The Baroreceptor Reflex: A Biological Control System with Applications in Chemical Process Control

4 AUTHORS, INCLUDING:

Babatunde A Ogunnaike
University of Delaware
189 PUBLICATIONS **2,268** CITATIONS

James Schwaber
Thomas Jefferson University
146 PUBLICATIONS **3,817** CITATIONS

The Baroreceptor Reflex: A Biological Control System with Applications in Chemical Process Control

Michael A. Henson,† Babatunde A. Ogunnaike,* and James S. Schwaber‡

*Neural Computation Program, Advanced Process Control and Modeling Group,
DuPont Central Science and Engineering, Wilmington, Delaware 19880-0101*

Francis J. Doyle III

School of Chemical Engineering, Purdue University, West Lafayette, Indiana 47907-1283

Many industrial chemical processes are difficult to control effectively using existing techniques because they are complex, interconnected, nonlinear systems which lack reliable on-line measurements of key process variables. Due to increasingly stringent demands on product quality, energy utilization, and environmental responsibility, more effective control strategies are needed for these processes. By contrast, extremely complex biological systems routinely operate under more stringent requirements on "product quality" and "failure tolerance" as a result of the robust, high performance computation and control functions provided by the brain. Thus, studying and understanding these biological control systems, and ultimately "reverse engineering" their functions, should provide ample alternative techniques for developing effective control systems for chemical processes. The objective of this paper is to present one such biological control system—the *baroreceptor reflex,* which provides short-term regulation of arterial blood pressure—and identify potential applications in chemical process control. Novel process monitoring, modeling, and control strategies which are currently being developed by "reverse engineering" the architectural and computational properties of this reflex are discussed. Preliminary results on techniques for sensor fusion based control, nonlinear modeling, and control of multiple-input, single-output systems which have been abstracted from the reflex are also presented.

1. Introduction

Effective monitoring, modeling, and control strategies are not available for many chemical processes primarily because of their intrinsic complexity. For example,

1. Most industrial processes have many input and output variables, and the relationships between these variables are often nonlinear, time varying, and for the most part poorly understood (Uppal *et al.,* 1974; Deshpande, 1985; Downs and Vogel, 1993; Garcia *et al.,* 1989). In addition, in order to achieve efficient process operation, it is often necessary to maintain many of these variables at or near constraints (Prett and Garcia, 1988).

2. Many processes lack on-line measurements of critical process variables required for advanced control (Deshpande, 1985; Ray, 1986); however, accurate and reliable measurements of less important variables which are related to key variables are often available.

3. Chemical processes are, in general, subject to actuator and sensor degradation and failure (Morari and Zafiriou, 1989).

Nevertheless, because of increasingly stringent economic and environmental demands, control systems which can provide high performance, robust operation of industrial processes are becoming a necessity.

By contrast, the brain provides effective control of physiological systems which are considerably more complex than industrial processes, and which are subject to more stringent requirements on performance and robust-

ness (Grodins, 1963; Jones, 1973). Within this context, the brain may be viewed as a *central* control system which regulates a highly interconnected system of nonlinear chemical/biochemical processing "plants" in the body. What is known of these systems indicates the following:

1. Each physiological system has many input and output variables which must be maintained within physiological constraints.

2. In order to obtain accurate and reliable measurements of critical physiological variables, the brain utilizes highly integrated measurement schemes with large arrays of partially redundant sensors.

3. These biological control systems are highly adaptive and remarkably tolerant to actuator and sensor failure.

Observe therefore that the brain has solved many difficult control problems similar to those encountered in industrial chemical processes.

The high performance, robust control functions provided by the brain motivate us to pose the following question:

Is it possible to "reverse engineer" a biological control system and use the understanding to develop novel approaches for process control system design and analysis?

A similar "grand challenge problem" was recently posed by Brockett (1992), and in this paper, we present a first attempt at providing an answer to this question. We do so by focusing on a particular biological control system—the baroreceptor reflex, which provides short-term regulation of arterial blood pressure. Apparently, there is no prior record of *how* knowledge obtained from biological control systems has been (or *can be*) used to develop new control engineering methods (Hacisalihzade, 1992).

The paper is organized as follows: In section 2, we present a brief description of the baroreceptor reflex; next, novel process monitoring, modeling, and control concepts based on the baroreceptor reflex are discussed in section

* Adjunct Professor, Department of Chemical Engineering, University of Delaware. To whom correspondence should be addressed. E-mail: ogunnaike@essptd.dnet.dupont.com.

† Currently at the Department of Chemical Engineering, Louisiana State University, Baton Rouge, LA 70803-7303.

‡ Adjunct Professor, Department of Neuroscience, University of Pennsylvania.
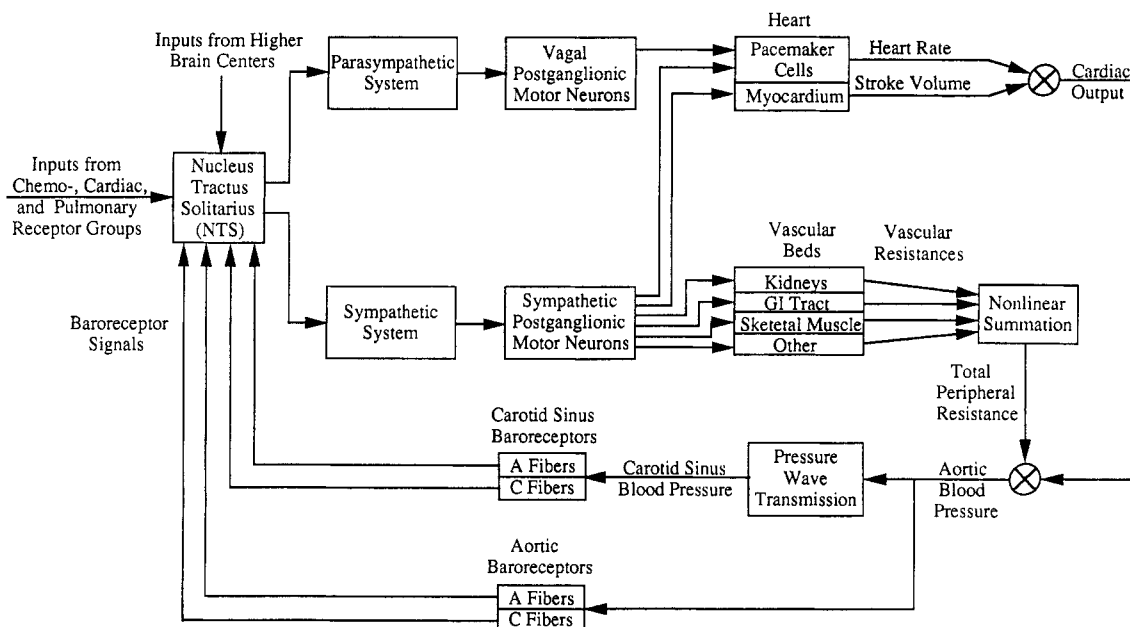
Figure 1. A block diagrammatic representation of the baroreceptor reflex.

3; and in section 4, the utility of reverse engineering the reflex is demonstrated by discussing some initial results for three specific problems of considerable industrial importance: sensor fusion based control, nonlinear modeling, and control of multiple-input, single-output systems.

2. The Baroreceptor Reflex

2.1. Overview. In conjunction with the respiratory system, the principal function of the cardiovascular system is the exchange of oxygen and carbon dioxide between body tissues and the external environment, in order to sustain *homeostasis*—the biological term for the coordinated actions which maintain the equilibrium states in a living organism (see Richter and Spyer, 1990; Spyer, 1990). Key physiological variables such as arterial blood pressure, circulating blood volume, and blood gas composition are monitored by mechanical- and chemical-sensitive neurons located in the main arteries, great veins, and the heart (Karemaker, 1987; Kirchheim, 1990). These widely dispersed signals are integrated in the autonomic nervous system and used to adjust cardiovascular function (Spyer, 1990).

Regulation of the cardiovascular system is achieved by several distinct feedback control systems or "reflexes." The *baroreceptor reflex* is primarily responsible for short-term regulation of arterial blood pressure (Karemaker, 1987; Kirchheim, 1976; Kumada *et al.*, 1990; Sagawa, 1983; Spyer, 1990). A block diagrammatic representation of the baroreceptor reflex is presented in Figure 1. The blood pressure in the aortic arch and carotid sinus is measured by a large array of stretch-sensitive neurons called "arterial baroreceptors" (Kirchheim, 1976). The baroreceptor signals are transmitted to the autonomic nervous system via fast conducting A (myelinated) fibers and slower conducting C (unmyelinated) fibers. In a specific region of the autonomic nervous system termed the "nucleus tractus solitarius (NTS)", the baroreceptor discharges are integrated with other cardiorespiratory signals, as well as inputs from higher brain centers.

The integrated sensory information from the NTS is processed by two distinct neural controllers: the parasympathetic and sympathetic nervous systems. The controllers adjust heart rate, stroke volume, and total peripheral resistance, which in turn determine the aortic

and carotid sinus pressures as shown in Figure 1. The effector mechanisms (heart and vascular beds) are manipulated by the parasympathetic and sympathetic systems via vagal and sympathetic postganglionic motor neurons, respectively. The parasympathetic system primarily manipulates cardiac pacemaker cells, which determine heart rate. The sympathetic system affects heart rate via cardiac pacemaker cells, stroke volume via the myocardium, and total peripheral resistance via vascular beds in the kidneys, gastrointestinal tract, skeletal muscle, and other organs.

The baroreceptor reflex exhibits a variety of interesting control characteristics; for example,

1. The reflex is more effective in handling pressure decreases (which can result in unconsciousness) than pressure increases (Kirchheim, 1976).

2. The reflex is nearly unstable and can produce sustained oscillations under certain conditions (Sagawa, 1983).

3. The gains of the carotid sinus and aortic baroreceptor reflexes are nonlinear and largest near the normal blood pressure (Kirchheim, 1976).

4. The carotid sinus and aortic reflexes interact nonlinearly as their individual effects are usually greater than their combined effects (Yamazaki and Sagawa, 1989).

5. The reflex is not required for long-term pressure control as demonstrated by studies in which mean blood pressure is regulated at normal levels despite complete elimination of the baroreceptor signals (Cowley *et al.*, 1973; Kumada *et al.*, 1990).

Many of these characteristics are desirable for chemical process control systems. For instance, controllers which are more effective in rejecting certain types of disturbances (*e.g.*, those which cause the most deleterious deviations of the outputs from their setpoints) would be beneficial for many chemical processes.

