7th International Conference on DEVELOPMENT AND APPLICATION SYSTEMS
S u c e a v a, R o m a n i a, M a y 27 – 29, 2 0 0 4

STATE OF THE ART ADVANCED PROCESS CONTROL

Maamar BETTAYEB
S. Faisal A. SHAH
Department of Electrical/Electronics and Computer Engineering
University of Sharjah, Sharjah, UAE
{maama , sfaisal}@sharjah.ac.ae

Abstract. *The stringent industrial requirements coupled with complex optimization issues make industrial processes challenging to control. These inherent challenges include mathematical modeling of physical processes, modeling deficiencies, multivariable interactions, time varying parameters, time delays, uncertainties, nonlinearities etc… It is far beyond the scope of conventional control algorithms to deal with these challenges. Over the past few decades, several advanced process control strategies have been proposed and deployed on commercial basis to overcome these challenges. The paper presents a succinct overview of advanced process control strategies including adaptive control, model predictive control, artificial intelligent control systems etc… The paper also details the status quo of advanced process control schemes in several industries like oil industry, petrochemical industry, paper and pulp etc…*
Keywords: *advanced process control, adaptive control, model predictive control, non linear control, soft computing, artificial intelligence.*

Introduction

The main objective of control systems in the process industry is to provide good regulatory control at some desired optimum operating point, to allow rapid and smooth transition to new optimal operating points if required, to ensure safe and reliable operation and handle normal and emergency conditions such as plant start up and shut down [1]. The classical control techniques were able to satisfy the simple requirements of process industries in the past. However, the rapid increase in production of various products, the requirement of high quality and intense market competition warrant the development of new control strategies. Specifically, these advance process mechanisms are justified by the following industrial requirements:

- Increased Throughput.
- Higher Quality Products.
- Increased Utilization of Raw Materials.
- Decreased Energy Utilization.
- Rise of Environmental and Safety Issues.
- Tighter material and energy integration.

Advanced process control (APC) is the leading edge technology to reduce costs and improve quality of chemical processes. It is based on models describing the process dynamics – mathematical models, neuronal networks, and fuzzy logic models, for example.
Using the methods of APC (model predictive regulations, neural nets, fuzzy control, etc.) specific process characteristics (interactions, multi variable systems, etc.) can be taken into account and suitable process control strategies can be derived. From this fact a significant benefit for the customer in the plant might be realized, for example by efficiency increase, throughput increase and quality improvement, raw material and energy savings and/or reduction of laboratory analyses.

Challenges in Industrial Process Control

In industrial process control, challenging problems are inherently present at all levels. The problems are so involved that they can not be handled with conventional control. These inherent characteristics include:

- Process dynamics are often not perfectly known.
- Detailed modeling leads to complex high order models, distributed parameters and nonlinear structure
- Linearization often leads to loss of physical information.
- Process plants have multivariable interactions
- Constraints on manipulated and controlled variables.
- Several important variables are not measured continuously.
- Sensor noise
- Varying environmental conditions
- Raw material quality fluctuations and changing process conditions.
- Disturbances
- Time delays are often present due to transportation lags and sensor time lag
- Non minimum phase behaviour of some processes
- Time varying nature

Overview of Potential Advanced Process Control Algorithms

Adaptive Control

In the adaptive control scheme, the controller parameters are adjusted (in an automatic fashion) to keep up with the changes in the process characteristics [2]. There are various types of adaptive control schemes , differing mainly in the way the controller parameters are adjusted. The most important ones are:

1. Scheduled Adaptive Control
2. Model Reference Adaptive Control
3. Self Tuning Adaptive Control

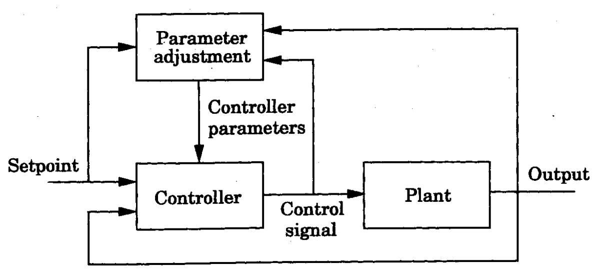

Fig 1. Generic Adaptive Control System

Adaptive control is suitable for systems that change with time or are not initially well known. It is not robust enough when the degree of uncertainty is high.

