Research on . . .

NEURAL NETWORKS, OPTIMIZATION, AND PROCESS CONTROL

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Research into the use of artificial neural networks (ANNs) in process control systems has increased dramatically in recent years. Optimization methods play a fundamental role in the training of ANNs as well as in the implementation of modern strategies for multivariable process control. Hence, as illustrated in Figure 1, there is a philosophical relationship among ANNs, optimization, and process control that guides our research program at the University of Connecticut (UConn).

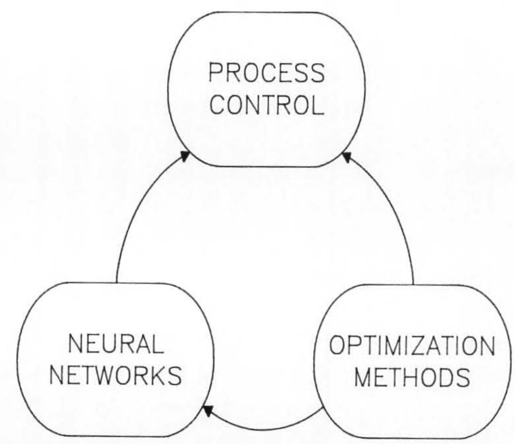

Figure 1. *Philosophical relationship guiding research program.*

In this article we will present an overview of several research projects that focus on these subject areas. Our goal is to stir the interest and increase the motivation of those students who are considering graduate studies in chemical engineering, and in particular, in neural networks, optimization, and process control.

The research at UConn is conducted in the Intelligent Process Systems Laboratory (IPS Lab), a lab associated with the Department of Chemical Engineering. Both the IPS Lab and the department are located at the UConn campus in Storrs, where about 12,500 undergraduates and 3,500 graduate students study under the guidance of some 1,200 faculty members. The Department of Chemical Engineering has about 120 undergraduates, 50 graduate students, and 13 faculty.

The IPS Lab is a relatively new facility that houses researchers and equipment for a number of interdisciplinary projects. A myriad of computer equipment, including RISC-based workstations and the newest personal computers, are available for use by student and faculty researchers. Access to the Cornell Supercomputer Center and high-end computers, such as the Sequent Symmetry S27 parallel computer and IBM vector machines, is possible through high speed networks.

Current projects range from fundamental theoretical studies to applied process implementations and include faculty from chemical, electrical, and mechanical engineering as well as researchers from local industry. The IPS Lab also interacts with other research programs at UConn, including the Biotechnology Center, the Booth Center for Computer Applications Research, the Environmental Research Center, the Institute of Material Science, and the Precision Manufacturing Center.

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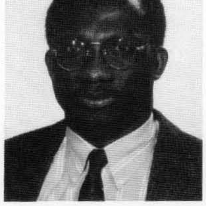

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CURRENT RESEARCH IN THE IPS LAB

The number and direction of individual research projects are influenced by technological needs of government agencies and industry, as well as developments in science and technology. Some of the research projects currently receiving attention by IPS Lab researchers are discussed in the following paragraphs.

Neural Network Architectures for Control

ANNs are computing tools made up of many simple, highly interconnected processing elements. ANNs are generating excitement both because they are able to model a wide range of complex and nonlinear problems with relative ease and because they have proven to be powerful and easy-to-implement tools for pattern recognition applications.

ANNs hold additional promise that make them particularly interesting to the process control researcher. For example, ANNs can be used to model complex processes without requiring the engineer to possess a fundamental understanding of the underlying physical phenomena. Further, they can model processes and recognize patterns when the data is imprecise or corrupted with "noise." Finally, ANNs are relatively easy for practitioners to employ in solving real-world problems compared to more traditional statistical and first-principles approaches.

In process control research, investigators have proposed using ANNs for modeling nonlinear process dynamics, for filtering noisy signals, for modeling the actions of human operators, for interpreting advanced sensor data, and for fault detection and diagnosis. Despite these efforts, there are still a number of issues which must be addressed if ANNs are to fulfill their promise in process control applications.

Knowledge is stored in ANNs by the choice of function used in each processing element (or neuron), by the way the neurons are connected to each other, and by the weighting values used in each neuron connection. These choices, taken together, comprise the network architecture. Three architectures receiving attention by researchers include feed forward nets such as the backpropagation ANN shown in Figure 2, recurrent nets such as the single layer Hopfield ANN shown in Figure 3, and vector quantizing nets such as the Kohonen ANN shown in Figure 4.