2.2. Arterial Baroreceptors. Baroreceptor neurons transduce blood pressure by producing action potentials (voltage "spikes") in response to deformations in the arterial wall (Kirchheim, 1976). Baroreceptors exhibit a variety of complex static and dynamic behaviors including the following: (1) activity which is closely related to the cardiac cycle and depends on both the mean pressure and rate of change of pressure (Kirchheim, 1976); (2) no change
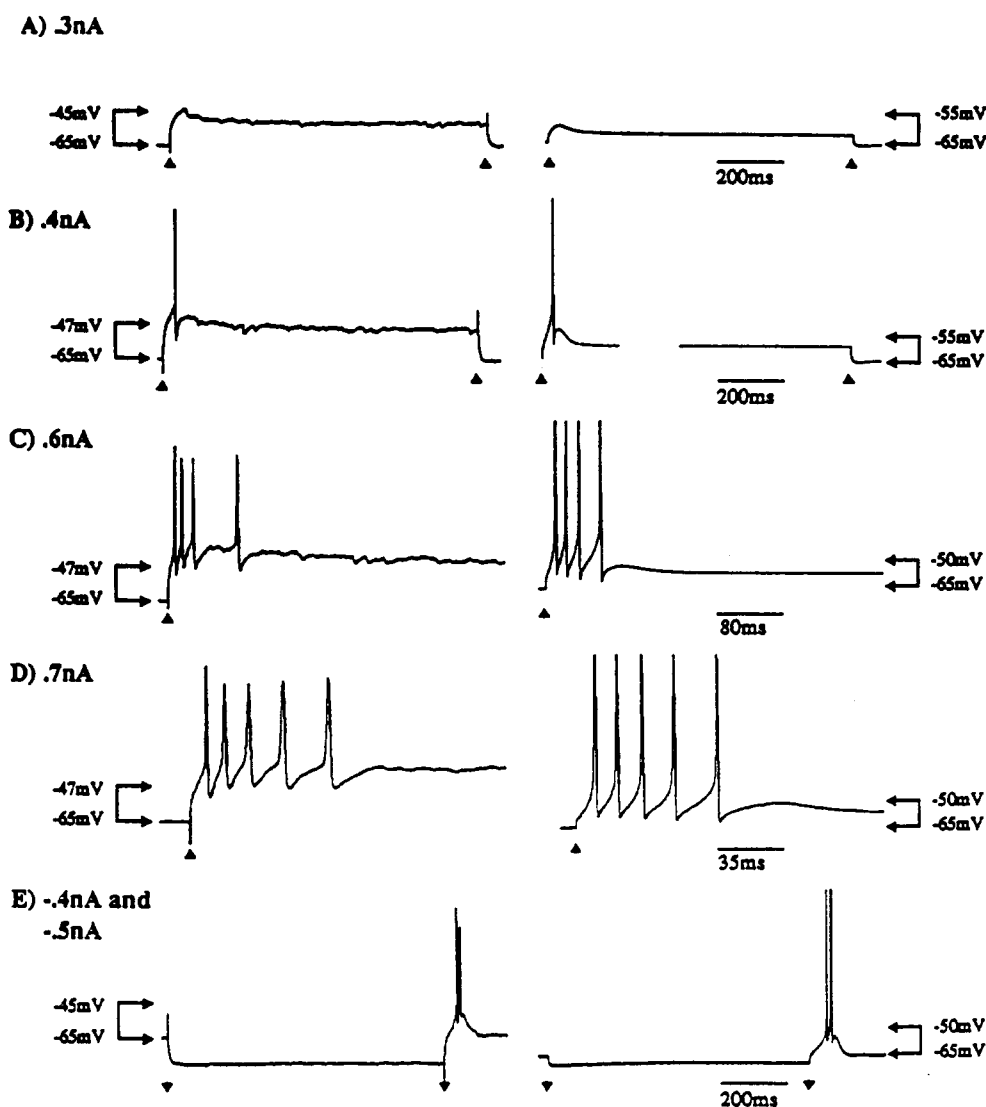
Experiment   **Simulation**

Figure 2. Activity of a NTS neuron for five different current injections.

in activity in response to mean pressure variations which occur outside the pressure range determined by the threshold and saturation pressures—and these pressure limits differ for individual baroreceptors (Kirchheim, 1976); (3) the use of a partially redundant array of baroreceptors to encode blood pressure (Kirchheim, 1976); (4) output signals that are transmitted to the autonomic nervous system by *myelinated* and *unmyelinated* fibers which have significantly different conduction velocities (Kirchheim, 1976); (5) the use of myelinated baroreceptors primarily for dynamic control of blood pressure, and unmyelinated baroreceptors primarily for steady-state control (Seagard *et al.*, 1993); (6) *nonlinearity*—baroreceptors exhibit hysteresis and asymmetric responses (Kirchheim, 1976); (7) *adaptation*—activity is "reset" in response to short-term and long-term changes in blood pressure (Kumada *et al.*, 1990); (8) *robustness*—increased reliance is placed on remaining pressure measurements if some baroreceptors are damaged (O'Leary and Scher, 1990).

By "reverse engineering" these measurement strategies, it should be possible to develop more effective monitoring techniques for chemical processes. For instance, process monitoring schemes based on arrays of cheap, partially redundant sensors would be significantly more robust to

sensor degradation and failure than existing techniques which employ only a single, expensive measurement device. A more detailed discussion of process monitoring strategies which may be abstracted from the reflex is presented in section 3.1.

2.3. NTS Neurons. Neurons in the nucleus tractus solitarius (NTS) region of the autonomic nervous system integrate signals from arterial baroreceptors and other receptor groups (Paton *et al.*, 1993). The activity of an NTS neuron in response to a series of current input changes is shown in the left-hand side of Figure 2 (Schwaber *et al.*, 1993). The magnitude of the current injection and the time response of the membrane voltage is shown for each test. The initiation and cessation of the current step change is denoted by triangles. The dynamic responses can be very complex. For instance, the input changes in Figure 2C,D produce a sequence of action potentials that "accommodate"; *i.e.*, the interspike frequency decreases with time.

Simulation results from a Hodgkin–Huxley neuron model (Hodgkin and Huxley, 1952) constructed to match the experimentally observed neuronal behavior are shown on the right-hand side of Figure 2. A Hodgkin–Huxley model describes the opening and closing of ionic channels which determine neuron activity. Based on an electrical

circuit analog, the model has the general form,

$$C_M \frac{dV_M}{dt} = \sum_{i=1}^{n} G_i(V_i - V_M) + I \qquad (1)$$

where V_M is the membrane voltage, C_M is the membrane capacitance, G_i is the time-, voltage-, and (perhaps) calcium-dependent conductance of the ith ionic channel, V_i is the reverse potential of the ith channel, I is the current input, and n is the number of ionic channels. As shown in Figure 2, the Hodgkin–Huxley model matches the experimental data quite accurately despite "manual" tuning of the model parameters. A systematic procedure for optimizing the model fit based on a random search algorithm has recently been proposed (Foster et al., 1993).

In addition to accommodation, NTS neurons exhibit complex behaviors such as (1) dynamic responses with variable time delays which depend on the magnitude of the input change (Paton et al., 1993), (2) activity which is strongly dependent on the relative timing and location of input signals (Mifflin and Felder, 1990), (3) activity in the absence of synaptic input (Paton et al., 1991), and (4) modulation of the baroreceptor reflex setpoint and gain (Mifflin and Felder, 1990; Spyer, 1990).

Effective process monitoring, modeling, and control strategies may be developed by "reverse engineering" the computations performed by NTS neurons. For instance, robust sensor data fusion schemes may be abstracted from the mechanism which the NTS employs for integrating cardiorespiratory signals. Other chemical process technologies which may be abstracted from NTS neurons are presented in section 3.

2.4. Parasympathetic and Sympathetic Systems. The parasympathetic and sympathetic nervous systems receive integrated sensory information from the NTS and regulate blood pressure via three principal effector mechanisms: heart rate, stroke volume, and flow resistances of various vascular beds (Kirchheim, 1976). The stroke volume and vascular resistances are manipulated primarily by the sympathetic system. Stroke volume adjustments yield significantly faster blood pressure responses than can be achieved by altering the vascular resistances. In addition, the relative changes in the individual vascular resistances can vary considerably depending on the characteristics of the pressure disturbance.

By contrast, the heart rate is manipulated by both branches of the autonomic nervous system. The heart rate provides significantly faster blood pressure responses than can be obtained with the stroke volume and vascular resistances (Karemaker, 1987). Heart rate regulation is complex because of the following:

1. The sympathetic and parasympathetic systems have opposite effects (Levy, 1990; Schmidt et al., 1971).

2. The effects of the parasympathetic system are considerably faster than those of the sympathetic system (Kirchheim, 1976; Scher and Young, 1963).

3. The parasympathetic system is employed only for dynamic control, while the sympathetic system is used primarily for steady-state control (Coleman, 1980).

4. The effects of the two systems do not sum linearly due to complex interactions which occur in both the autonomic nervous system and the heart itself (Levy, 1984, 1990).

Effective control strategies for chemical processes may be reverse engineered from the control architectures and algorithms used to regulate heart rate and blood pressure. For example, parallel control schemes which are much more robust than conventional cascade control to sensor degradation and failure may be abstracted from para-

sympathetic and sympathetic control of heart rate. A more detailed discussion of process control strategies which can be based on reflex characteristics is presented in section 3.3.

3. Implications for Process Monitoring, Modeling, and Control

In standard process control terminology, the baroreceptor reflex is an adaptive, nonlinear, multivariable control system which provides high performance, robust control of the highly complex cardiovascular system. The brief overview presented in section 2 illustrates how the reflex has successfully solved monitoring and control problems which are similar to those encountered in industrial chemical processes. Also evident is the fact that the highly integrated measurement and control strategies employed in the reflex are markedly different from the decentralized schemes typically employed for chemical process applications. The implications of the reflex functions and characteristics for process technology are now examined from the perspective of three partially overlapping areas: process monitoring, process modeling, and process control. Specific techniques for sensor data fusion, nonlinear modeling, and control of multiple-input, single-output systems which have been derived from the reflex are presented in section 4.

3.1. Process Monitoring. Accurate, reliable process monitoring systems are essential for effective operation of industrial chemical processes. Existing process monitoring schemes are often inadequate because (i) many process variables are measured with single sensors which have limited dynamic ranges and are prone to failure; (ii) sensors are placed using ad-hoc techniques; (iii) available process measurements are not utilized effectively; and (iv) especially in the polymer industry, measurements of key process variables are available only after lengthy laboratory analysis. In this section, some potential applications of the baroreceptor reflex in the development of improved process monitoring strategies are described. The discussion is divided into three areas: sensor technology; sensor placement and data fusion; and inferential measurement.

Sensor Technology. Several properties of baroreceptor neurons may inspire the development of more effective sensor technology. Arterial blood pressure, for example, is measured by a large array of baroreceptors, each of which has a limited range of sensitivity that is determined by its threshold and saturation pressures. An analogous measurement scheme based on an array of sensors with limited and partially overlapping operating ranges can be employed for chemical process applications. This approach should yield improved accuracy and robustness because each individual sensor can be designed to be more accurate in its range of operation, and the failure of any one sensor will cause little degradation in the overall performance.