Model Predictive Control

Model Predictive Control (MPC) has enjoyed remarkable industrial success where others have failed primarily because, to date, it is the only methodology that allows the important performance criteria to be incorporated directly into the controller design formulation [2].

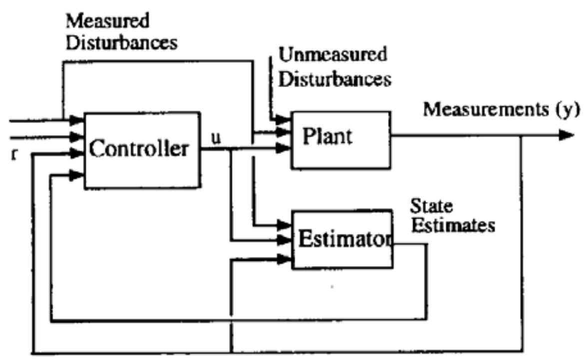

Fig 2. Block diagram for Model Predictive Control System

Basically, the algorithm generates a model of the system that used in :

i) prediction of future output values from known inputs
ii) computing the future values of the manipulated variables which will force the system output to follow some desired trajectories.

There are many factors that contributed to the success of MPC. MPC utilizes the step or impulse response as a process description, which allows time delays and complex dynamics to be represented with ease. MPC is more suitable for complex processes involving large number of manipulated and controlled variables. It has capability of handling the physical constraints.

Multivariable Predictive Control (MVPC)

The Multivariable Predictive Control (MVPC) technology is more suited for processes involving many variables, multiple interactions and significant response delays between inputs and outputs. The MVPC controller incorporates both feedback and feedforward type control actions in controlling both the present and predicted trajectories of the controlled variables. Constraint pushing and cost optimization can also be easily added to the control matrix. While it is possible to configure several DCS blocks with feedforwards, ratios, etc., MVPC provides an elegant approach that can reduce lifetime maintenance costs and generate higher benefits.

Non Linear Control

As a matter of fact, virtually all physical systems are nonlinear in character. When the nonlinearities of a process are mild, the classical approach of linearizing the process around an operating point and designing a controller for the linearized model is recommended. When the nonlinearities are more pronounced, the classical controller will not be effective, and alternative approaches are called for. The various adaptive control schemes will usually work well under these conditions.

Fuzzy Logic

Fuzzy logic belongs to artificial intelligent (AI) control systems. These techniques are useful for ill-defined industrial processes where little information is available about the dynamic behaviour of the process. Such a situation arises, for example in the case of plant start up and shut down. This technique provides a mean of both capturing human expertise and dealing with uncertainty.

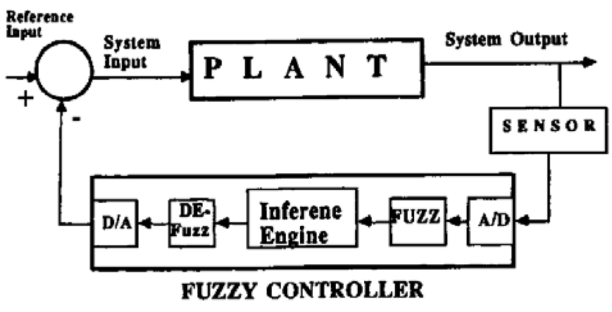

Fig 3. Control System using Fuzzy Logic

Neural Network

Another popular technique from AI control is Neural Networks. Based on the idea of the human brain, the neural network is a network of input nodes, hidden layers, and output nodes with weighted inputs to each node in the hidden layers.

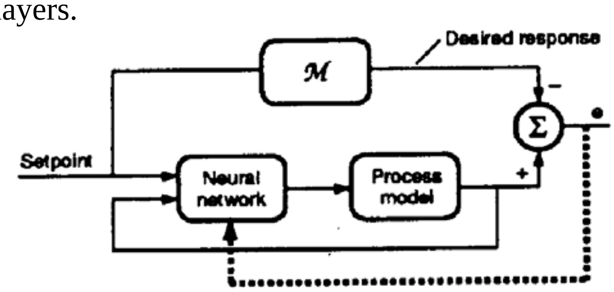

Fig 4. Control System using Neural Network

When the modeling is expensive or difficult it can be avoided using Neural Networks. In contrast to normal modeling equations that may involve a specific algebraic form with parameters, neural network models have no fixed functional form. One simply specifies the structure of the network and then fits the input weights as parameters. Neural networks have been applied to process control in many ways. One of the most successful has been in interpreting spectra and other data from on-line instrumentation [3]. Other applications include dynamic modeling, the use of neural networks as controllers, and in-process fault diagnosis [4-8].

