Process Control and Optimization Theory -- Application to Heat Treating Processes

Jake Fotopoulos, Lead Process Controls Engineer, Air Products and Chemicals, Inc.

Abstract

This paper presents a tutorial on control and optimization theory and provides examples on how it can be applied to heat treating processes. Traditional process control is discussed first and is followed by a presentation of advanced multivariable, model-based predictive process control techniques that can be used to optimize highly nonlinear and interactive processes. Then there is an example of how these techniques are used to control complex chemical processes at Air Products and Chemicals, Inc. The paper concludes with a discussion on how these techniques can be used in the heat treating industry. Heat treating processes are highly non-linear and interactive, featuring complex dynamics and transport phenomena with part quality parameters which are difficult to measure and control online. Examples are presented which illustrate how advanced control can provide significant benefits in the operation of these types of processes. These benefits can be obtained for any heat treating process. Specific applications discussed are brazing, carburizing and sintering.

I. Introduction

Many of Air Products operating facilities are large, complex plants. These plants feature types of chemical processes which are nonlinear and highly interactive. Since they can be difficult to control, they tend to run at conservative operating limits. Traditional control strategies do not handle nonlinearities, interaction or the multiple process constraints very well and typically react to process disturbances after they have already occurred. In addition, traditional controllers do not optimize the process. Optimization and reliable control of these plants using advanced control techniques can result in substantial, sustainable benefits. These benefits include:

- Steady state efficiency and capacity improvements
  - Economic optimum targets
  - Superior control at multiple constraints
  - Optimum tradeoffs between multiple products
  - Multiple plant and pipeline optimization
- Dynamic efficiency improvements
  - Faster and more efficient ramping
  - Load following of production requirements
  - Disturbance rejection
- Productivity improvements
  - Automation of operator interventions

Pub. No. 330-06-038-US

Process Control and Optimization Theory -- Application to Heat Treating Processes

Jake Fotopoulos, Lead Process Controls Engineer, Air Products and Chemicals, Inc.

Air Products' core group of experienced advanced control experts have implemented a corporate-wide advanced control program. This program has delivered savings in energy, capacity, yield and productivity. The advanced control techniques used in these facilities can apply to any complex industrial process. These techniques, along with an example, are described in section II. A discussion follows in Section III describing how these techniques can be used to optimize heat treating processes.

II. Advanced Control Theory

In this section, the concept of multivariable control and optimization will be described. Before getting into the details, it is important to first define some common terminology that will be used in the discussion. The following terminology will be used extensively in the remainder of this paper:

- **Input (Independent) Variable** - A variable that independently stimulates the process and can induce change in the internal conditions of the process. One may or may not have the ability to manipulate these variables. Examples include flow rate of gas into a furnace, the setpoint of a furnace temperature controller and the ambient air temperature.

- **Output (Dependent) Variable** - A variable by which information about the internal state of the process can be obtained. One cannot directly manipulate these types of variables. Examples include the dew point in the furnace atmosphere or the furnace temperature.

- **Manipulated Variable** - An input variable that can be altered (or manipulated) in order to achieve a control objective.

- **Controlled Variable** - A variable that is to be controlled by making changes to manipulated variables.

- **Disturbance Variable (Feedforward)** - An input variable that one has no control over. An example might be the ambient air temperature outside the furnace.

- **Single-Input, Single-Output (SISO)** - A system with one input and one output.

- **Multi-Input, Multi-Output (MIMO)** - A system with multiple inputs and multiple outputs.

Traditional process control features a series of single-input, single-output (SISO) controllers. For every variable that needs to be controlled, a single, unique manipulated variable is chosen and used for control. The temperature in the furnace is controlled by manipulating a heating element. A large chemical plant may feature dozens of single-input, single-output controllers. Each controller operates independently and does not depend on the actions of other controllers to determine how to move its manipulated variable. When interaction exists in the process, the individual controllers may not be capable of maintaining control.