Consider also the fact that baroreceptors desensitize or "reset" their activity in response to sustained changes in mean arterial pressure. By analogy, it may be advantageous to design sensors which actually modify their output based on the temporal history of the measured variable. This approach would, for example, enable the sensor to adapt to the current operating conditions, and therefore automatically improve its effective dynamic range. In this case, the sensor functions as an *active* component of the process monitoring system rather than in its traditional role as a simple "passive" transducer.

Sensor Placement and Data Fusion. In a typical industrial process, hundreds or even thousands of measurements are available. Ideally, all this information should be employed in the process monitoring and control

system. In most cases, however, only a few key process variables are selected based on physical considerations and the remaining process measurements are essentially ignored. This approach is becoming less acceptable with the increased awareness that high performance and robust operation of industrial chemical processes requires the development of more effective sensor placement and sensor data fusion techniques.

These issues are particularly important for multistage and distributed parameter processes such as distillation columns (Lang and Gilles, 1990; Kresta *et al.*, 1991) and plug-flow reactors (Kresta *et al.*, 1991; MacGregor *et al.*, 1991), respectively. For example, process monitoring and control schemes for packed bed reactors are often based on a single temperature sensor which is placed to measure the "hot spot" of the temperature wave propagating down the reactor (Doyle, 1991). Additional temperature sensors which may be available are not employed, and sensor failure results in complete loss of control. More effective use of correlated process data can be achieved, for example, by employing techniques based on principal component analysis and projection to latent structures (Kresta *et al.*, 1991; MacGregor *et al.*, 1991; Kaspar and Ray, 1992). However, these methods are restricted to linear, steady-state analysis.

More effective sensor placement and data fusion techniques for chemical processes may be abstracted from the baroreceptor reflex. Consider, for instance, that NTS neurons appear to reconstruct the blood pressure wave by integrating measurements from hundreds of arterial baroreceptors. By reverse engineering this biological measurement scheme, more effective process monitoring (and control) strategies for multistage and distributed parameter processes may be developed. For example, this approach could be applied to a packed bed reactor in order to reconstruct the temperature wave propagating down the reactor. As discussed in section 4.1, a related fusion approach based on redundant sensors can be used to improve the accuracy and reliability with which the value of a single process variable is determined. An alternative sensor-data-integration-plus-control-strategy abstracted from the reflex is also described in section 4.1.

Also, recall that NTS neurons integrate a widely dispersed set of cardiorespiratory measurements. This function may be mimicked in process applications by using Hodgkin–Huxley models of NTS neurons (Schwaber *et al.*, 1993) to develop nonlinear sensor data fusion techniques. As compared to techniques based on artificial neural networks (Kramer, 1991; Holcomb and Morari, 1992; Qin and McAvoy, 1992), Hodgkin–Huxley neuron models are likely to represent dynamic relationships between process variables more directly.

Inferential Measurement. In order to develop high performance process monitoring and control strategies, critical process variables must be measured directly or inferred from available measurements. For processes such as polymerization reactors (Ray, 1986) and fermentors (Johnson, 1987), on-line sensors which provide accurate, reliable measurements of key process variables are usually not available and inferential measurement techniques must be employed. Multivariate statistical techniques such as projection to latent structures can be used to develop linear, steady-state correlations between the desired process variables and available process measurements. However, if the underlying relationships are significantly dynamic and/or nonlinear, these correlations will be accurate only over relatively small operating regions.

Under these conditions, nonlinear inferential measurement schemes abstracted from the baroreceptor reflex may be beneficial. Each baroreceptor neuron has an effective operating range determined by its threshold and saturation pressures, and these pressure limits differ for individual baroreceptors. An accurate and reliable measurement of the mean blood pressure is obtained by integrating signals from hundreds of baroreceptors. An analogous approach can be employed for inferential measurements in chemical process applications. Several sensors could be accurately correlated to the desired process variable (typically using laboratory measurements) in small, partially overlapping operating regions, and one of the sensor data fusion techniques discussed above could then be used to infer the unmeasured variable from the available sensor measurements. As compared to inferential measurement schemes based on a single sensor, the biologically-inspired approach should yield more accurate estimates and superior robustness to sensor degradation and failure.

3.2. Nonlinear Process Modeling. Most advanced controller design techniques require an explicit dynamic model of the process to be controlled. The performance and robustness of the resulting control system depend critically on the model adequacy. For most processes of practical importance, the development of a fundamental model is often too time consuming and/or costly. Even if they are readily available, fundamental models are often too complex to be used for model-based controller design. However, empirical process models can be identified directly from carefully acquired input–output data. Although a variety of linear identification schemes are available, these techniques cannot account for process nonlinearities.

Several nonlinear process identification schemes based on artificial neural networks (ANNs) have recently been proposed (Bhat and McAvoy, 1990; Chen *et al.*, 1990; Hunt *et al.*, 1992). Although the development of ANNs was inspired by massively parallel neural networks in the brain, the simple sigmoidal activation functions used in most ANNs cannot produce the rich time- and state-dependent behaviors observed in real biological neurons (Hille, 1984). Hence, multilayer feedforward ANNs can approximate only static functions (Cybenko, 1989).

Clearly, a dynamic network can be obtained by using a recurrent architecture in which past values of the process inputs and outputs are introduced to the first layer of the network (Hunt *et al.*, 1992). However, because of the arbitrariness of the recurrent structure, as well as the large number of neurons and connections, this approach generally yields a very nonparsimonious process model. Another approach to incorporating dynamics involves the use of linear filters at the output of a multilayer feedforward ANN (Montague *et al.*, 1991). In this approach, the dynamic behavior is limited to overdamped responses that can be constructed from cascades of linear dynamical elements. (See Scott and Ray (1993) for an alternative technique for generating dynamic neural networks.)

Inherently dynamic neural networks can be developed for nonlinear process identification—as well as for other computational tasks—by exploiting the rich dynamic characteristics of *real* biological neurons. Compared to ANNs, biologically-plausible Hodgkin–Huxley neuron models are likely to provide more parsimonious representations of nonlinear dynamic systems. Hodgkin–Huxley models of NTS neurons appear to be suitable for such applications due to their rich state- and time-dependent characteristics (see Figure 2). A single NTS neuron model should provide sufficient prediction accuracy for some single-input, single-output processes. In this case, the desired input-output characteristics can be obtained by using a nonlinear parameter estimation scheme, such as that recently proposed by Foster *et al.* (1993). For more complex multiple-input, multiple-output processes,

multilayer network architectures may be necessary. In order to reduce the computational requirements, alternative parameter estimation schemes and/or simplified neuron models (Bush and Sejnowski, 1991) which retain the relevant biological features may be employed.

3.3. Process Control. Efficient operation of industrial chemical processes requires effective control system design and analysis tools. With the notable exception of model predictive control (Prett and Garcia, 1988; Muske and Rawlings, 1993), most controller design techniques do not adequately address several key issues of importance in process control applications (*e.g.*, multiple inputs and outputs, variable constraints, process economics). Improved control system performance can be achieved by developing model-based control architectures and algorithms which address these key issues by exploiting *specific* process characteristics and operating objectives. Although control architecture development has received little attention recently, the prevalence in the chemical process industries of ratio, cascade, and inferential control strategies (Seborg *et al.*, 1989)—alternatives to the ubiquitous feedback controller—demonstrates the usefulness of alternative control architectures. As novel, problem specific control structures are introduced, controller design techniques which achieve the desired control objectives must be developed. Several process control architectures and design strategies which may be reverse engineered from the baroreceptor reflex are discussed below.

Control of Nonsquare Systems. Many controller design techniques require the number of manipulated input and controlled output variables to be equal. For some processes, additional inputs and outputs which can yield improved process performance are available but are not employed in the control system. By contrast, nonsquare control structures are very common in the baroreceptor reflex. The following are two specific examples:

1. *Heart rate manipulation via myelinated and unmyelinated baroreceptors.* Two measured outputs (myelinated and unmyelinated baroreceptor signals) with significantly different steady-state and dynamic characteristics are used to manipualte a single input (heart rate).

2. *Parasympathetic and sympathetic control of blood pressure.* Two manipulated inputs (cardiac output and total peripheral resistance) with significantly different steady-state and dynamic characteristics are used to control a single output variable (arterial blood pressure).

As discussed further in section 4, effective process control strategies can be developed by reverse engineering these nonsquare biological control structures.

Gain-Scheduled Control. Gain-scheduled controllers are often applied to processes in which the steady-state gain varies significantly over the operating range of interest (Bequette, 1991). In order to compensate for static nonlinearities, the controller gain is designed to be a nonlinear function of a "scheduling" variable (*i.e.*, a measured output) which provides an adequate characterization of the operating conditions. The major difficulties in gain scheduling are (i) the selection of an appropriate scheduling variable and (ii) the design of the scheduling algorithm (Rugh, 1991). The baroreceptor reflex also appears to employ some form of gain scheduling as the controller gain depends nonlinearly on the blood pressure and is largest at normal blood pressures. By reverse engineering the underlying biological algorithm, improved gain scheduling strategies may be developed for chemical processes.

Adaptive Control. Adaptive control strategies have been applied to a variety of industrial chemical processes (Astrom, 1987). The parameters of the process model, or of the feedback controller, are adjusted on-line in order to account for the effects of unmeasured disturbances and modeling errors. The dynamics of the parameter estimator are usually chosen to be faster than the inherent process dynamics. By contrast, the baroreceptor reflex employs adaptation on a wide variety of time scales. Many of these adaptive mechanisms occur on time scales which are either significantly less than or considerably greater than the second time scale encountered in beat-by-beat control of blood pressure. For example, short-term adaptation in neurons occurs on the time scale of milliseconds. On the other hand, baroreceptor activity is adapted or "reset" in response to sustained changes in mean arterial pressure on the time scale of minutes and even weeks. Novel adaptive control strategies for chemical process applications may be developed by reverse engineering both the short-term and long-term adaptive mechanisms observed in the baroreceptor reflex.

Multiple-Time-Scale Control. Because of widely varying process, measurement, and actuator dynamics, industrial control systems must process information, and effect changes, on several different time scales. Analogously, the baroreceptor reflex operates on multiple time scales due to the significantly different dynamics of the cardiovascular system, baroreceptor fibers, and effector mechanisms. The baroreceptor reflex therefore appears to offer considerable promise as a biological paradigm for developing effective process control systems which operate on multiple time scales.

As an example, consider parasympathetic and sympathetic manipulation of the heart rate. Each system causes specific neurotransmitters to be released from cardiac nerve fibers; the neurotransmitters affect the heart rate by binding to cardiac pacemaker cells. Complex interactions which occur on widely differing time scales have been observed near the synapses between the nerve endings and pacemaker cells (Levy, 1984, 1990). Additionally, the nerve endings have autoreceptors which subserve a negative feedback function by attenuating neurotransmitter release when high concentrations are present (Wetzel and Brown, 1985). The dynamics associated with the autoreceptors are significantly slower than the dynamics of the synaptic interactions. By reverse engineering the multiple time scale behavior observed in heart rate manipulation (as well as other control structures in the reflex), effective control strategies may be developed for industrial chemical processes.