Each of these architectures has a number of variations. For example, when considering the backpropagation ANN, the number of neurons in the input and output layer is typically determined by the application. However, the number of hidden layers and the number of neurons within each hidden layer must be chosen by the engineer and is often determined by trial-and-error. In one research project, we are employing analysis tools such as singular value decomposition and variational ap-

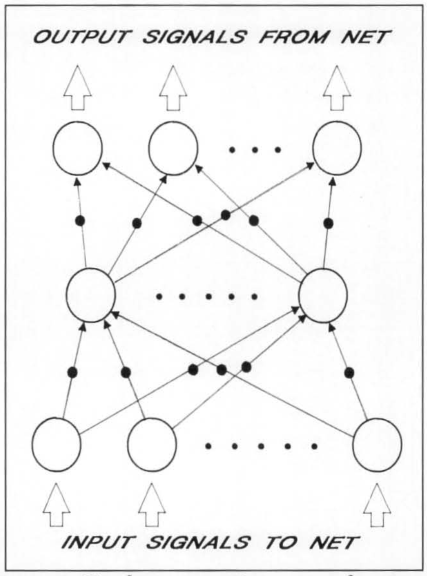

Figure 2. *Backpropagation neural network.*

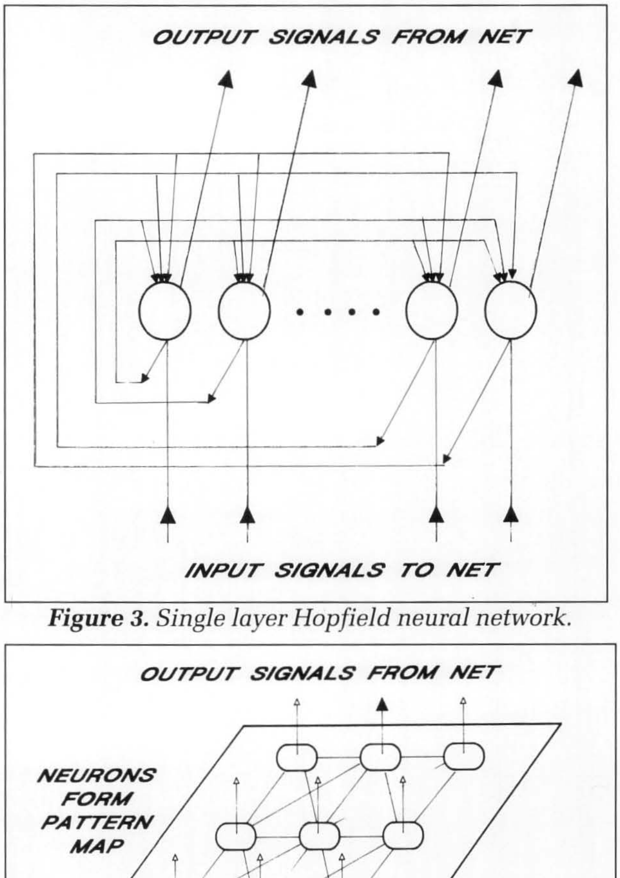

Figure 3. *Single layer Hopfield neural network.*

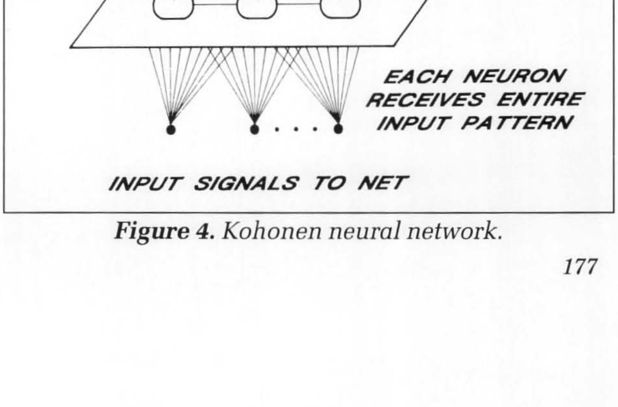

Figure 4. *Kohonen neural network.*

proaches[1] to develop a theoretically sound methodology for determining appropriate net architectures for particular applications.

Once an architecture is chosen, the engineer must make decisions about ANN training. Typically, training data is either historical data from the actual process or simulated data generated from computer models of the process. A network is repeatedly exposed to this data until it "learns by example" as it converges on the process relationships contained in the data.

Thus, the engineer must decide how much training data is adequate, whether this data properly spans the entire range of expected operation, and how much training is required before the ANN can be considered converged. The answers to these and similar questions, especially as they pertain to ANN applications in process control, are also under study at the IPS Lab. In one recent effort,[2] we compared the strengths and weaknesses to two ANN architectures when employed for pattern-based adaptive process control.

