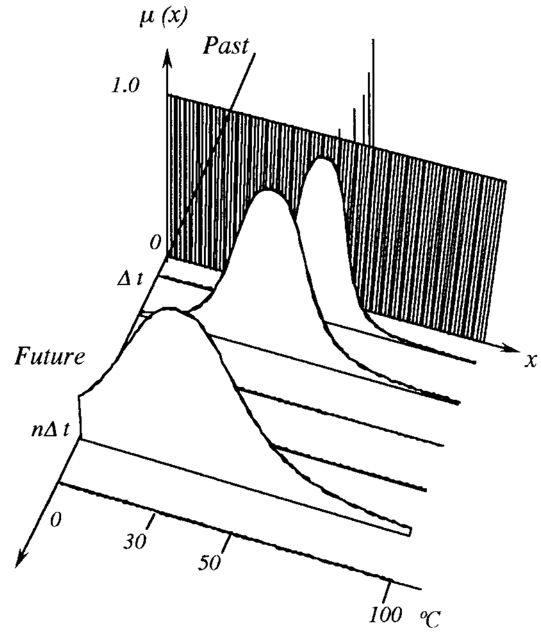

Fig. 5. Fuzzy prediction of a decreasing value of temperature.

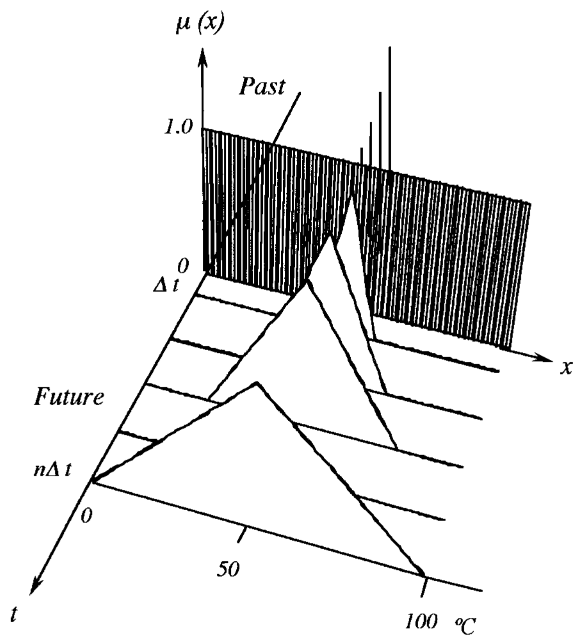

Fig. 4. Predictions as triangular fuzzy numbers.

membership function shapes for modeling the predicted values may be used such as the triangular numbers shown in Fig. 4. In Fig. 5, a prediction for lower temperatures in the future is shown. Again the predicted values become fuzzier as the prediction horizon increases; this time, however, their normal point also moves toward lower temperatures.

What does the fuzziness of a prediction depend on? First of all, to make any prediction about $n\Delta t$ when at $t = 0$ requires a model which accurately reflects the governing principles of the process. Next, consideration must be given on how far into the future to look for (how many Δt's), i.e., how the future is modelable in terms of fuzzy numbers.

At first glance the problem seems intractable, too many parameters to be adjusted, too many application specific factors, too much fuzziness and several interrelated questions that need to be addressed. How is the anticipatory time step Δt to be determined and how is the prediction horizon $n\Delta t$ to be determined as well. Most importantly, how is the fuzziness of a prediction to be modeled, i.e., how is the shape of the membership function to be determined, that is, if we choose the bell-shaped functions as done above how do we adjust the parameters a, b, c, etc. We try to answer some of these questions in the present research keeping in mind that prediction is always based on a model since the future can not be measured in a physical sense and, therefore, the modeling of predicted values has to be seen as part of the broader modeling process. For a more general discussion of these issues, see the outstanding work of Rosen on anticipatory systems [7].

III. General Methodological Approach

A system that makes decisions in the present on the basis of what may be happening in the future is envisioned to be different from conventional decision systems in two important respects: In the *language* used to formulate its anticipatory behavior and in the method of *prediction* used to access future states.

Consider the typical systems formulation in modern control theory. A system is described by a set of difference (differential) equations of the form

$$\begin{aligned} x(t+1) &= \boldsymbol{A}x(t) + \boldsymbol{B}u(t) + w(t); \quad x(t_0) = x_0 \\ y(t) &= \boldsymbol{C}x(t) + v(t) \end{aligned} \tag{6}$$

where

$\{u(t)\}$	$r \times 1$ input sequence;
$\{y(t)\}$	$m \times 1$ output sequence;
$\{x(t)\}$	$n \times 1$ state sequence;

$\boldsymbol{A}, \boldsymbol{B}$, and $\boldsymbol{C}$	appropriate transition matrices;
x_0	some initial state;
$w(t)$ and $v(t)$	noise terms.