Neural Controllers. Recently, there has been considerable interest in using multilayer feedforward artificial neural networks (ANNs) for nonlinear process control applications (Ydstie, 1990; Hernandez and Arkun, 1992; Nahas *et al.*, 1992; Pottmann and Seborg, 1992). However, ANN-based control strategies suffer from similar difficulties as nonlinear process identification techniques based on ANNs: (i) the static activation functions cannot produce the rich dynamic behavior of *real* biological neurons and (ii) the recurrent network architectures used to introduce dynamics are largely arbitrary and require a large number of neurons and connections.

By exploiting the neural computational mechanisms in the baroreceptor reflex, inherently dynamic neural controllers may be developed for nonlinear process applications. As noted previously, Hodgkin–Huxley models of NTS neurons appear to be suitable for such applications as a result of their rich time- and state-dependent characteristics. Two alternative controller design approaches based on biological neuron models are envisioned. In the *indirect* approach, a Hodgkin–Huxley neuron model is trained to approximate the process dynamics, and the resulting process model is then used in a model-based controller design strategy. In the *direct* approach, the
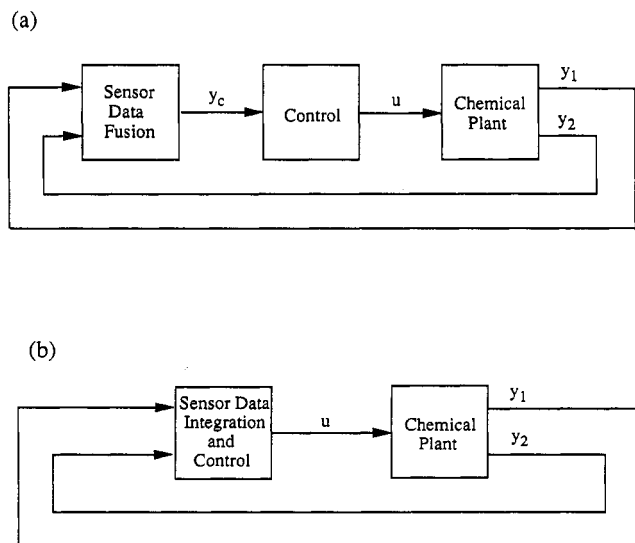
(a)

(b)

Figure 3. (a) Sequential and (b) integrated control approaches for one-input, two-output processes.

neural controller is constructed directly by training the Hodgkin–Huxley model to approximate the inverse of the process dynamics.

4. Specific Process Applications

4.1. Process Control Based on Sensor Data Integration. In this section, two process control strategies based on the integration of measurements from multiple sensors are described. Each technique has been abstracted from a specific control mechanism observed in the baroreceptor reflex. Figure 3 depicts the two techniques for the case where two output measurements are available and a single input is manipulated. The control strategies differ as follows:

1. In the *sequential approach* shown in Figure 3a, two measurements (y_1 and y_2) of the *same* output variable are available, and the sensor data integration and control calculations are handled sequentially. First, the two measurements are reduced to a single value (y_c) using sensor data fusion. The controller then uses the fused measurement to compute the manipulated input (u).

2. In the *integrated approach* shown in Figure 3b, measurements of two *different* output variables are available, and the sensor integration and control calculations are integrated. In this case, there is no explicit sensor data fusion as in the sequential approach.

The biological inspiration and design strategy for both sensor integration approaches are outlined below.

Sequential Approach. The sequential sensor fusion approach was inspired by the redundant measurement scheme employed in the baroreceptor reflex. Recall that the autonomic nervous system receives hundreds of blood pressure measurements from baroreceptor neurons located in the aortic arch and carotid sinus. An accurate, robust pressure measurement is obtained by integrating these partially overlapping measurements. Even though the specific computational mechanisms employed for the integration are not yet fully understood, as summarized below, a reasonable analogous technique based on this *multiple sensor data integration concept* can be developed for chemical processes.

Consider the situation in which n *separate* sensors produce measurements y_i, $i = 1, 2, ..., n$, of the *same* process variable to be controlled. Further consider that each measurements is related to the true, but unknown

value η according to

$$y_i = \eta + e_i \qquad (2)$$

The measurement error e_i associated with sensor i is a combination of a random component ϵ_i, whose mean is zero and variance is σ_i^2, and a deterministic component β_i, whose mean may be nonzero, *i.e.*,

$$e_i = \beta_i + \epsilon_i \qquad (3)$$

Representing each of these n sensors by the ordered pair (y_i, σ_i^2)—the measurement it produces, and a measure of the associated precision—there are three major problems of interest:

1. *The Analysis Problem.* (i) How should the sensor outputs be combined to yield a *single*, composite measurement y_c to be used for control; and how is y_c related to the true value, η? (ii) What is the variance, σ_c^2, associated with y_c, and how does it relate to the individual variances σ_i^2?

2. *The Nominal Design Problem.* Given that the objective is to produce a process measurement with an associated precision level indicated by σ_*^2, a prespecified number; and given n sensors represented by (y_i, σ_i^2), such that $\sigma_i^2 > \sigma_*^2$ for all i (*i.e.*, no single available sensor is able to meet the measurement objective), (i) *how many* sensors are needed to meet the specified objective, and (ii) how should their outputs be combined?

3. *The Robust Design Problem.* Given the possibility of sensor deterioration and/or failure, (i) *how many* sensors are needed to meet the above specified nominal design objective, and (ii) how should the sensors be combined?

For brevity, we outline below the solution to a special case of the *analysis problem* and its application to the *nominal design problem*; a full discussion is available in Ogunnaike *et al.* (1994).

Consider the situation in which the sensors are all unbiased. It can be shown that under these circumstances, the composite measurement obtained as

$$y_c = \sum_{i=1}^{n} \omega_i y_i \qquad (4)$$

where the weights ω_i are given by

$$\omega_i = \frac{1/\sigma_i^2}{\sum_{i=1}^{n} 1/\sigma_i^2} \qquad (5)$$

has the following properties:

1. y_c is unbiased and has the smallest variance of all the unbiased estimates that can be derived from the n measurements.

2. The associated variance, σ_c^2, is given by

$$\frac{1}{\sigma_c^2} = \sum_{i=1}^{n} \frac{1}{\sigma_i^2} \qquad (6)$$

and it will always be smaller than the variance associated with any of the individual sensors; *i.e.*, $\sigma_c^2 < \sigma_i^2$ for all i.

3. The above results hold regardless of the underlying probability distribution of the random errors ϵ_i, so long as the errors are mutually independent.

4. If the errors ϵ_i are assumed to be independently and identically distributed Gaussian, then the "maximum likelihood principle" yields the same combination strategy as indicated in (4).

Note that these results provide one set of answers for the questions involved with the *analysis problem*; we now show how they may be applied in providing a solution to
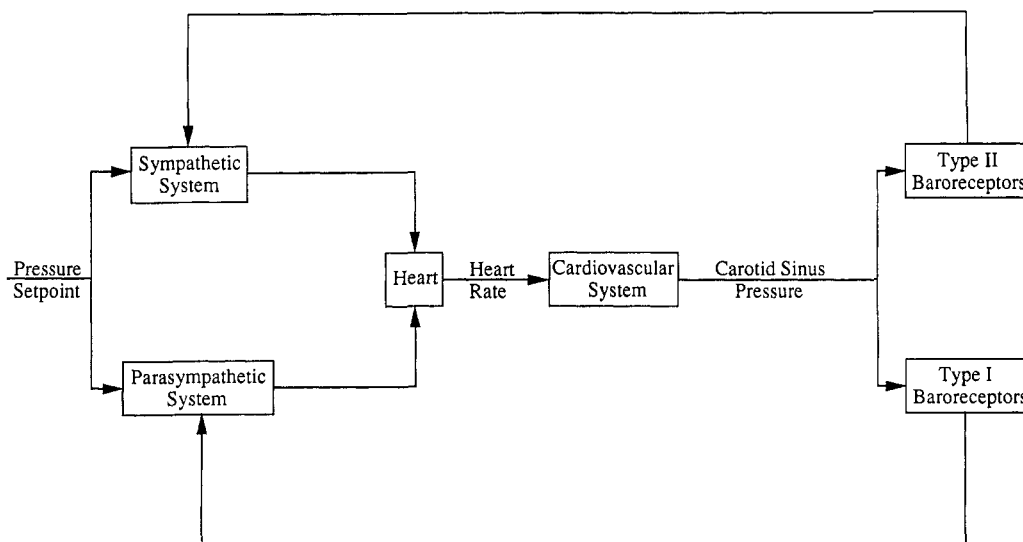
Figure 4. Simplified representation of the baroreceptor reflex for the integrated control strategy.

the *nominal design problem*. We start by defining the *relative precision*, ρ_i, of sensor i as

$$\rho_i = \sigma_*^2/\sigma_i^2 \qquad (7)$$

Observe that, from the *nominal design problem* statement (that no single sensor is precise enough to meet the measurement objective), $\sigma_*^2 < \sigma_i^2$ for all available sensors. Thus the relative precision for each of the sensors must lie in the range $0 < \rho_i < 1$.

Now, when the sensor outputs are combined as prescribed by the expressions in (4) and (5), the following results are direct corollaries of the solution to the analysis problem just presented above:

1. The relative precision of the combined measurement, ρ_c, is the sum of the relative precisions of the individual sensors, *i.e.*, $\rho_c = \sum_{i=1}^n \rho_i$. (This follows directly from (6) and from the definition of relative precision in (7).)

2. An ensemble consisting of m of the available n sensors, whose outputs are combined as indicated, will therefore meet or exceed the specified measurement objective if $\sum_{i=1}^m \rho_i \geq 1$, since this implies that the resulting ensemble variance $\sigma_c^2 \leq \sigma_*^2$.

These results therefore provide the following strategy for solving the *nominal design problem* in chemical process sensor data fusion:

1. Obtain the relative precision of each of the available n sensors as indicated in (7).

2. Choose m of the n sensors such that $\sum_{i=1}^m \rho_i \geq 1$.

3. The composite measurement given by

$$y_c = \sum_{i=1}^m \omega_i y_i \qquad (8)$$

with ω_i as in (5) will meet or exceed the required measurement objective.

A fuller discussion of these and other additional issues, as well as illustrative example applications, is available in the cited reference.