To illustrate these concepts, consider the simple holding tank in Figure 1. A stream of hot water (with flow rate F_A) and a stream of cold water (with flow rate F_B) are fed into the holding tank and mixed. A stream of process water (with flowrate F_C) is removed from the tank.

 Pub. No. 330-06-038-US

Jake Fotopoulos, Lead Process Controls Engineer, Air Products and Chemicals, Inc.

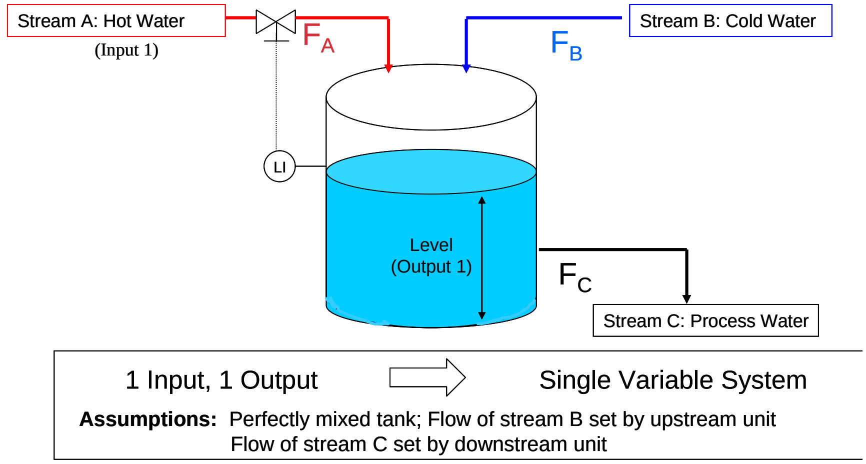

Figure 1: Simple Holding Tank Control Strategy

The flow of hot water can be manipulated but assume that the flows of the other two streams cannot be manipulated (they are set by other units in the plant connected to the holding tank). The objective in this example is to control the level in the tank and prevent it from overfilling or from draining. The level in the tank is the controlled (or output) variable and is the only process variable of interest. The only available variable to accomplish this is the flow of hot water into the tank, the manipulated (or input) variable. Because this system has only one input and one output, it is a single variable system.

A SISO controller can be designed that will make changes to the flow of hot water whenever the level deviates from a set value. As more process water is taken from the tank, the controller will increase the flow of hot water into the tank and fill it until the level returns to its setpoint.

Now, consider the same holding tank, illustrated in Figure 2, expanded to include more process variables. In this system, the cold water flow can now be manipulated and is no longer set by another process unit. In addition, the temperature of each of the streams (T_A, T_B and T_C) is measured. For simplicity, the assumption is made that the tank is perfectly mixed and that the temperature of the process water stream is equal to the temperature in the tank.

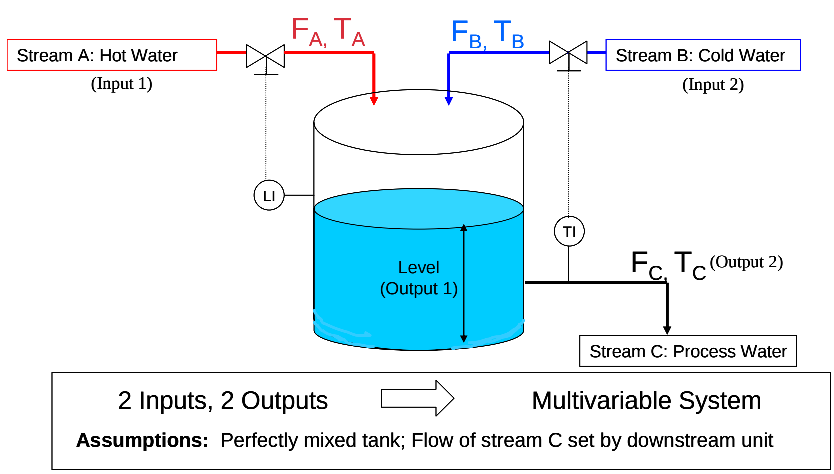

Figure 2: Simple Holding Tank Control Strategy

Pub. No. 330-06-038-US

The control problem now includes monitoring and controlling the temperature of the process water stream, as well as the level of water in the tank. Now there are two inputs (flow of stream A and flow of stream B) and two outputs (level and temperature). Having more than one input and/or more than one output makes this a multivariable system. The remainder of this paper will deal with the analysis and control of these types of systems.