Definition: A system is called *anticipatory* if $x(t+1)$ and $y(t)$ in (6) are not uniquely determined by $x(t)$ and $u(t)$ alone, but use information pertaining to some future state $x(t+\Delta t)$ and/or input $u(t+\Delta t)$.

Looking at (6) we observe that it is rather difficult to include future information in this formulation, except by containing it within the noise terms as in the case of nondeterministic systems. Another point of view, however, is to look at the equation signs "$=$" as assignment operators "$:=$," i.e.,

$$\begin{aligned} x(t+1) &:= \boldsymbol{A}x(t) + \boldsymbol{B}u(t) + w(t) \\ y(t) &:= \boldsymbol{C}x(t) + v(t) \end{aligned} \tag{7}$$

where, the assignment operator, "$:=$" is an *if/then* rule, which assigns the right hand side (RHS) of (7) to the left hand side (LHS) upon update. Now we are in the realm of logical implications where we can easily include terms such as $x(t+\Delta t)$, and $u(t+\Delta t)$ in *if/then* rules. The calculus of fuzzy *if/then* rules is well known and provides an interesting alternative and enhancement of formulations such as (6) particularly for the purpose of qualitative and complex system modeling. Thus, an anticipatory system can be described by a finite collection of fuzzy *if/then* rules

$$R^N = \{R^1, R^2, L, R^n\}. \tag{8}$$

Each rule is a *situation/action* pair, denoted as $x \rightarrow u$, where both *present* and *anticipated situations* are considered in the LHS and current action in the RHS. The rules of (8) may be rewritten as

$$\begin{aligned} R^N &= \{x^1 \rightarrow u^1, x^2 \rightarrow u^2, L, x^n \rightarrow u^n\} \\ &= \phi_{j=1}^{n}(x^j \rightarrow u^j) \end{aligned} \tag{9}$$

where ϕ is an appropriate implication operator [9], [16]. In many cases we can further partition the set of rules in (9) into rule-bases (RB) with each rule-base being responsible for one action, i.e.,

$$R^n = \bigcup_{p=1}^{r} [\mathrm{RB}^p]. \tag{10}$$

Rule-bases (10) can be made to reflect temporal partitions, that is we can have rules that describe the state of the system at t, i.e., of the form

$$x(t) \rightarrow u(t) \tag{11}$$

as well as rules that describe the possible state of the system some time latter, i.e.,

$$x(t+\Delta t) \rightarrow u(t). \tag{12}$$

Thus an anticipatory fuzzy algorithm can infer the current action $u(t)$ on the basis of the present state $x(t)$ as well as anticipated ones $x(t+\Delta t), x(t+2\Delta t), L, x(t+n\Delta t)$.

Generally, the rules of (10) describe relations of a more general type than that of functions, i.e., *many-to-many* mappings. Such mappings have the linguistic form of fuzzy *if/then* rules, e.g.,

$$\text{if } x \text{ is } A(t) \text{ then } y \text{ is } B(t) \tag{13}$$

where x is a fuzzy variable whose arguments are fuzzy sets denoted as A, and y is a fuzzy variable whose arguments are the fuzzy sets B. Similar rules pertaining to future states are of the form

$$\text{if } x \text{ will} - \text{be } A(t+\Delta t) \text{ then } y \text{ is } B(t). \tag{14}$$

Evaluating of formulations consisting of rules such as (13) and (14) is called *generalized modus ponens* (it amounts to drawing conclusions on the basis of imprecise premises). In *generalized modus ponens* we are given a fuzzy implication, such as (13) or (14), and an input that *imperfectly* matches (i.e., matches to some degree) the antecedent part of the rule and we can compute a new consequent using well-defined operations of composition [16].

Anticipatory control strategies may be based on global fuzzy variables such as *performance* where a decision at each time t is taken in order to maximize current as well as anticipated performance pertaining to $t+\Delta t$. *Performance* in this case is a fuzzy variable (with an appropriate set of fuzzy values) that summarizes information about the system allowing the system to make decisions about its change of state. The observation/prediction of such variables can be addressed by the methodology presented in the next two sections.

IV. Prediction Through Neural Networks

We present here a neural computing methodology for generating fuzzy numbers which constitutes essentially a fuzzification (symbolization) of predictions in accordance with the discussion in Section II. The process of fuzzifying the output of prediction is somewhat keen to measurement and hence we have referred to it as *virtual measurement* [13], [14].