Integrated Approach. The integrated control strategy in Figure 3b has been reversed engineered from the simplified representation of the baroreceptor reflex shown in Figure 4. Recall from Figure 1 that blood pressure measurements from arterial baroreceptors are transmitted to the autonomic nervous system via both A (myelinated) and C (unmyelinated) fibers. Figure 4 employs an alternative, but closely related, classification of barore-

ceptor types based on *firing characteristics* rather than fiber type (Seagard *et al.*, 1990, 1992). *Type I* baroreceptors exhibit the following characteristics: hyperbolic response patterns with sudden onset of firing at the threshold pressure; high sensitivities and small operating ranges; and acute resetting (*e.g.*, a short-term shift of the activity in the direction of the prevailing pressure). By contrast, *type II* receptors exhibit sigmoidal response patterns with spontaneous firing below the threshold pressure; low sensitivities and large operating ranges; and lack of acute resetting. These characteristics indicate that type I and type II baroreceptors primarily measure rate of change of pressure and mean pressure, respectively.

Type II receptors have large myelinated fibers with high conduction velocities, while type I receptors have unmyelinated and small myelinated fibers with comparatively low conduction velocities. Due to their measurement properties and high conduction velocities, type II receptors contribute primarily to dynamic control of blood pressure (Seagard *et al.*, 1993). By contrast, type I receptors are mostly used for steady-state pressure control because they provide accurate, but slow, measurements of mean blood pressure.

Additional experimental data (Coleman, 1980) demonstrate that the parasympathetic and sympathetic systems are primarily involved in dynamic and steady-state manipulation of the heart rate, respectively. Thus, the results of Seagard *et al.* (1993) and Coleman (1980) suggest a differential neural pathway in which type I and type II baroreceptors preferentially affect the parasympathetic and sympathetic systems, respectively. As shown in Figure 4, this hypothesis results in a control architecture in which the heart rate is manipulated by two parallel controllers which selectively process input from type I and type II baroreceptors.

We have developed a novel parallel control strategy for chemical process applications from our current understanding of the contributions of type I and type II baroreceptors to blood pressure control (Pottmann *et al.*, 1994). The control strategy is applicable to processes for which measurements of two *different* output variables are available; the measurements should have the following characteristics: (1) *primary measurement*—a measurement of the process output to be controlled which exhibits unfavorable (*e.g.*, delayed) dynamic responses to changes in manipulated input and disturbance variables; (2) *secondary measurement*—a measurement of a different
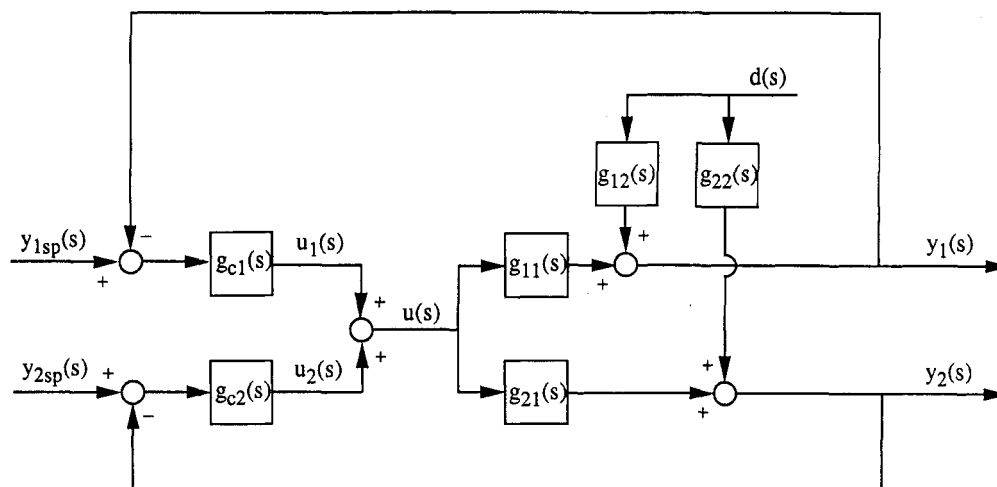
Figure 5. Parallel architecture for the integrated control strategy.

process output which exhibits more favorable dynamic responses to input changes.

The controller design is based on the following parallel model:

$$y_1(s) = g_{11}(s) \, u(s) + g_{12}(s) \, d(s) \qquad (9)$$

$$y_2(s) = g_{21}(s) \, u(s) + g_{22}(s) \, d(s) \qquad (10)$$

where y_1 and y_2 are the primary and secondary measurements, respectively, u is the manipulated input, and d is an unmeasured disturbance. By the problem definition, the transfer functions g_{21} and g_{22} associated with the secondary measurement have better dynamic characteristics (e.g., smaller time delays) than the transfer functions g_{11} and g_{12} associated with the primary measurement. It is easy to show that the parallel model allows more general disturbance models to be specified than a conventional cascade model.

The parallel control architecture abstracted from the baroreceptor reflex is shown in Figure 5. The relationship between the proposed architecture and the biological control structure depicted in Figure 4 is easily recognized by identifying the two parallel controllers with the sympathetic and parasympathetic systems, the chemical process with the cardiovascular system, and the two output measurements with the type I and type II baroreceptor signals. The parallel controller has the form

$$u(s) = g_{c_1}(s)[y_{1_{sp}}(s) - y_1(s)] + g_{c_2}(s)[y_{2_{sp}}(s) - y_2(s)] \qquad (11)$$

where $y_{1_{sp}}$ and $y_{2_{sp}}$ are setpoints for y_1 and y_2, respectively. The secondary setpoint $y_{2_{sp}}$ is chosen to assist the controller in reducing the error between the y_1 and its setpoint; a reasonable choice is

$$y_{2_{sp}}(s) = g_{sp}(s) y_{1_{sp}}(s) \qquad (12)$$

It is easy to show that the parallel control architecture in Figure 5 is more general than a conventional cascade control structure (Luyben, 1973; Yu, 1988; Seborg et al., 1989). However, the actual controller design and implementation are based on a reparametrized form of the parallel controllers which provides (i) a more convenient controller parametrization for H_2-optimal controller synthesis and (ii) improved tolerance to measurement degradation and loss. A detailed description of the controller design methodology, as well as its advantages as compared to conventional cascade control, is presented by Pottmann et al. (1994).

4.2. Nonlinear Process Modeling. Single Neuron Computation. The range of behavior exhibited by

neurons in the NTS is due in part to the varied computational abilities of single neurons in the architecture. For example, NTS neurons receive a strong positive input from the baroreceptors, but their activity does not encode the input pattern in any obvious manner. Specifically, NTS neurons recorded in vivo show strong positive responses to shock of the incoming nerves, or to activation of the baroreceptors by stretch; but they very rarely demonstrate the bursting pattern or the pulse-synchronous activity of the baroreceptor neurons (Schwaber, 1986). NTS neurons show time- and voltage-dependent responses to inputs, and these neuronal dynamics may largely account for the observed responses. These dynamic features are captured in a Hodgkin–Huxley model (see section 2.3) by specific classes of ion channels (e.g., accommodation is captured by the calcium channel). From a process perspective, this suggests that neuronal elements used for computational modeling can be "tailored" to exploit particular dynamic characteristics (e.g., oscillatory behavior, large dead time).

It is important to make a distinction at this point. While we are seeking to utilize the biologically derived neuron models in our process applications, we must necessarily abandon some of the finer details of the strict biological neuron in favor of more general (canonical) structures for dynamic modeling. As such, we look to the neurons in the baroreceptor reflex for inspiration in the form of efficient computational building blocks, as well as hierarchical model structures.

With these considerations in mind, we have sought to derive a synthetic neuron which contains only a very simple dynamic mode corresponding to the Hodgkin–Huxley behavior discussed earlier. A candidate structure is revealed in the key role played by calcium in modulating neuronal dynamics. One model describing this dynamic regulation (Abbott and LeMasson, 1993) shows the dependence of the maximal conductances through the membrane channels ($\bar{g}_i$) as a function of the calcium concentration:

$$\tau_i([Ca]) \frac{d\bar{g}_i}{dt} = F_i([Ca]) - \bar{g}_i \qquad (13)$$

where [Ca] is the intracellular calcium concentration and F_i is the limiting value of the conductance. In modeling terms, this may be recognized as a canonical first-order system with variable time constant and gain:

$$\tau(u) \frac{dy}{dt} = K(u) - y \qquad (14)$$

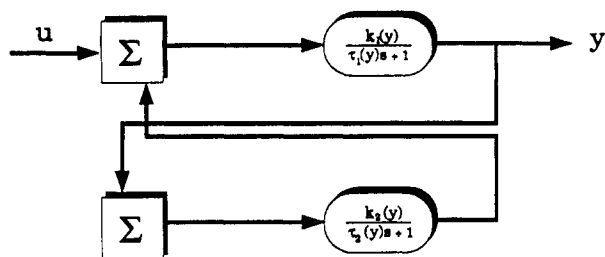where u, the process input, is the calcium concentration and y, the process output, is the conductance. This

Figure 6. Dynamic network architecture for CSTR model.

suggests a simple building block for process modeling. As opposed to the traditional sigmoidal activation function, we will construct a network which contains nonlinear *dynamic* processing elements of the type described above. In particular, if we consider a first-order approximation of the gain and time constant and, for the purpose of computational tractability, restrict their *functional dependence to y only*, the following representation for a single neuron (denoted $\mathcal{N}_i$) is obtained:

$$\mathcal{N}_i(y,u): \quad (\tau_{i0} + \tau_{i1}y)\frac{dy}{dt} = (K_{i0} + K_{i1}y)u - y \quad (15)$$

The model architecture we will employ is based on a fully recurrent Hopfield network (Hopfield, 1990). The flexibility of this structure (using the proposed processing element) can be understood by examining a simple interconnection of linear first-order elements. If the elements are connected in a feedback configuration, with one system in the main path and one system in the feedback loop, a second-order transfer function results. The coefficients of the first-order elements can be chosen to give arbitrary (overall) second-order performance. This *cannot* be accomplished with many of the traditional time series neural network approaches to process modeling. Neural network strategies typically produce a feedforward cascade of linear dynamic elements, leading to an overdamped process response. Through simple algebraic manipulations, one can show that the proposed structure shares similar properties with the recurrent Hopfield network. In fact, it is possible to characterize mathematically a large class of dynamic systems which can be constructed from such building blocks (Doyle and Shaw, 1994).