A current investigation considers the use of faster optimization algorithms such as successive quadratic programming and conjugate gradients coupled with efficient trust region techniques to significantly speed up training times of ANNs. Implementation of these techniques on parallel computers will also be investigated.[3]

Pattern-Based Adaptive Process Control

A controller continually adjusts a process input variable so that the controlled output variable successfully tracks a desired value or set point. A well-tuned controller manipulates the input variable both to minimize the impact of unplanned disturbances and to track any changes in the set point value.

Many chemical processes are nonlinear and/or have a process character which changes with time. A process may have a changing character, for example, due to fouling or catalyst deactivation over time. Hence the tuning of a controller on such processes must be self-adjusting or adaptive if desirable performance is to be maintained.

One approach for making process controllers adaptive is to employ a process model internal to the controller architecture which describes the dynamic behavior of the process. If, whenever the process character changes, this model is updated so that it remains descriptive of the current process dynamics, then a wide variety of popular model-based control algorithms such as Internal Model Control or Dynamic Matrix Control can be used to maintain desirable process control performance.

The traditional method for updating the controller process model is through regression of recently sampled process input-output data. The result is a correlative model between the manipulated variable and controlled variable that can be used in many adaptive algorithms. This traditional architecture is illustrated in Figure 5.

In the IPS Lab, a different approach to controller model updating is under study that may ultimately prove easier for industrial practitioners to employ. In this research, the performance of the controller is assessed by evaluating the patterns exhibited in the controller error, which is the difference between the desired set point and the measured value of the controlled variable. The pattern recognition capabilities of a neural network are exploited to perform this analysis and to relate observed patterns to required updates in controller model parameters. A

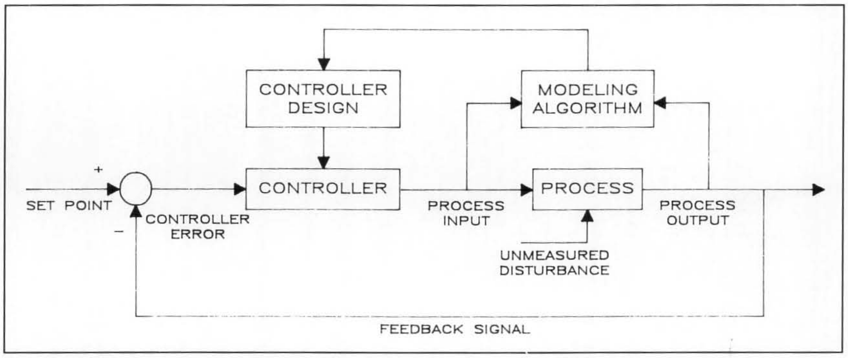

Figure 5. *Model-based adaptive process control architecture.*

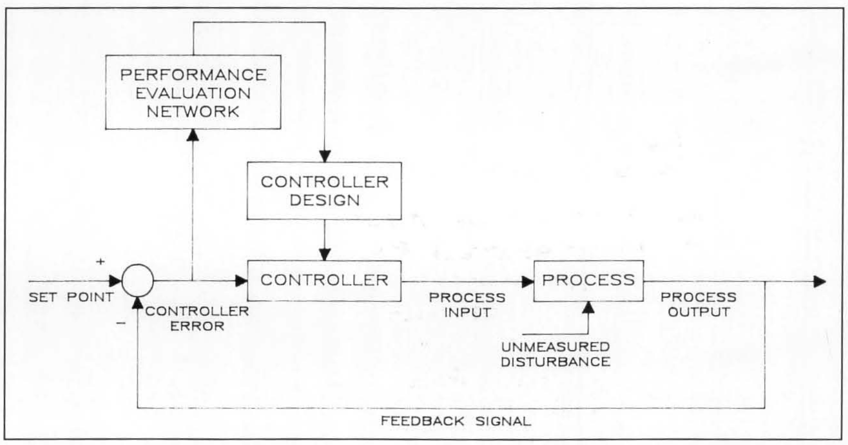

Figure 6. *Pattern-based performance feedback adaptive controller.*

The design of a neural network which can recognize both the oscillatory and non-oscillatory patterns that are associated with aggressive, desirable, and sluggish controller performance is reasonably straightforward.

pattern-based performance analysis architecture is illustrated in Figure 6.