In virtual measurements neural networks are used to perform a mapping $f\colon M \rightarrow E$ where, the domain M is the hyperspace of accessible variables such as temperatures and pressures in an engineering system and the output range E is a set of fuzzy numbers that constitute our predictions of fuzzy values referred to as *virtual measurement values* (VMV's) [6]. A fuzzy number is a normal and convex fuzzy set on the reals uniquely represented by a membership function. The fuzzy numbers used here have trapezoidal shapes. Trapezoidal membership functions may be described by a set of four numbers, e.g., a given number $c = \{o_1, o_2, o_3, o_4\}$ where $0 \leq o_1, o_2, o_3, o_4 \leq 1$ and $\{o_1, o_2, o_3, o_4\}$ (from left to right) represents the universe of discourse components of the four corners of the trapezoid (from left to right). Such representation offers considerable computing speed advantages. The methodology for predicting fuzzy numbers has been exposed in [14] and [15] and its main points are summarized in the following steps.

1) Decide how many fuzzy values are necessary to adequately cover the range of the fuzzy variable to be predicted.

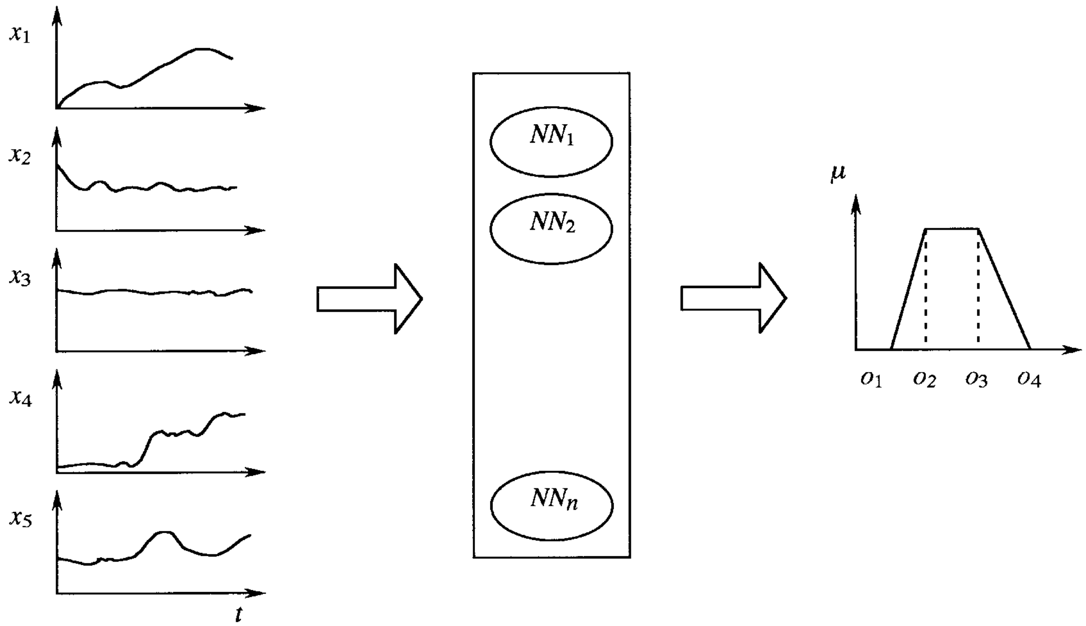

Fig. 6. Virtual measurement approach to fuzzifying predictions.

2) Determine the number of physically measurable variables that will be the basis (i.e., the input) of the virtual instrument.
3) Train one neural network per VMV, e.g., a program trained on five VMV's will require five trained networks.
4) Design an appropriate logic using the *index of dissemblance* to select which membership function will be the predicted value of the instrument at any given time.

The networks comprising the virtual instrument are trained (in a process analogous to "calibration") with time series input vectors, and vectors representing fuzzy numbers as outputs. Each network learns to map a constellation of input patterns to a particular linguistic label. The situation is illustrated in Fig. 6 where five inputs are used and n networks; hence this virtual instrument is calibrated with n fuzzy numbers. After training all networks receive on-line time signals as inputs and produce a set of membership functions as outputs. Generally the outputs will be somewhat different from the membership functions the networks were trained for (the prototypes) and moreover one or at most two (if we allow overlap of membership functions) will represent correct values while the rest need to be ignored. It is thus important to identify the correct output. Since we consider each network's output to be a fuzzy number we use a *dissemblance index* to estimate the outputs that are closest to the set of prototype membership functions on which we trained the networks and select one as the predicted fuzzy value.