To illustrate the effectiveness of the proposed structure, we now consider the problem of modeling a nonlinear CSTR. The specific process example is a stirred-tank jacketed reactor in which a first-order irreversible reaction occurs. This simple example will serve as a preliminary test bed for the proposed modeling strategies. The dimensionless mass and energy balances for this system are given by (Uppal *et al.*, 1974)

$$\dot{x}_1 = -x_1 + \mathcal{D}a(1 - x_1)\exp\left(\frac{x_2}{1 + x_2\gamma}\right)$$

$$\dot{x}_2 = -x_2 + \mathbf{B}\mathcal{D}a(1 - x_1)\exp\left(\frac{x_2}{1 + x_2\gamma}\right) + \beta(u - x_2)$$

As shown in Figure 6, a simple network is constructed which consists of two dynamic processing elements which are fully (recurrently) interconnected. Using a first-order Taylor series to represent the nonlinear elements (gain, time constant), one arrives at a model structure with eight parameters. (This can be contrasted with traditional artificial neural networks which typically require on the order of 12 parameters merely to capture, in a time series fashion, the behavior of a simple *linear* dynamical system.) The network was trained using a random search procedure
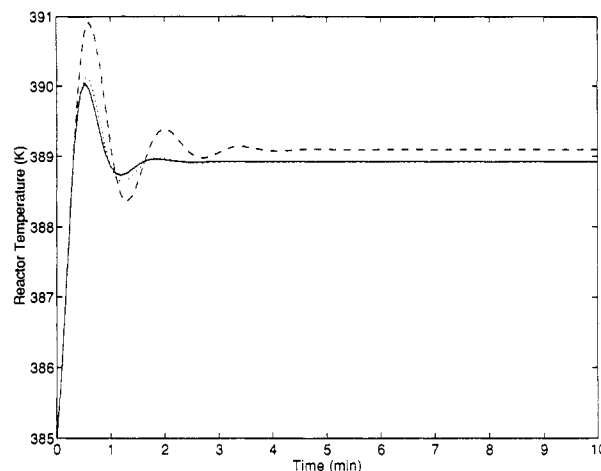

Figure 7. Response to a +4 deg step change in the coolant temperature (linear, dashed; neuron, dotted; true CSTR, solid).
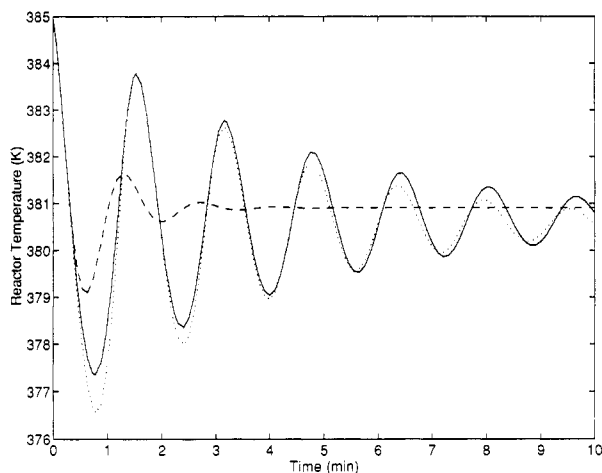

Figure 8. Response to a −4 deg step change in the coolant temperature (linear, dashed; neuron, dotted, true CSTR, solid).
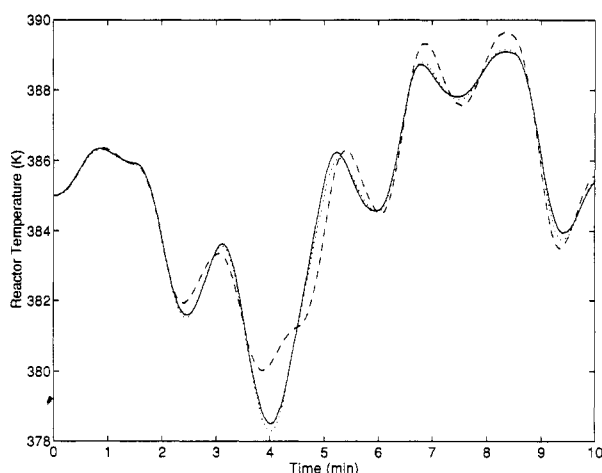

Figure 9. Response to a random sequence of step changes (PRBS) in the coolant temperature (linear, dashed; neuron, dotted; true CSTR, solid).

(Salcedo *et al.*, 1990). The outputs of the network model, a linear model, and the true CSTR process, in response to symmetric input sequences, are shown in Figures 7 and 8; the response to a random sequence of steps is shown in Figure 9. As can be seen in these figures, the "true process" behavior is extremely nonlinear, and while the linear model fails to track the reactor accurately, the proposed network model exhibits rather accurate tracking of the true process over the range of these simulations.
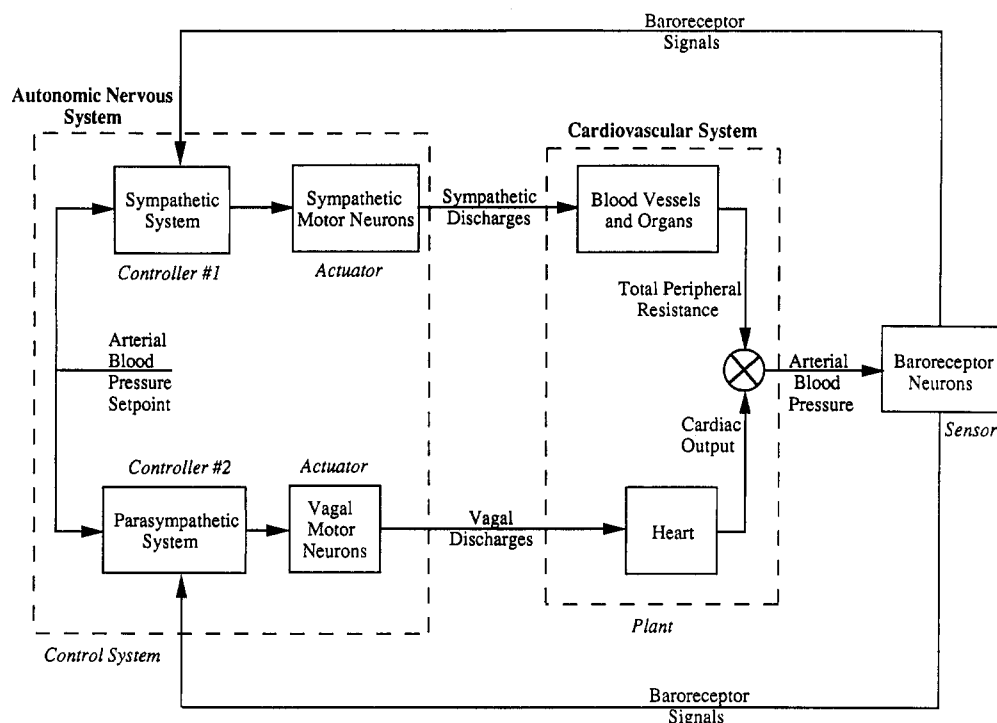
Figure 10. Simplified representation of the baroreceptor reflex for habituating control.

Network Level Computation. Experimental evidence (Graves *et al.*, 1991; Paton *et al.*, 1991) suggests that a second-order hierarchical network structure is responsible for the encoding of pressure data in the NTS. The first-order neurons (baroreceptors) have a distributed sensitivity to the measured variable (blood pressure) and its rate of change. In effect, the baroreceptors use static, threshold-type behavior to map or "schedule" the spatial pressure distribution onto the second-order (NTS) neurons. This leads to second-order neurons which have a "competitive" response to the output of the first-order neurons; specific first-order neurons provide an excitatory (positive) input, while neighboring neurons provide an inhibitory (negative) input. This lateral inhibition mechanism provides "competition" between the second-order dynamic neurons, and thus leads to a scheduled response. Therefore each second-order neuron provides a response which is both *static* (dependent on the thresholds of the corresponding first-order neurons) and *dynamic* (dependent on the velocity of pressure increase).

Such behavior can be exploited in the formulation of scheduling algorithms for use in controller design (Doyle *et al.*, 1994). Just as "competition" between second-order neurons leads to a selective dynamic response, a "selectively" scheduled nonlinear controller can be designed for a process system. There are two avenues for achieving this functionality: the *implicit* and the *explicit*. In the *implicit* formulation, a control architecture consisting of a number of individual dynamic elements is designed to provide appropriate compensation over a wide operating regime. The second-order network structure is employed to provide the appropriate scheduling between these dynamic components. The individual entities do not represent distinct control laws, but rather basis elements of a larger dynamic structure.

The *explicit* formulation involves using the second-order network structure directly to model the open-loop response of a highly nonlinear system; here, the scheduling functionality is exploited for transitions between open-loop dynamic behavior. A control law can be synthesized using traditional model-based control techniques (*e.g.*, model predictive control (MPC), internal model control (IMC)).

The resultant closed-loop system displays uniformly linear input–output response over the global operating regime.

One particularly attractive feature of these algorithms is the graceful transition exhibited between operating regimes: there is not a *discrete* set of operating levels but rather a *continuum*. This is in direct contrast to traditional scheduling approaches which utilize look-up tables for control law parameters which are calculated for a discrete set of operating levels. Additional details about this technique may be found in Doyle *et al.* (1994).

4.3. Control of Multiple-Input, Single-Output Processes. We have developed a novel control strategy for multiple-input, single-output processes by reverse engineering the baroreceptor reflex (Henson *et al.*, 1994). The technique is based on the simplified block diagrammatic representation of the reflex shown in Figure 10. The effects of the sympathetic system on the heart have been neglected; hence, the only couplings are those between the parasympathetic system and cardiac output, and between the sympathetic system and total peripheral resistance. The effect of the parasympathetic system on arterial blood pressure is fast, while that of the sympathetic system is comparatively slow (Karemaker, 1987; Kumada *et al.*, 1990). However, sustained variations in the cardiac output are undesirably "expensive", whereas long-term variations in the peripheral resistance are more acceptable. Cardiac output is therefore a fast, but expensive, manipulated variable as compared to the peripheral resistance.

The brain implements "habituating" control by coordinating the use of both the sympathetic and parasympathetic systems in order to provide high performance control while minimizing the long-term cost of the control actions. For instance, consider an external disturbance (*e.g.*, standing up) which causes the blood pressure to drop below the desired value. The parasympathetic system induces a rapid increase in blood pressure by enhancing cardiac output. A significantly slower increase in blood pressure is caused by the sympathetic system increasing peripheral resistance. As the enhanced peripheral resistance begins to affect the blood pressure, the parasym-
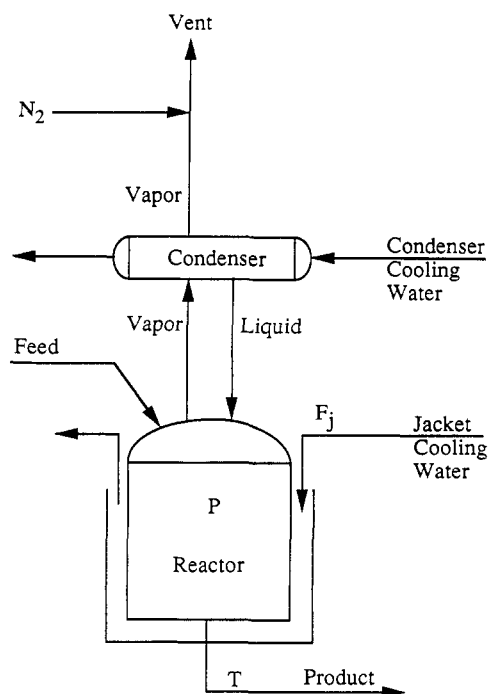
Figure 11. Polymerization process.

pathetic controller *habituates* by returning cardiac output to its initial steady-state value.