Note that there is no physical difference between the process in Figure 2 and the single variable system from Figure 1. The temperatures physically existed in the single variable system except they were not of interest or could not be measured. The type of system is therefore determined by how many handles and measurements are available.

One of the most common methods used to control multivariable processes is to design a series of single-input, single-output (SISO) controllers. Each output variable is controlled by manipulating a single, unique input variable. This results in a set of input/output pairs. (Note that this implies we have a square multivariable system; the number of inputs equals the number of outputs.) Different combinations of input/output pairs constitute different controller configurations.

For the multivariable holding tank system, there are two distinct input/output pairs- two possible controller configurations. In “Controller Configuration 1,” the hot stream flow is manipulated to maintain the level in the tank while the cold stream flow is manipulated to maintain the temperature of the process water stream. Of course, it is also possible to control this system with the reverse configuration, where the hot stream flow controls the temperature and the cold stream flow controls the level (“Controller Configuration 2”).

In general, an n-input, n-output system (also known as a nxn system) has n! possible controller configurations. So a 3x3 system has 3! or 6 possible configurations. A 4x4 system has 4! or 24 possible configurations.

When examining the two possible controller configurations for the holding tank multivariable system, one can see a characteristic of multivariable processes that can pose a difficult challenge to the design of a successful control scheme. If the first controller increases the flow of hot water to maintain the tank level (“Controller Configuration 1”), it will affect the level (its intention) and the temperature (the water in the tank will get hotter). The flow of cold water will be increased by the other controller to lower the temperature back to our desired value. What happens next? The level will also change from the increase in cold water flow, forcing the hot flow stream to react once again. The two controllers will react to changes caused by each other's actions and may ultimately end up fighting each other in their attempt to keep the process under control.

This is known as **Interaction** and needs to be considered when designing a control scheme for multivariable systems. Most chemical and heat treating processes are multivariable systems that are highly interactive. There are many challenges to designing a successful SISO control scheme for a multivariable process. These include:

- **Selecting the appropriate input/output pairs**. These selections are made based on how strongly the inputs affect the outputs. An effort should be made to select pairings that minimize interaction between the SISO controllers.

- Once the pairings are selecting, the **individual SISO controllers must be designed** and tuned. Interaction from other SISO controllers should be accounted for during the design. In many instances, because of the existence of interaction, these controllers are detuned (run more conservatively) in order to work properly.

- Finally, in order to be able to account for interaction in the controller design, it is important to **quantify the inherent interaction of the process**.

To overcome some of the difficulties in using SISO controllers on a multivariable process, some of the following techniques are used:

- **Cascade control**: Two SISO controllers are linked, with output of the primary controller changing the setpoint of the second controller. Controlling purity by manipulating the setpoint of a flow controller is an example of cascade control.
- **Feedforward control**: Changes in measured disturbances are sent to the SISO controller. The idea is that the controller can begin to account for the effect of the disturbance before it actually affects the output variable being controlled.
- **Ratio control**: Manipulating one flow rate in order to keep the ratio between it and another flow rate constant is an example of ratio control.
- **Override control**: When more outputs exist than inputs, override control is often used. Input 1 is used to control output 1 unless output 2 exceeds a certain value. In that case, input 1 switches to control output 2.

So far, the focus of the discussion has been on using SISO controllers for multivariable control. This is the most common strategy used to control multivariable systems in practice. There are, however, a number of multivariable controllers in existence. The most common is used to not only control the process but to also optimize it. It is called Model Predictive Control (also known as MPC) and is the multivariable control strategy currently used at Air Products.