Using physically observable quantities to predict fuzzy values offers some unique advantages. A set of complicated time series is mapped to the universe of discourse of human linguistics through an artificial neural network which acts as an interpreter of vital information supplied from the system. The information encoded in a time series is in the form of rate of increase/decrease, and maximum/minimum values attained over a period of time. The network is trained to represent this kind of "hidden" information in the form of membership functions which can be used for fuzzy inferencing. The membership function provides sufficient information to predict the value of a fuzzy variable in the near future. Furthermore, a network trained to recognize a specific complicated time pattern (i.e., have a "crisp" value as output), will lose much of its ability to deal with noisy input signals since it will tend, for distorted inputs, to produce averaged forms of the desired output, missing therefore vital pieces of information.

As an example of the prediction method consider the following experiment. Actual data obtained during a start-up of the high-flux isotope reactor (HFIR) was used in order to test the methodology for predicting fuzzy values. HFIR is a three-loop pressurized water research reactor operated at the Oak Ridge National Laboratory. A flow control valve on the secondary side of the system is used as the main mechanism for flow control (there is also a "trim flow control valve" for finer flow adjustments, as well as control rods). Although the signal sent to the motor of the valve is known, the actual position of the secondary flow control valve is not known and is rather hard to predict. The disk position is something that the operators of the plant "learn" how to estimate intuitively on the basis of experience. However, valve aging and varying plant operating conditions as well as operator experience are major factors for substantial variations in the estimate of valve position.

Five parameters were chosen as the basis for predicting the secondary flow control valve position: *neutron flux, primary flow pressure variation* (ΔP), *core inlet temperature, core outlet temperature,* and *secondary flow*. All but the last one of the above mentioned time series, contain average values of the corresponding parameters of the three loop system. Fig. 7 shows one of them, the secondary flow signal normalized in the range between zero and one. The parameters were selected in order to provide sufficient description of both the primary and secondary sides of HFIR during start-up. The time

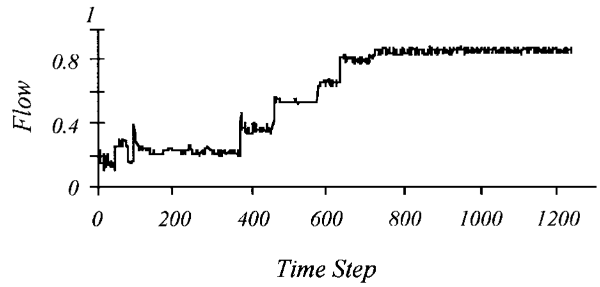

Fig. 7. Secondary flow signal during start-up.

series of these five parameters are used to train five neural networks where each one of them has five nodes at the input layer and four nodes at the output layer (ten nodes in the hidden layer). In each network NN (Fig. 6) there are five input nodes each receiving a time series from a physically measurable variable, and four output nodes representing the four corners of a trapezoidal membership function. The output is a membership function uniquely labeling a fuzzy value of the fuzzy variable describing the position of the secondary flow control valve, referred to as *valve_position*. The data used for network training is normalized in the interval 0.1–0.9 and sampled every 16 s, with a total of 1240 samples available. Designing a virtual instrument to predict *valve_position*, requires first to partition its membership of discourse with the appropriate number of VMV's. We choose five values, namely, *closed, partially_closed, medium, partially_open* and *open*. Each value is represented by a membership function, i.e., $\mu_{closed}, \mu_{partially\_closed}, \mu_{medium}, \mu_{partially\_open}$, and μ_{open}. These five membership functions describe the position of the valve at every instant during the start-up period. The universe of discourse on which these membership functions are defined is the interval [0,1]. Thus, μ_{open} associates each point in the universe of discourse with the fuzzy value *open* at this point.