Similar *habituating control strategies* can be employed in chemical process applications. Many process control systems employ only slow, cheap variables as the manipulated inputs although additional fast, but expensive, inputs are available. In a habituating control system, the fast (secondary) inputs can be used to track setpoint changes rapidly and reject disturbances. As the slower (primary) inputs begin to affect the outputs, the fast inputs can habituate by slowly returning to their previous steady-state values. Because the expensive secondary inputs are used only during transients, improved performance can be obtained with little additional cost. Superior control can also be obtained for processes in which nonminimum phase elements limit the performance achievable with the primary inputs. Because multiple inputs are employed, the robustness of habituating control schemes is superior to that of the typical single-input, single-output control techniques in the event of actuator saturation or failure.

As a physical example, consider the process for manufacturing acrylic resins shown in Figure 11. The process consists of a continuous stirred tank polymerization reactor and an overhead condenser. The feed to the reactor consists of monomer, initiator, and solvent. The condenser is used to condense solvent and monomer vapors, and a cooling water jacket is available to cool the reactor contents. The process also includes a vent line for condensibles and a nitrogen admission line which can be used to regulate the reactor pressure P. One of the control objectives is to control the reactor temperature T; the cooling water flow rate, F_j, and P (which can be changed almost instantaneously via nitrogen admission) are the principal manipulated variables. The reactor pressure P has a much more rapid and direct effect on T than does F_j. However, because significant and/or extended pressure fluctuations affect the reaction kinetics adversely, it is desirable to maintain P near its setpoint. A habituating control strategy can be developed for this process by considering F_j as the primary input and P as the secondary input.

In general, processes which can benefit from habituating control have the following characteristics: (i) control system performance is limited by the nature of the dynamic
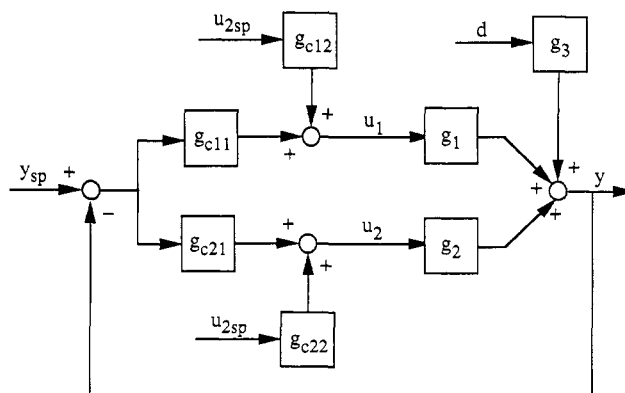

Figure 12. Parallel control architecture for habituating control.

effect exerted on the outputs by the primary manipulated inputs, but secondary inputs are available whose effect on the outputs is characterized by superior dynamics; and (ii) the long-term cost associated with manipulating the secondary inputs is greater than that associated with the primary inputs. We have proposed two habituating controller design strategies for linear processes with two inputs and one output: the *direct synthesis* approach and the *model predictive control* approach. In the model predictive control formulation, the quadratic objective function employed in standard model predictive control techniques (Prett and Garcia, 1988; Garcia *et al.*, 1989) is modified to include a penalty on the deviation of the secondary input from a desired setpoint.

The direct synthesis technique is based on transfer function models of the form

$$y(s) = g_1(s)\, u_1(s) + g_2(s)\, u_2(s) \tag{16}$$

where y is the controlled output and u_1 and u_2 are the primary and secondary inputs, respectively. The transfer function g_2 is assumed to be stable and minimum phase since u_2 is employed as a result of its favorable dynamic effect on y. Because there are two manipulated inputs and one controlled output, the combination of control actions required to produce the desired output y_{sp} at steady state is nonunique. An additional objective is therefore required to obtain a well-defined control problem. In this case, the habituating controller is designed such that the secondary input u_2 tracks a desired value $u_{2_{sp}}$ asymptotically. The controller design and implementation is based on the parallel control architecture shown in Figure 12. The parallel controllers are analogous to the sympathetic and parasympathetic systems and have the form

$$u_1(s) = g_{c_{11}}(s)[y_{sp}(s) - y(s)] + g_{c_{12}}(s)\, u_{2_{sp}}(s) \tag{17}$$

$$u_2(s) = g_{c_{21}}(s)[y_{sp}(s) - y(s)] + g_{c_{22}}(s)\, u_{2_{sp}}(s) \tag{18}$$

The objective is to design the controller transfer functions $g_{c_{ij}}$.

In order to demonstrate the performance that can be achieved with the habituating control technique, consider the following process model:

$$y(s) = \frac{-2s + 1}{(2s + 1)^2} u_1(s) + \frac{1}{2s + 1} u_2(s) \tag{19}$$

The transfer function g_1 contains a right-half-plane zero that limits the performance achievable with u_1 alone. An internal model controller (Morari and Zafiriou, 1989) and a habituating controller based on direct synthesis are compared in Figure 13 for a unit setpoint change in y_{sp}. By using the secondary input u_2 during transients, the direct synthesis controller (solid line) yields excellent
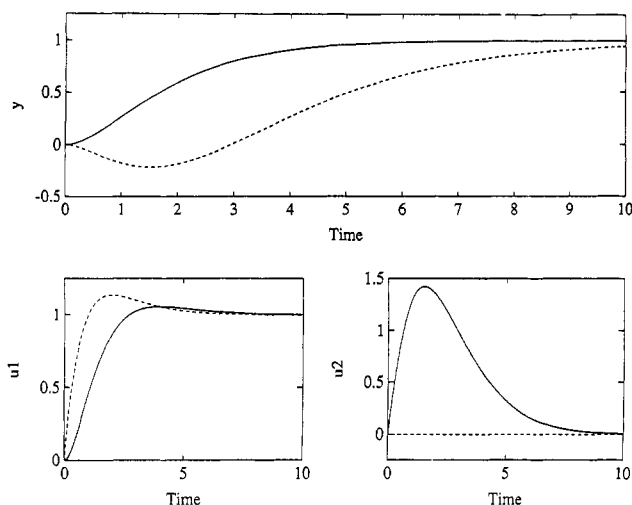
Figure 13. Habituating and internal model control for a setpoint change.

performance without an inverse response in the output. By contrast, the internal model controller (dashed line) produces very sluggish setpoint tracking with a large inverse response. Additional simulation results, as well as comparisons with related control techniques (Doyle *et al.*, 1992; Mandler *et al.*, 1986; Popiel *et al.*, 1986), are presented by Henson *et al.* (1994).

5. Conclusions and Future Work

The baroreceptor reflex—the control system responsible for short-term regulation of arterial blood pressure—has successfully solved many difficult control problems similar to those encountered in industrial chemical processes. The main premise of this work is that novel strategies for process monitoring, modeling, and control can be developed by reverse engineering the architectural and computational properties of this biological control system. We have presented here a general overview of this alternative philosophy to the design of effective control systems; we have also presented a summary of some *specific* preliminary results for sensor fusion based control, nonlinear modeling, and control of multiple-input, single-output system which have been abstracted from the baroreceptor reflex. Future work will focus on further development *and* industrial applications of the monitoring, modeling, and control approaches described in this paper.

Acknowledgment

Literature Cited

Abbott, L. F.; LeMasson, G. Analysis of Neuron Models with Dynamically Regulated Conductances. *Neural Comput.* **1993**, *5*, 823–842.

Astrom, K. J. Adaptive Feedback Control. *Proc. IEEE* **1987**, *75*, 185–217.

Bequette, B. W. Nonlinear Control of Chemical Processes: A Review. *Ind. Eng. Chem. Res.* **1991**, *30*, 1391–1413.

Bhat, N.; McAvoy, T. J. Use of Neural Nets for Dynamic Modeling and Control of Chemical Process Systems. *Comput. Chem. Eng.* **1990**, *14*, 573–583.

Brockett, R. W. 1991 IEEE Control Systems Award Acceptance Speech. *IEEE Control Syst. Mag.* **1992**, Aug, 42.

Bush, P. C.; Sejnowski, T. J. Simulation of Reconstructed Cerebellar Purkinje Cells Based on Simplified Channel Kinetics. *Neural Comput.* **1991**, *3*, 321–332.

Chen, S.; Billings, S. A.; Grant, P. M. Nonlinear System Identification Using Neural Networks. *Int. J. Control* **1990**, *51*, 1191–1214.

Coleman, T. G. Arterial Baroreflex Control of Heart Rate in the Conscious Rat. *Am. J. Physiol.* **1980**, *238* (Heart Circ. Physiol.), H515–H520.

Cowley, A. W.; Liard, J. F.; Guyton, A. C. Role of Baroreceptor Reflex in Daily Control of Arterial Pressure and Other Variables in Dog. *Circ. Res.* **1973**, *32*, 564–576.

Cybenko, G. Approximation of Superpositions of a Sigmoidal Function. *Math. Control Signals Syst.* **1989**, *2*, 303–314.

Deshpande, P. B. *Distillation Dynamics and Control*; Instrument Society of America: Research Triangle Park, NC, 1985.

Downs, J. J.; Vogel, E. F. A Plant-Wide Industrial Process Control Problem. *Comput. Chem. Eng.* **1993**, *17*, 245–255.

Doyle, F. J. Robustness Properties of Nonlinear Process Control and Implications for the Design and Control of a Packed Bed Reactor. Ph.D. Dissertation, California Institute of Technology, Pasadena, CA, 1991.

Doyle, F. J.; Shaw, A. M. A Dynamic Computational Element for Network Modeling of Process Systems. 1994, in preparation.

Doyle, F. J.; Allgower, F.; Oliveira, S. L.; Morari, M. On Nonlinear Systems with Poorly Behaved Zero Dynamics. *Proc. Am. Control Conf.* **1992**, 2571–2575.

Doyle, F. J.; Rybak, I.; Schwaber, J. S. A Biologically-Motivated Dynamic Nonlinear Scheduling Algorithm for Control. *Proc. Am. Control Conf.* **1994**, 92–96.

Foster, W. R.; Paton, J. F. R.; Hopfield, J. J.; Ungar, L. H.; Schwaber, J. S. Matching Neuron Models to Experiment. In *Computation and Neural Systems 1992*; Eeckman, F., Ed.; Kluwer Academic Pres: Boston, 1993; pp 81–88.

Garcia, C. E.; Prett, D. M.; Morari, M. Model Predictive Control: Theory and Practice—A Survey. *Automatica* **1989**, *25*, 335–348.

Graves, E. B.; Schwaber, J. S.; Paton, J. F. R.; Spyer, K. M.; Rogers, W. T. Modeling Reveals Mechanisms of Central Computation in the Baroreceptor Vagal Reflex. *Soc. Neurosci. Abstr.* **1991**, *17*, 993.

Grodins, F. S. *Control Theory and Biological Systems*; Columbia University Press: New York, 1963.

Hacisalihzade, S. S. Biomedical Applications of Control Engineering. *IEEE Control Syst. Mag.* **1992**, Dec, 4–5.