Genetic Algorithms

Genetic Algorithms (GA) is a kind of evolutionary computation that finds a global optimum solution by emulating the natural genetic evolution. In many control optimization problems, the cost functions could be non-differentiable and/or discontinuous with various forms of constraints; as a result, the classical gradient/heuristics search strategies will fail. GA and some other evolutionary computation techniques have been recognized as the attractive future directions in developing industrial optimization solutions.

Expert Systems

Perhaps the most mature area of AI applications is that of expert systems. An expert system is a computer program with a user-friendly interface, a knowledge base, and a logic system. These combine to allow the program to provide advice and information, and to answer questions based on the knowledge database and logical rules preprogrammed into the system. Expert systems are useful for complex control processes when the information is imprecise and uncertain. They can provide the results offhand by avoiding time consuming process modeling.
Today expert systems can be rapidly configured using powerful development tools which aid the creation of the knowledge base and the rules. In process control, expert systems are being used to provide assistance in control system design, as well as in guiding data interpretation, alarm handling, failure detection, and controller action in real time [2, 9-11].

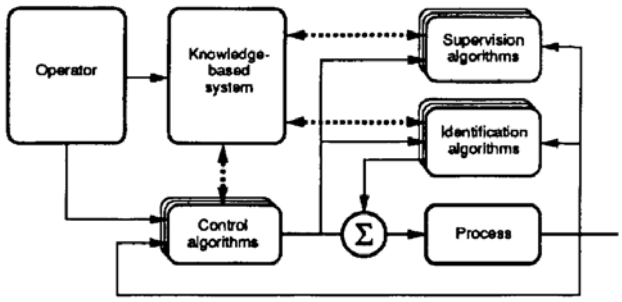

Fig 5. Use of Expert Systems in Control

Soft Computing

The combination of expert systems, fuzzy logic, neural network and evolution computing is termed as the soft computing [12]. Each of these components has its own strengths and weaknesses. Expert systems are mainly concerned with uncertainty, fuzzy logic with imprecision, neural networks with learning and evolutionary computation with optimisation. A good hybrid system brings the advantages of these technologies together. Their synergy allows a hybrid system to accommodate common sense, extract knowledge from raw data, use human –like reasoning mechanisms, data with uncertainty and imprecise

Survey of Applications in Process Control Industry

Applications of Model Predictive Control

1. Aircraft flight control, jet engine control [13, 14]
2. Superheater, steam generators, utility boiler [15, 16]
3. Transonic wind tunnel [17]
4. Fluid catalytic cracking units [18, 19, 20]
5. Batch reactor [21]
6. Several processes in the pulp and paper industry [22, 23]
7. Hydrocracker reactor [24, 25, 26]
8. Distillation columns [27]
9. Polymer extruder [28]
10. Olefins plant [24, 29]

Applications of other advance process control mechanisms will be presented in the full paper.

References

[1] M. Bettayeb and U. Al-Saggaf (1991) *DCS Control and Application Software: Present and Future trends*, Journal of Engineering, vol. 1 no. 1, India,

[2] B. A. Ogunnaike, W. H. Ray (1994) *Process Dynamics, Modeling and Control*, Oxford University Press,

[3] M. Piovoso, A. Owen (1991) *Application of Neural Nets to Sensor and Data Analysis* in Chemical Process Control IV, (Y. Arkun and W.H. Ray Ed.), AIChE,

[4] N. Bhat, and T. J. McAvoy, (1990) *Use of Neural Nets for Dynamic Modelling and Control of Chemical Process Systems*, Comp. Ch.E., vol. 573, no. 14,

[5] S. J. Qin and T. J. McAvoy (1992) *A Data-based Process Modeling Approach and its Applications*, Proceedings 3rd IFAC Symposium Dynamics and Control of Chemical Reactors, Distillation Columns and Batch Processes (DYCORD 92), 321,

[6] G. M. Scott and W. H. Ray, (1993) *Creating Efficient Nonlinear Neural Network Process Models that Allow Model Interpretation*, J. Process Control, 3,

[7] G. M. Scott and W. H. Ray (1993) *Experiences with Model-based Controllers Based on Neural Network Process Models*, J. Process Control, 3,