The membership functions representing the output of the predictive instrument in this particular study have trapezoidal shape or the degenerated (triangular) form of it, which is very useful for computations in the fuzzy control area. The membership function for *closed*, i.e., μ_{closed} is defined by a trapezoid with peak coordinates $\{(0.02, 0), (0.05, 1), (0.10, 1), (0.2, 0)\}$. Similarly, *partially_closed*, is represented by the trapezoid with coordinates $\{(0.15, 0), (0.2, 0), (0.30, 1), (0.4, 0)\}$, *medium* by $\{(0.35, 0), (0.4, 1), (0.50, 1), (0.6, 0)\}$, *partially_open* by $\{(0.5, 0), (0.6, 1), (0.7, 1), (0.75, 0)\}$, and *open* by $\{(0.7, 0), (0.82, 1), (0.85, 1), (0.90, 0)\}$. It is evident from the above geometrical schemes that there is an overlap between the membership functions used. The reason for the overlap is the fuzziness in the definition of the different states of valve position. Fig. 8 shows the prediction of the instrument during a startup of the reactor (1240 time steps). The valve is initially *closed* as seen by the membership function in the origin of the three-dimensional graph. It goes through the "medium" range rather quickly in the vicinity of 400–500 time steps and finally it becomes fully open after the 800 time step. Notice that this confirms rather well the trend shown in Fig. 7 where the secondary flow reaches its maximum value after about the 800 time step. To test the ability of each network to predict the valve position by calculating the right membership function at any particular time step, different levels of noise were introduced in the input signals. Initially up to 10% noise was introduced to each of the five input signals and the set of networks was tested with the "noisy" vectors. The appropriate networks fired at the corresponding time steps calculating the coordinates of the peaks of the corresponding membership functions with 98% accuracy. Henceforth there was an excellent prediction of the position of the disc valve during the whole time interval under consideration. In addition, 20% noise was introduced to all five input signals and the networks were tested again. The response of the system was indistinguishable form the previous case.

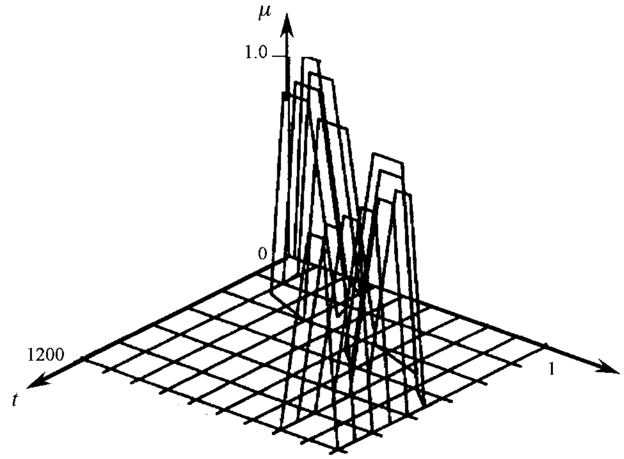

Fig. 8. Fuzzy values for valve position during start-up.

Even when an input signal was dropped, actually replaced with random noise, the predictive instrument still predicted the valve position rather accurately. A series of statistical tests were conducted to confirm that the output of the instrument is actually within random error from the previous case. This is a significant tolerance to the informational hazard that the instrument was exposed to. Even with about 20% of its input information lost this system still rather accurately measured the valve position. Similar results were obtained by dropping the other input signals one by one.

V. Prediction Through Other Neural Models

Radial basis networks (RBN's) are appropriate networks for creating predictive models of a nonlinear system [19]. We examine here RBN's in conjunction with an anticipatory system using fuzzy rules to encode power maneuvers in the experimental HIFIR. We use a three layer RBN to replace the unknown and generally nonlinear model of the reactor. The unknown plant dynamics f are approximated by the RBN's nonlinear function approximation capability through a learning process, which results in an implicit model of the nuclear reactor. The weights of RBN are adapted using on-line monitoring of the plant input-output measurements. In this HIFIR application, a locally trained RBN gives a suitable plant model with one-step-ahead predictive capabilities that provides control input for power tracking control.

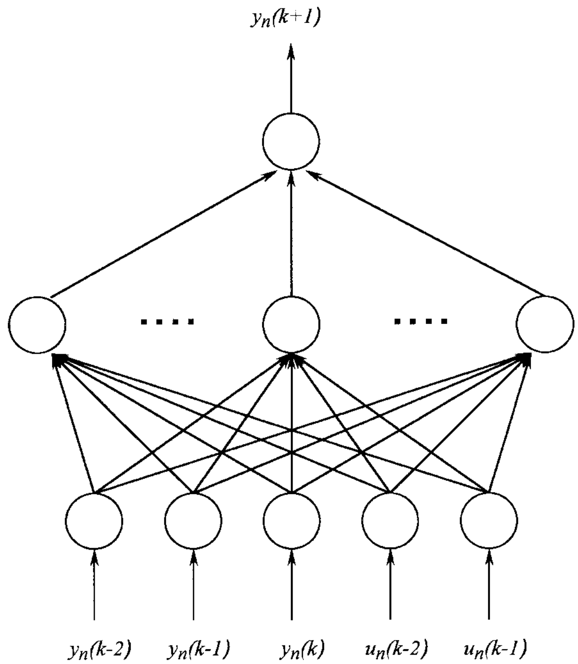

Fig. 9. Radial basis function network architecture.