Henson, M. A.; Ogunnaike, B. A.; Schwaber, J. S. Habituating Control Strategies for Process Control. *AIChE J.* **1994**, in press.

Hernandez, E.; Arkun, Y. A Study of the Control Relevant Properties of Backpropagation Neural Net Models of Nonlinear Dynamical Systems. *Comput. Chem. Eng.* **1992**, *16*, 227.

Hille, B. *Ionic Channels of Excitable Membranes*; Sinauer Associates: Sunderland, MA, 1984.

Hodgkin, A. L.; Huxley, A. F. A Quantitative Description of Membrane Current and its Application to Conduction and Excitation in Nerve. *J. Physiol. London* **1952**, *117*, 500–544.

Holcomb, T. R.; Morari, M. PLS Neural Networks. *Comput. Chem. Eng.* **1992**, *16*, 393–411.

Hopfield, J. J. Dynamics and Neural Network Computation. *Int. J. Quantum Chem.* **1990**, Quantum Chem. Symp. 24, 633–644.

Hunt, K. J.; Sbarbaro, D.; Zbikowski, R.; Gawthrop, P. J. Neural Networks for Control Systems—A Survey. *Automatica* **1992**, *28*, 1083–1112.

Johnson, A. The Control of Fed-Batch Fermentation Processes—A Survey. *Automatica* **1987**, *23*, 691–705.

Jones, R. W. *Principles of Biological Regulation: An Introduction to Feedback Systems*; Academic: New York, 1973.

Karemaker, J. M. Neurophysiology of the Baroreceptor Reflex. In *The Beat-by-Beat Investigation of Cardiovascular Function*; Kitney, R. I., Rompelman, O., Eds.; Clarendon Press: Oxford, 1987; pp 27–49.

Kaspar, M. H.; Ray, W. H. Chemometric Methods for Process Monitoring and High-Performance Controller Design. *AIChE J.* **1992**, *38*, 1593–1608.

Kirchheim, H. R. Systemic Arterial Baroreceptor Reflexes. *Physiol. Rev.* **1976**, *56*, 100–176.

Kramer, M. A. Nonlinear Principal Component Analysis Using Autoassociative Neural Networks. *AIChE J.* **1991**, *37*, 233–243.

Kresta, J. V.; MacGregor, J. F.; Marlin, T. E. Multivariate Statistical Monitoring of Process Operating Performance. *Can. J. Chem. Eng.* **1991**, *69*, 35–47.

Kumada, M.; Terui, N.; Kuwaki, T. Arterial Baroreceptor Reflex: Its Central and Peripheral Neural Mechanisms. *Prog. Neurobiol.* **1990**, *35*, 331–361.

Lang, L.; Gilles, D. Nonlinear Observers for Distillation Columns. *Comput. Chem. Eng.* **1990**, *14*, 1297–1301.

Levy, M. N. Cardiac Sympathetic and Parasympathetic Interactions. *Fed. Proc.* **1984**, *43*, 2598–2602.

Levy, M. N. Autonomic Interactions in Cardiac Control. *Ann. N.Y. Acad. Sci.* **1990**, *601*, 209–221.

Luyben, W. L. Parallel Cascade Control. *Ind. Eng. Chem. Fundam.* **1973**, *12*, 463–467.

MacGregor, J. F.; Marlin, T. E.; Kresta, J.; Skagerberg, B. Multivariate Statistical Methods in Process Analysis and Control. In *Chemical Process Control IV*; Arkun, Y., Ray, W. H., Eds.; CACHE, AIChE: Austin, TX, 1991; pp 79–99.

Mandler, J. A.; Morari, M.; Seinfeld, J. H. Control System Design for a Fixed-Bed Methanation Reactor. *Chem. Eng. Sci.* **1986**, *6*, 1577–1597.

Mifflin, S. W.; Felder, R. B. Synaptic Mechanisms Regulating Cardiovascular Afferent Inputs to Solitary Tract Nucleus. *Am. J. Physiol.* **1990**, *259* (Heart Circ. Physiol.), H653–H661.

Montague, G. A.; Willis, M. J.; DiMassimo, C.; Morris, J.; Tham, M. T. Dynamic Modeling of Industrial Processes with Artificial Neural Networks. *Proc. Int. Symp. Neural Networks Eng. Appl.* **1991**.

Morari, M.; Zafiriou, E. *Robust Process Control*; Prentice Hall: Englewood Cliffs, NJ, 1989.

Muske, K. R.; Rawlings, J. B. Model Predictive Control with Linear Models. *AIChE J.* **1993**, *39*, 262–287.

Nahas, E. P.; Henson, M. A.; Seborg, D. E. Nonlinear Internal Model Control for Neural Network Models. *Comput. Chem. Eng.* **1992**, *16*, 1039–1057.

Ogunnaike, B. A.; Pottmann, M.; Schwaber, J. S. Sensor Data Fusion in Chemical Process Analysis and Control. 1994, in preparation.

O'Leary, D.; Scher, A. M. Time Course Recovery of Arterial Pressure Control After Carotid Denervation. *Am. J. Physiol.* **1990**, *258* (Heart Circ. Physiol.), H73–H79.

Paton, J. F.; Rogers, W. T.; Schwaber, J. S. Tonically Rhythmic Neurons Within a Cardiorespiratory Region of the Nucleus Tractus Solitarii of the Rat. *J. Neurophysiol.* **1991**, *66*, 824–838.

Paton, J. F. R.; Foster, W. R.; Schwaber, J. S. Characteristic Firing Behavior of Cell Types in the Cardiorespiratory Region of the Nucleus Tractus Solitarii of the Rat. *Brain Res.* **1993**, *604*, 112–125.

Popiel, L.; Matsko, T.; Brosilow, C. Coordinated Control. In *Chemical Process Control III*; Morari, M., McAvoy, T. J., Eds.; Elsevier Science Publishers: NY, 1986; pp 295–319.

Pottmann, M.; Seborg, D. E. A Nonlinear Predictive Control Strategy Based on Radial Basis Function Networks. In *Proc. IFAC DYCORD+92 Symp.* **1992**, 309–314.

Pottmann, M.; Henson, M. A.; Ogunnaike, B. A.; Schwaber, J. S. A Parallel Control Strategy Abstracted from the Baroreceptor Reflex. *Am. Control Conf.* **1994**, 97–101.

Prett, D.; Garcia, C. *Fundamental Process Control*; Butterworths: Stoneham, MA, 1988.

Qin, S. J.; McAvoy, T. J. Nonlinear PLS Modeling Using Neural Networks. *Comput. Chem. Eng.* **1992**, *16*, 379–391.

Ray, W. H. Polymerization Reactor Control. *IEEE Control Syst. Mag.* **1986**, Aug, 3–8.

Richter, D. W.; Spyer, K. M. Cardiorespiratory Control. In *Central Regulation of Autonomic Functions*; Loewy, A. D., Spyer, K. M., Eds.; Oxford University Press: New York, 1990; pp 189–207.

Rugh, W. J. Analytical Framework for Gain Scheduling. *IEEE Control Syst. Mag.* **1991**, *Jan.*, 79–84.

Sagawa, K. Baroreflex Control of Systemic Arterial Pressure and Vascular Bed. In *Handbook of Physiology, Sec. 2 The Cardiovascular System, Vol. III Peripheral Circulation and Organ Blood Flow*; Shepherd, J., Abboud, F., Eds.; American Physiological Society: Bethesda, MD, 1983; pp 453–496.

Salcedo, R.; Goncalves, M. J.; de Azevedo, S. F. An Improved Random-Search Algorithm for Non-linear Optimization. *Comput. Chem. Eng.* **1990**, *14*, 1111–1126.

Scher, A. M.; Young, A. C. Servoanalysis of Carotid Sinus Reflex Effects on Peripheral Resistance. *Circ. Res.* **1963**, *12*, 152–162.

Schmidt, R. M.; Kumada, M.; Sagawa, K. Cardiac Output and Total Peripheral Resistance in Carotid Sinus Reflex. *Am. J. Physiol.* **1971**, *221*, 480–487.

Schwaber, J. S. Neuroanatomical Substrates of Cardiovascular and Emotional-Autonomic Regulation. In *Central and Peripheral Mechanisms in Cardiovascular Regulation*; Magro, A., Osswald, W., Reis, D., Vanhoutte, P., Eds.; Plenum Press: New York, 1986; pp 353–384.

Schwaber, J. S.; Graves, E. B.; Paton, J. F. R. Computational Modeling of Neuronal Dynamics for Systems Analysis: Application to Neurons of the Cardiorespiratory NTS in the Rat. *Brain Res.* **1993**, *604*, 126–141.

Scott, G. M.; Ray, W. H. Creating efficient nonlinear neural network process models that allow model interpretation. *J. Proc. Cont.* **1993**, *3* (3), 163–178.

Seagard, J. L.; van Brederode, J. F. M.; Dean, C.; Hopp, F. A.; Gallenburg, L. A.; Kampine, J. P. Firing Characteristics of Single-Fiber Carotid Sinus Baroreceptors. *Circ. Res.* **1990**, *66*, 1499–1509.

Seagard, J. L.; Gallenburg, L. A.; Hopp, F. A.; Dean, C. Acute Resetting in Two Functionally Different Types of Carotid Baroreceptors. *Circ. Res.* **1992**, *70*, 559–565.

Seagard, J. L.; Hopp, F. A.; Drummond, H. A.; Wynsberghe, D. M. V. Selective Contribution of Two Types of Carotid Sinus Baroreceptors to the Control of Blood Pressure. *Circ. Res.* **1993**, *72*, 1011–1022.

Seborg, D. E.; Edgar, T. F.; Mellichamp, D. A. *Process Dynamics and Control*; John Wiley and Sons, Inc.: New York, 1989.

Spyer, K. M. The Central Nervous Organization of Reflex Circulatory Control. In *Central Regulation of Autonomic Functions*; Loewy, A. D.; Spyer, K. M.; Eds.; Oxford University Press: New York, 1990; pp 168–188.

Uppal, A.; Ray, W. H.; Poore, A. B. On the Dynamic Behavior of Continuous Stirred Tank Reactors. *Chem. Eng. Sci.* **1974**, *29*, 967.

Wetzel, G. T.; Brown, J. H. Presynaptic Modulation of Acetylcholine Release from Cardiac Parasympathetic Neurons. *Am. J. Physiol.* **1985**, *248* (Heart Circ. Physiol.), H33–H39.

Yamazaki, T.; Sagawa, K. Summation of Sinoaortic Baroreflexes Depends on the Size of Input Signals. *Am. J. Physiol.* **1989**, *257* (Heart Circ. Physiol.), H465–H472.

Ydstie, B. E. Forecasting and Control Using Adaptive Connectionist Networks. *Comput. Chem. Eng.* **1990**, *14*, 583–599.

Yu, C.-C. Design of Parallel Cascade Control for Disturbance Rejection. *AIChE J.* **1988**, *34*, 1833–1838.