Take as an example a process that responds to a set point change with a large overshoot, followed by slowly damping oscillations. One possible explanation is that the gain and/or time constant of the controller model is small relative to that of the actual process. Alternatively, an explanation for a slow response after a set point change is that the gain and/or time constant of the controller model is too large. Hence, the manner in which a poorly performing controller is mistuned can be inferred from the patterns displayed in the recent history of the controller error.

The design of a neural network which can recognize both the oscillatory and non-oscillatory patterns that are associated with aggressive, desirable, and sluggish controller performance is reasonably straightforward. The challenge is to associate these transient patterns with the required updating of the controller model parameters in order to restore desired performance. Methods for achieving this are under study in the IPS Lab, and recent successes are based on approximating all real processes with a generic or "ideal" simulated process.[2,4,5]

Pattern-Based Process Excitation Diagnostics

The traditional method for updating the process model internal to an adaptive controller (as illustrated in Figure 5) is based on regression of recently sampled process input-output data. To ensure that a properly descriptive process model results from the regression, data samples must be collected when the process is experiencing a meaningful or "sufficiently exciting" dynamic event. During such an event, the changes in the manipulated process input must impart changes to the process output variable that clearly dominate both the measurement noise and any dynamics resulting from unmeasured disturbances.

The engineer often uses simple criteria for excitation, such as when the difference between the model-predicted estimate of the output variable and the actual measurement of that variable exceed some minimum value. Unfortunately, such an approach is not very reliable for detecting when the process is experiencing input-output excitation and fails altogether when the disturbance dynamics dominate the event.

Thus, we are studying innovative methods for the diagnosis of process excitation that are reliable and easy to use. In this work, we initially focused on patterns exhibited in the process input variable alone under the assumption that if the process input was experiencing significant dynamics, then the process will be sufficiently excited for reliable data regression.[6]

Building on this idea, current research exploits the pattern recognition capabilities of ANNs to construct an improved excitation diagnostic tool. The approach under study considers the recent histories of both the input and output sampled data patterns together as a complete process "snapshot." The neural network is being trained to observe the behavior of both variables simultaneously and to signal whenever a dynamic event that is producing process input-output data suitable for model regression is in progress.

Control Design with Objective Prioritization

Controller designs based on the use of an internal controller model, such as Dynamic Matrix Control (DMC), are finding their way into industrial practice. One advantage to the DMC architecture is that in many applications, relatively simple process models are adequate to achieve good control performance. Further, DMC can handle soft control constraints in a straightforward and systematic manner.

A multivariable DMC implementation where control objectives are to be balanced against economic objectives may be achieved through the use of weights.[7] However, this strategy forces the engineer to specify a large number of weights, which is equivalent to specifying a large number of tuning parameters. The problem is compounded when engineers are responsible for many control loops in a large plant, compelling them to resort to *ad hoc* or trial-and-error tuning.

A method for circumventing this problem is the modular multivariable controller design methodology. In this approach, manipulated variables are designated as primary or secondary, where primary variables are the last to be allowed to achieve a desired optimum level. Unfortunately, in order to