The network input vector is represented by $x \in R^{m+n+2}$, where $m = 2, n = 1$. The output is denoted as y_n. The network output is a nonlinear function of the weighted sum of the activation levels found in each of the N hidden units of the network, i.e.,

$$y(k+1) = f[\boldsymbol{x}(k)] = \sum_{i=1}^{N} w_i \boldsymbol{e}^{-D_i[\boldsymbol{x}(k), c_i]} \tag{15}$$

where

$$\boldsymbol{x}^T(k) = [y_p(k), H, y_p(k-m); y(k), y(k-1)]$$

and

$$D_i[\boldsymbol{x}(k), c_i] = (\boldsymbol{x} - c_i)^T(\boldsymbol{x} - c_i), \qquad i = 1, \ldots, N. \tag{16}$$

The symbol c_i in (16) stands for the center value of the ith unit. The architecture of the RBN is shown in Fig. 9. In the present application, the network has five inputs, one output and eleven units in the hidden layer. A *least-mean-square* (LMS) algorithm is used for the purpose of achieving on-line learning. The LMS adjusts network weights in order to minimize the mean-square-error; which is defined as the difference between actual plant output y_p and the predictive network output y_n. The weights of the network are updated at the kth time step according to the rule

$$w_i(k+1) = w_i(k) + \Delta w_i(k) \tag{17}$$

where

$$\Delta w_i(k) = \alpha \cdot [y_p(k+1) - y_n(k+1)] \cdot e^{-D_i[\boldsymbol{x}(k), c_i]} \tag{18}$$

α is the learning rate and $i = 1, \cdots, N$ are the hidden units.

The neurofuzzy anticipatory controller is based on one-step-ahead predictive control which generates $u(k)$ so that the predicted output $y_n(k+1)$ by the RBN becomes the desired output $y_d(k+1)$. This algorithm has been widely accepted as a conceptually viable approach to model-based controller design. Because the control law tends to be sensitive to plant modeling uncertainties an adaptive learning network is used.

The control input is generated from the inverse dynamics, i.e., $u(k) = g[y_d(k+1), y_n(k+1), x(k)]$ where $g[\cdot]$ is generally a nonlinear function. From an analysis of historical data from the process, a fuzzy inference system suitable for this task has been developed [19]. The fuzzy inference system is developed off-line as follows. First, using a subclustering algorithm we estimate the number of membership functions (MF) involved in the input and output variables. Then, we fine-adjust and increase the number of MF's (so as to improve the accuracy) using a fuzzy c-means algorithm to find the center of each MF. As has been widely shown in the literature, fuzzy c-means clustering can provide accurate parameters to construct the MF. In order to increase the accuracy of our system eight clusters were identified. The input to the fuzzy inference is $y_n(k+1)$ and the output is $u(k)$. The fuzzy rulebase consists of eight rules

$$\text{if } (y)n(k+1) \text{ is state } (i)\}, \text{ then}\{u(k) \text{ is } u(i)\}, \quad i = 1, \ldots, 8. \tag{19}$$

After the fuzzy inference is performed, the result $u(k)$ is checked by another rule based on the simplified assumption

$$\Delta u(k) = \gamma(y_d(k+1) - y_n(k+1)) \tag{20}$$

where γ is a scale factor can be found through linear regression of input-output data (a linear relation exists between these variables). The final control input to the plant model is

$$u(k) = u(k) + \Delta u(k). \tag{21}$$

Application

In this section the tracking control problem of HFIR power is simulated using a prespecified desired trajectory. A power loading problem is considered for the purpose of demonstrating the applicability of the anticipatory control method. The reference model is simulated using another RBN which is trained extensively off-line and has been checked by real-time operation data with high accuracy results. The system, initially at a steady state power level of 28%, is required to track the desired trajectory given in Fig. 10. The overall neurofuzzy anticipatory architecture is depicted in Fig. 11.

The simulation proceeds in the following manner:

1) *Learning Phase* $(stepsk = 1, \cdots, 50)$. In this phase the system is getting input-output pairs from plant simulation to train off-line the predictive RBN, while at the same time the plant is using a conventional proportional–integral (PI) control method. This off-line learning phase prevents the fundamental conflict of control and identification in adaptive control theory and also it provides stability for the RBN.

2) *Operation Phase* $(stepsk = 51, \cdots, 200)$. After the learning phase, the anticipatory control method is successfully applied to the unlearned region of power level. The simulation results show quite well the bump-less transfer mode and the excellent tracking capability of the neurofuzzy controller.