The traditional feedback controllers discussed above will react to disturbances only after they have affected the process. A sudden change in feed gas composition will not be seen by a dew point controller until it causes the dew point to deviate from its setpoint. In many cases, by the time the controller can react to a disturbance, it may be too late. A predictive controller, like MPC, will generate new setpoints for the manipulated variables based on what it thinks the future behavior of the process will be. These controllers have dynamic models of the process built-in and use them to predict what will happen based on past events. If the feed gas composition changes, the models will predict what the dew point change will be in the future and the controller can start taking action immediately instead of waiting until the dew point reacts to the new feed. Predictive controllers try to react and reject the disturbance before it has affected the process.

MPC takes this a step further and also uses the process models to optimize the process. This is illustrated in Figure 3. Time k is the current time. A target (optimal) value for the output is calculated by the controller. The controller now calculates a move plan (set of changes to the manipulated variable) that will take the output to the target. This move plan is constructed based on predicting where the output is going, using information about previous input moves and dynamic models of the process.

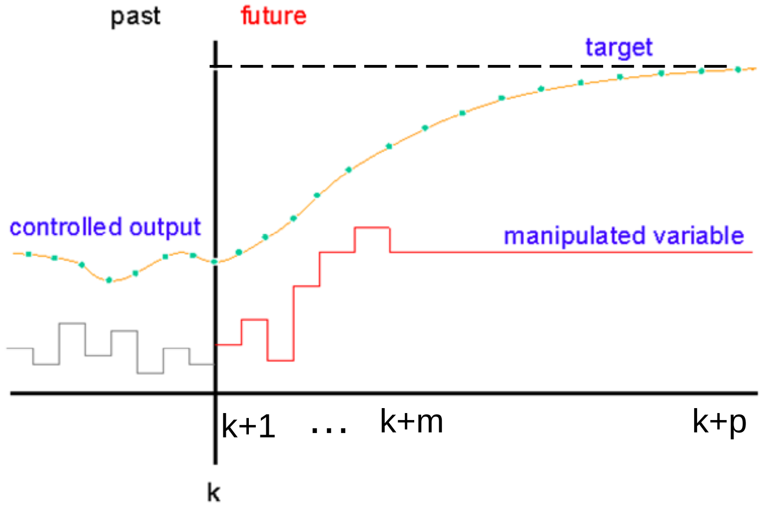

Figure 3: Model Predictive Control

A traditional control system, which can be implemented on a Distributed Control Platform (DCS) or a Programmable Logic Controller (PLC) is pictured in Figure 4. It is a SISO control strategy for a multivariable reactor process. Cascade controllers and ratio controllers are used to improve the controller performance.

The characteristics of this type of control strategy include:

(1) **Most of the setpoints of the controllers are fixed.** It usually takes operator intervention to change the setpoint. No optimization is taking place and the process usually runs at non-optimal conditions.

(2) **Feedback control is used.** Control action is generally taken only after a disturbance or event has already occurred and affected the process. Adding a feedfoward component to the SISO controller can help improve the control.

(3) Because a **SISO control strategy** is used, each Control Variable (output) is paired with a single, unique Manipulated Variable (input). The interaction issues described previously are present.