[8] Venkatsubramanian, V. (1991) *A Neural Network Methodology for Process Fault Diagnosis*, in Chemical Process Control IV, (Y. Arkun and W. H. Ray, Ed.), AIChE,

[9] Moore, R. L. and M. A. Kramer (1986) *Expert System in On-line Process Control*, in Chemical Process Control III, (M.Morari, T. J. McAvoy, Ed.), Elsevier, 839,

[10] Morris, A. J., G. A. Montague, and M.T. Tham (1991) *Towards Improved Process Supervision- Algorithms and Knowledge-based Systems*, in Chemical Process Control IV, (Y. Arkun and W.H. Ray, Ed.), AIChE,

[11] G. Stephanopoulos (1991) *Towards the Intelligent Controller - Formal Integration of Pattern Recognition with Control Theory, in Chemical Process Control IV*, (Y. Arkun and W. H. Ray, Ed.), AIChE,

[12] M. Negnevitsky (2002) *Artificial Intelligence : A guide to intelligent systems*, Addison Wesley,

[13] Mehra, R. K., et al. (1978) *Model Algorithmic Control Using IDCOM for the F100 Jet Engine Multivariable Control Design Problem*, in Alternatives for Linear Multivariable Control (ed. M. Sain et al.), NEC, Chicago,

[14] Rault, A., J. Richalet and P. LeRoux (1975) *Commands Auto Adaptive d'Un Avion*, Adersa/Gerbois,

[15] Lectique J., A. Rault, M. Tessier, and J. L. Testud (1978) *Multivariable Regulation of a Thermal Power Plant Steam Generator*, IFAC World Congress, Helsinki,

[16] Testud, J. L. (1979) *Commande Numerique Multivariable du BaIlon de Recuperation de Vapeur*, Adersa/Gerbios,

[17] Moreau, P. and J. P. Littnaun (1978) *European Transonic Wind Tunnel Dynamics, Simplified Model*, Adersa/Gerbios,

[18] Cutler, C. R. and F. H. Yocum (1991) *Experience with the DMC Inverse for Identification*, in Proc. of CPC IV, 297-317,

[19] Martin, G. D., J. M. Caldwell, and T. E. Ayral (1986) *Predictive Control Applications for the Petroleum Refining Industry*, Japan Petroleum Institute - Petroleum Refining Conf., Tokyo, Japan, 27-28 October.

[20] Prett, D. M. and R. D. Gillette (1979) *Optimization and Constrained Multivariable Control of a Catalytic Cracking Unit*, AIChE National Mtg., Houston, Texas; also Proc. Joint Aut. Control Conf., San Francisco,

[21]Garcia, C. E. (1984) *Quadratic Dynamic Matrix Control of Nonlinear Processes. An Application to a Batch Reaction Process*, AIChE Annual Mtg, San Francisco,

[22] Matsko, T. N. (1985) *Internal Model Control for Chemical Recovery*, Chem. Eng. Progress, 81, (12), 46,

[23]Ricker, N. L., T. Subramanian, and T. Sim (1989) *Case Studies of Model Predictive Control in Pulp and Paper Production*, in Model Based Process Control, (ed. T. J. McAvoy, Y. Arkun, and E. Zafiriou), Pergamon Press, Oxford,

[24] Caldwell, J. M. and G. D. Martin (1987) *On-line Analyzer Predictive Control*, Sixth Annual Control Expo Conf, Rosemont, IL, 19-21 May,

[25] Cutler, C. R. and R. B. Hawkins (1987) *Cons trained Multivariable Control of a Hydrocracker Reactor*, Proc. Am. Control Conf, Minneapolis, 1014,

[26] Cutler, C. R. and R. B. Hawkins (1988) *Application of a Large Predictive Multivariable Controller to a Hydrocracker Second Stage Reactor*, Proc. Am. Control Conf, Atlanta,
284,

[27] Georgiou, A., C. Georgaki, and W. L. Luyben (1988) *Nonlinear Dynamic Matrix Control 1 for High-purity Distillation Columns*, AIChE J., 34,1287,

[28] Wassick J. M. and D. T. Camp (1988) *Internal Model Control of an Industrial Extruder*, Proc. ACC, Atlanta, 2347,

[29] Gerstle, J. G. and D. A. Hokanson (1991)*Opportunities for Dynamic Matrix Control 'in Olefins Plants*, AIChE Spring Meeting, Houston, Texas