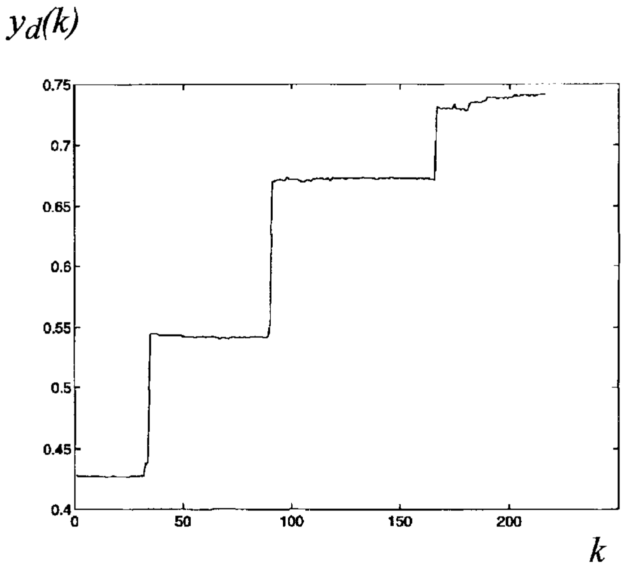

Fig. 10. Desired system trajectory.

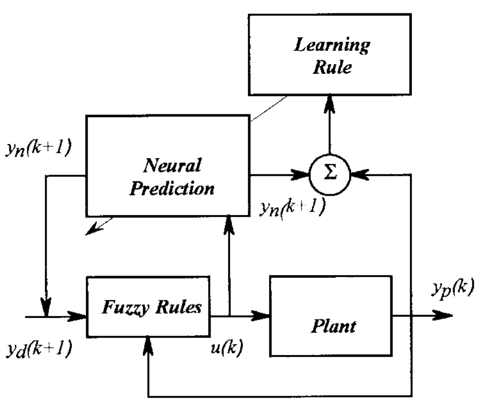

Fig. 11. Overall structure of neurofuzzy anticipatory control system.

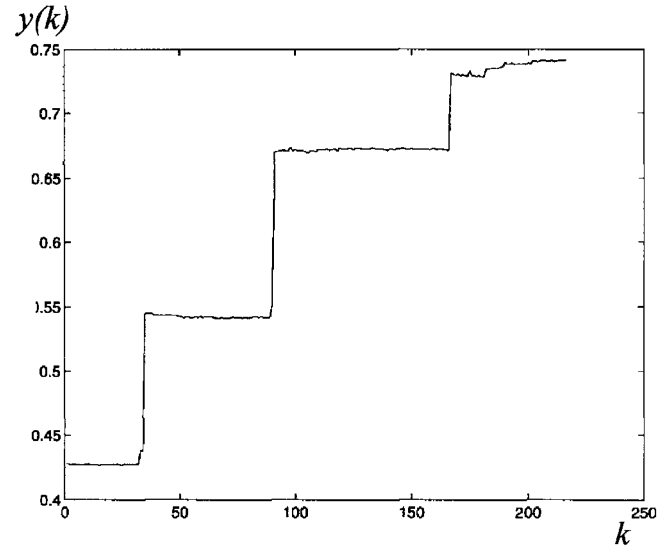

Fig. 12. Plant output model.

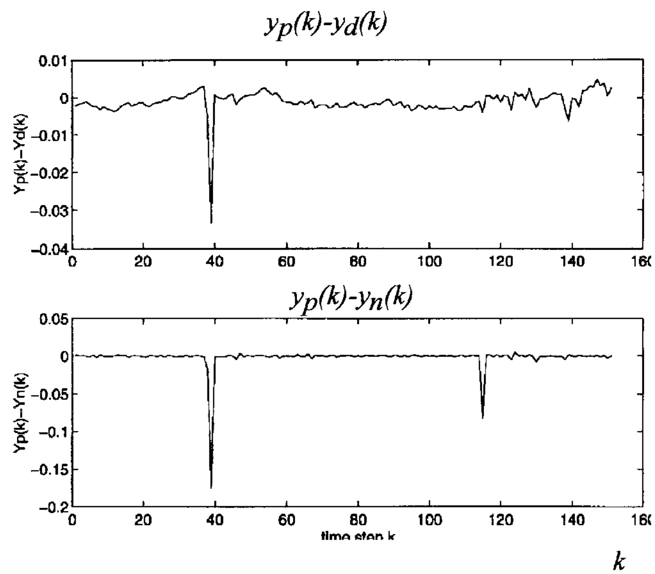

Fig. 13. Error between plant output model and desired trajectory.