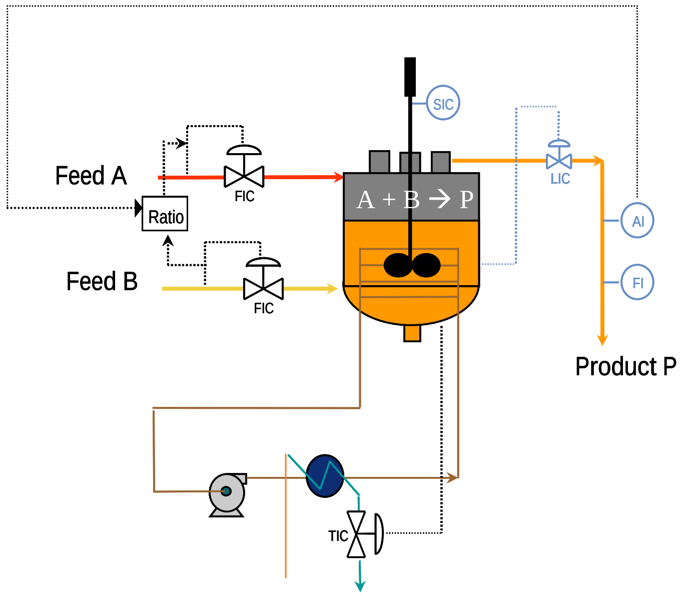

Figure 4: SISO Control of a Reactor Process

An MPC scheme for the same reactor process is pictured in Figure 5. The main characteristics of this type of controller include:

(1) The MPC controller attempts to **optimize the process**. Dynamic models representing how the process behaves are used to predict future behavior and to determine the optimal operating point.

(2) The **predictions of the future behavior** are also used to determine the control action taken by the controller. Disturbances can be rejected before they affect the process.

(3) MPC is a **multi-input, multi-output (MIMO)** controller. No input/output pairings need to be identified. All manipulated variables are moved simultaneously to control all the controlled variables. Interaction is accounted for with the dynamic models and used as an advantage in the control. Also, the number of inputs does not need to be equal to the number of outputs. MPC can handle non-square systems very easily.

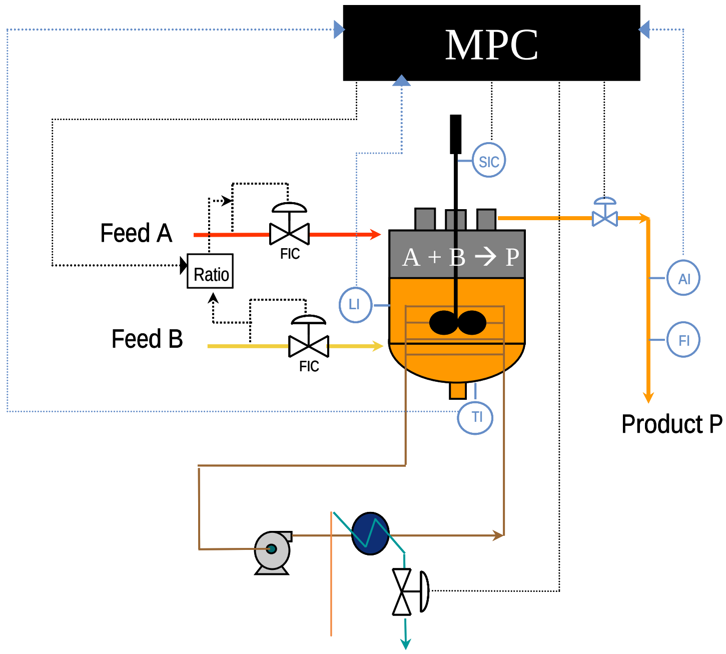

Figure 5: MPC Control of a Reactor Process

The prediction of future behavior, the optimization of the process and the control of the process are all based on having accurate plant-specific dynamic models available. These models describe the relationship between the inputs and outputs of the process.

Multivariable interactions are accurately predicted and completely accounted for by an MPC controller. Economic optimum operating targets are calculated by MPC for all of the manipulated and controlled variables (these are steady-state targets). MPC also calculates the optimal path for the process to take to reach those targets while maintaining acceptable control. Any measured disturbances can be handled within the same MPC framework by including them as feedforward variables. Dynamic models of how these measured disturbances affect the process must be available.

How are dynamic models used by MPC obtained? The first step is to perform plant testing and collect actual process data after a series of moves are made in the manipulated variables. In step testing a process, each manipulated variable is moved, one at a time (holding all others fixed), to observe the effect on the controlled variables. Each MV is typically moved eight to ten times and held, on average, for a time equal to the steady-state time of the process. So the overall testing time is dependent on the number of moves made, the number of MVs as well as the steady-state time of the process.