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a Catalytic Reactor," PhD Thesis, Purdue University (1990)
19. Arce, P., B.R. Locke, and B. Trigatti, "Transport and Reaction in Laminar Regime: A Boundary and Integral-Spectral Equation Approach," preprint (1992)
20. Peacocke, A.R., *An Introduction to the Physical Chemistry of Biological Organization,* Oxford (1989)
21. Nicolis, G., and I. Prigogine, *Self-Organization in Nonequilibrium Systems From Dissipative Structures to Order Through Fluctuations,* John Wiley and Sons, New York (1977)
22. Higgins, J., *I. & E.C.,* **59**, 19 (1967)
23. Norel, R., and Z. Agur, "A Model for the Adjustment of the Mitotic Clock by Cyclin and MPF Levels, *Science,* **251**, 1076 (1991)
24. Rachevsky, N., *Mathematical Biophysics,* University of Chicago Press, Chicago, IL (1948)
25. Gmitro, J.I., and L.E. Scriven, "A Physicochemical Basis for Pattern and Rhythm," in *Intracellular Transport,* K.B. Warren, ed., Academic Press (1966)
26. Othmer, H.G., and L.E. Scriven, "Interactions of Reaction and Diffusion in Open Systems," *I. & E. C. Fund.,* **8**, 302 (1969)
27. Britton, N.F., *Reaction-Diffusion Equations and Their Applications to Biology,* Academic Press, London (1986)
28. Martin, M.H., M.H.M. Goldsmith, and T.H. Goldsmith, "On Polar Auxin Transport in Plant Cells," *J. Math. Biol.,* **28**, 197 (1990)
29. Almirantis, Y., and S. Papageorgiou, "Cross-Diffusion Effects on Chemical and Biological Pattern Formation," *J. Theoret. Biol.,* **151**, 289 (1991)
30. Newell, A.C., in *Lectures in the Science of Complexity,* edited by D.L. Stein, Addison-Wesley, Redwood, p. 107 (1989)
31. Ahlers, G., in *Lectures in the Science of Complexity,* edited by D.L. Stein, Addison-Wesley, Redwood, p. 175 (1989)
32. Bodenschatz, E., J.R. de Bruyn, G. Ahlers, and D.S. Cannell, *Phys. Rev. Lett.,* **67**, 3078 (1991)
33. Rehberg, I., S. Rasenat, M. de la Torre, W. Schöpf, F. Hörner, G. Ahlers, and H.R. Brand, *Phys. Rev. Lett.,* **67**, 596 (1991)
34. Swift, J., and P.C. Hohenberg, *Phys. Rev. A.,* **15**, 319 (1977)
35. Elder, K.R., J. Viñals, and M. Grant, *Phys. Rev. Lett.,* **68**, 3024 (1992)
36. Pelce, P., *Dynamics of Curved Fronts,* Academic Press, New York (1988)
37. Mullins, W.W., and R.F. Sekerka, *J. Appl. Phys.,* **34**, 323 (1963)
38. Caroli, B., C. Caroli, and B. Roulet, *J. Physique,* **48**, 1423 (1987)
39. Viñals, J., and D. Jasnow, in *Computer Simulations in Condensed Matter Physics IV,* edited by D.P. Landau, *et al.,* Springer-Verlag, New York (1992)
40. Bennett, M.J., K. Tsiveriotis, and R.A. Brown, *Phys. Rev. B.,* **45**, 9562 (1992) ❐

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obtain the correct ordering for both the manipulated and the controlled variables, the engineer requires a great deal of process understanding.

An alternative methodology under study in the IPS Lab is very ambitious in that it seeks to pose the multivariable control design with objective prioritization as a multilevel optimization problem with binary variables. Binary variables can be visualized as on-off keys that switch controller and economic objectives and constraints on or off as appropriate to achieve the desired prioritization.

FUTURE DIRECTIONS

As our research in neural networks, optimization, and process control matures, the focus in the IPS Lab is shifting to demonstration of the methods in collaboration with local industry. One project has begun which seeks to use neural network-based methods for controlling the quality of parts produced from an injection molding process. A second project is employing similar methods for controlling the incineration of hazardous wastes. A third effort is exploring the use of neural networks for optimizing the efficiency of combustion of pulverized coal.

Such real-world implementations are important in process control research. When developments are restricted to simulated processes, the complete process character can be specified by the same researcher who is responsible for the control system developments. Real plants, on the other hand, have a process character that is specified by nature, thereby truly testing the effectiveness of new developments.

Perhaps the most important aspect, however, is that real-world demonstrations permit developments to be tested by the ultimate user of the technology—the industrial practitioner. It is only when the technology is in the practitioner's hands that laboratory developments receive the critical evaluations which help guide subsequent improvements and refinements, and define new avenues for fruitful research.

REFERENCES

1. Achenie, L.E., and L.T. Biegler, "A Superstructure Based Approach to Chemical Reactor Network Synthesis," *Comp. Chem. Eng.,* **14**, 23 (1990)
2. Cooper, D.J., L. Megan, and R.F. Hinde, Jr., "Comparing Two Neural Networks for Pattern Based Adaptive Process Control," *AIChE J.,* **38**, 41 (1992)
3. Vegeais, J.A., D.B. Garrison, and L.E.K. Achenie, "Parallel NCUBE Implementation of a Layered, Feed-Forward Neural Network," AIChE meeting, Los Angeles, CA; Nov. (1991)
4. Cooper, D.J., L. Megan, and R.F. Hinde, Jr., "Disturbance Pattern Classification and Neuro-Adaptive Control," *IEEE Cont. Sys.,* **12**, 42 (1992)
5. Hinde, R.F., Jr., and D.J. Cooper, "Adaptive Process Control Using Pattern-Based Performance Feedback," *J. of Proc. Cont.,* **1**, 228 (1991)
6. Cooper, D.J., and A.M. Lalonde, "Process Behavior Diagnostics and Adaptive Process Control," *Computers and Chem. Eng.,* **14**, 541 (1990)
7. Prett, D.M., C.E. Garcia, and B.L. Ramaker, *The Second Shell Process Control Workshop,* Butterworths (1990) ❐