The plant model output y_p is shown in Fig. 12, while the error $(y_p(k) - y_d(k))$ is shown in Fig. 13. The results are very encouraging. It should be noted that during a step increase in power loading the worst error is 3.3%. Because of the stiffness inherent in most nuclear systems, it is very hard to perform accurate prediction. From our simulation experience, the data's predictive utility disappeared very fast as it became "older." Thus, there is little need to increase the training data set as the time passes by; we can simply shift the sample data window along the time axis. This is preferable since the network can be trained using a smaller set of data, saving training time which is very important for an on-line operation. A possible drawback is that a network trained with a relatively small set of "stiff" data can not learn well all complex characteristics of the system. So the predicted "future" tends to be more "fuzzy" compared with the power level output; the predicted power level $y_p(k)$ being accurate enough except at the time of step increase. This suggest that the fuzzy inference system plays an important role in tracking power level and stabilizing the plant system. The control output from real world operation (PI control) and from neurofuzzy anticipatory control are shown in Fig. 14 where we can clearly see the smooth behavior of the simulation result.

VI. Conclusions

Neurofuzzy approaches to anticipation aim at integrating the predictive capabilities of neural computing with the clarity and convenience of articulation found in fuzzy algorithms. They offer a promising emerging technology for systems whose own predictive capabilities provide foresight and hence greater behavioral flexibility. An important feature of the presented approach is that predictions about the future are modeled as fuzzy numbers which are obtained through neural models while fuzzy *if/then* rules encode system-specific knowledge for using such neural anticipations at the present. Virtual measurement as well as radial basis functions networks offer the possibility of timely and reliable estimation of variables

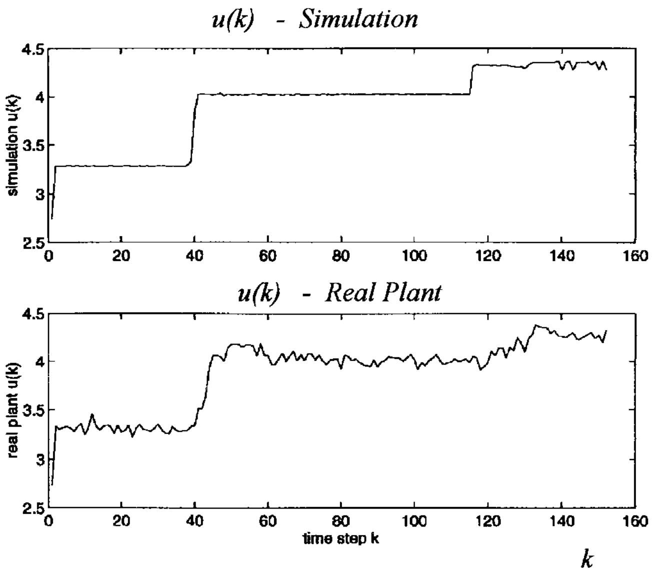

Fig. 14. Comparison of plant and neurofuzzy anticipatory controller.

useful for anticipatory control where change of states is based in present as well as future states. The virtual measurements contemplated for prediction are a form of *expert measurement*, i.e., prediction heuristics for system-specific fuzzy variables with functional significance. The values of such variables are overlapping categories modeled as fuzzy numbers.

To address the prediction problem, neural networks perform a mapping of physically observable dynamic variables to fuzzy values each uniquely and unambiguously defined by a membership function. The failure-tolerant characteristics of such predictive instruments have been demonstrated by performing rather accurate measurements and predictions of fuzzy values even with missing or partially distorted inputs. During the course of the lifetime of an anticipatory system both the physical characteristics of the system and the predictive models change. Calibration or fine-tuning of such predictive models may be achieved by additional training of the neural models used and research in needed for establishing ways that signal the need for new training phases.

The neurofuzzy approach to anticipation has been illustrated through the anticipatory control of a nuclear power plant. The approach uses a neural network model that embodies the nonlinear behavior of a reactor and a fuzzy inference method to determine the one-step-ahead predictive control input. The results of the application to the tracking control of reactor power indicate that the controller has excellent robustness and performance features.

There are additional issues to be resolved in neurofuzzy approaches to anticipation, one of the most important being developing formal criteria for the stability of the system. Although the use of fuzzy algorithms protects from excessive sensitivity to initial conditions, there is need for knowing when the system cannot operate in an anticipatory mode and for determining the time window of anticipation on a more formal basis. Furthermore, the control algorithms appear to be sensitive to various implications and defuzzification methods. An important area for future research is obtaining quantitative estimates of such sensitivities for specific systems operating under various environmental and internal changes.

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Lefteri H. Tsoukalas (S'88–M'89), for photograph and biography, see this issue, p. 530.