The test is designed to generate a significant response to the output variables but the following must always be considered when running this type of test in the field:

(1) Process safety is never compromised and (2) Production specifications and process constraints are never violated.

The data generated from the test is analyzed using a commercial model identification software package. For each input/output pair, a dynamic model is identified from the plant test data. This model will represent how the output will change when a unit step change is made in the input. An example is pictured in Figure 6. The final change in the output for this unit input change is called the Steady-state

Gain. Identifying accurate steady-state gains for the process is critical in designing a successful MPC controller. The set of all input/output dynamic curves constitute a Matrix of Dynamic Models. This matrix is used by the MPC controller for prediction, control and optimization.

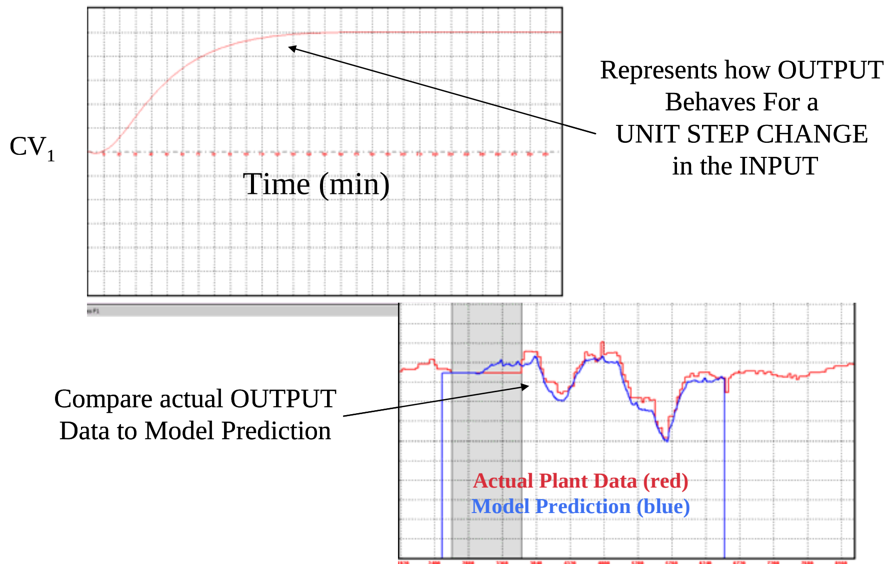

Figure 6: Dynamic Models used by MPC

Unlike traditional control strategies that require an operator or production engineer to determine appropriate setpoints for each controller, MPC controllers use actual plant costs to optimize operation of the process. Feed costs, product prices and other economic data are included in the controller as are production constraints, operating constraints, physical constraints and bounds (limits) for key variables. The controller will attempt to minimize a cost function subject to all of these constraints. The result is the calculation of all the necessary setpoints that meet process constraints and runs the process at the lowest cost possible.

As an example of the effectiveness of MPC, consider the process trend in Figure 7. The trend is 30 days of data for two key product output specifications in a large, highly complex chemical process under operator control. One can see that there is significant variability for these product specifications. This product is fed into another unit in the facility and the variability caused operational problems in the downstream unit. Figure 8 illustrates a 30 day trend of the same process variables under MPC control. There is a significant reduction in process variability. Because the large spikes have been removed due to tighter control, the process can be run more aggressively, pushing the setpoint for these variables closer to the constraint. Not only is the process run at a lower cost, the resulting reduction in variability eliminated the operability problems in the downstream unit.

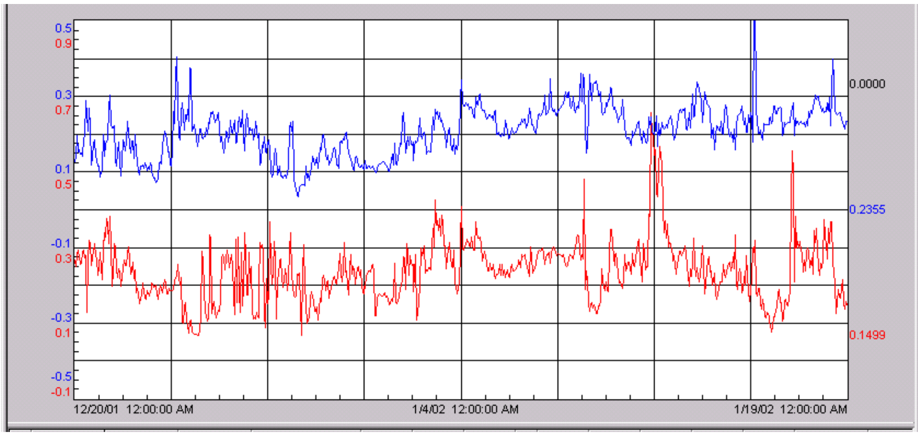

Figure 7: Output Variables under Operator Control

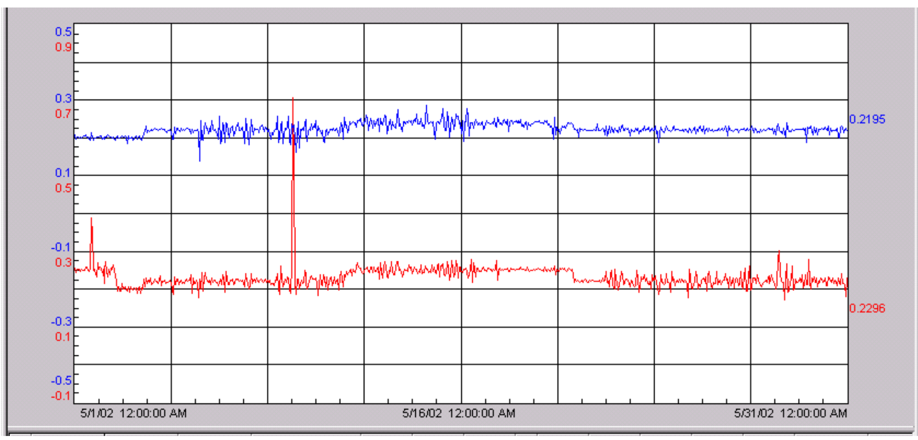

Figure 8: Output Variables under MPC Control

III. Application to Heat Treating Processes

This section describes how the techniques and theory presented in this paper can be applied to various heat treating processes. What makes these types of processes even more challenging to control than a complex chemical process is that the variables that ultimately need to be controlled cannot be easily measured online during production runs. Control systems are normally designed to control process variables, those that are easily measurable in real-time. In heat treating, the parameters of most interest are quality variables which are usually measured after the production run is complete. The challenge is to link the unmeasurable quality parameters to the appropriate measurable process variables and then design a multivariable control strategy that will directly control the process variables. By eliminating variability in process variables, one can indirectly eliminate variability in the quality variables.

A. Brazing

Brazing is a heat treating process that joins metals through the use of a filler metal and heat, at a temperature below the melting point of the metals being joined. If successful, the brazed joint is often stronger than the base metals being joined. In furnace brazing, the process can be run in a controlled gaseous atmosphere or in an evacuated chamber. Following brazing, the metals are quenched in a different zone of the furnace.

Process Control and Optimization Theory -- Application to Heat Treating Processes

Jake Fotopoulos, Lead Process Controls Engineer, Air Products and Chemicals, Inc.

A continuous belt furnace is pictured in Figure 9. The quality variables for this process may be such parameters as joint strength, distortion or may be an aesthetic parameter. These are nearly impossible or very costly to measure online. The process parameters include furnace temperatures, furnace pressures, atmosphere compositions and furnace dew point. These parameters are much easier to measure and should be used in the control strategy.

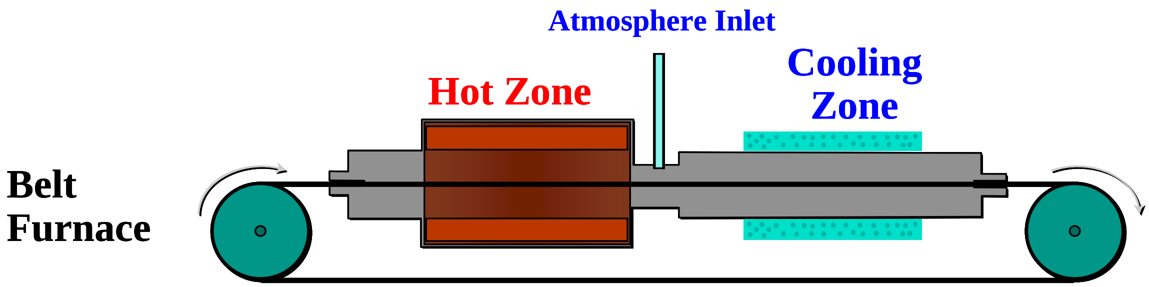

Figure 9: Continuous Furnace Brazing Process

A multivariable control strategy can provide tremendous benefits to the brazing process. Current fixed operating conditions such as inlet gas flows, furnace temperature setpoints and belt speed can be used as manipulated variables to maintain a reducing atmosphere in the furnace. Figure 10 illustrates a graph of furnace temperature vs. atmosphere dew point for a typical brazing process. For points below the Metallic Oxide line, the atmosphere is a reducing one. If large variability exists in either the furnace temperature or the atmosphere dew point, then it is necessary to operate the furnace well below the oxidation/reduction line. This is conservative and tends to be less efficient and more costly than the optimal operating conditions. A reliable multivariable control strategy will allow the furnace to be run right up against this line, under the most economic optimum conditions. Other advantages of an advanced control strategy include:

- Identification of dynamic models of key process parameters to changes in temperature, inlet gas flows and belt speed.
- Use the predictive capability of the models to prevent poor quality parts by taking control action before a problem can occur.
- Link final part quality to measurable furnace process parameters using empirical (black box) or statistical models.
- Link multiple furnaces in an overall facility optimization strategy.

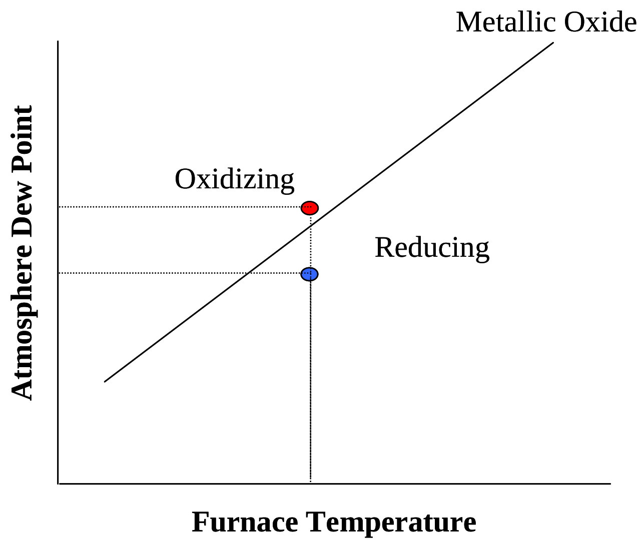

Figure 10: Oxidation/Reduction Line for a Brazing Process

The potential benefits of advanced control and optimization of furnace brazing include:

- Improved part quality and performance
- Reduced furnace cycle times
- Improved oxidation/reduction potential control
- Reduced atmosphere consumption
- Early warning of some furnace maintenance issues

B. Carburizing

In a carburizing process, carbon is diffused in the surface layer of a component in a high temperature environment under a controlled atmosphere. The objective is to improve the surface properties such as the hardness of the component. It is critical to control the carbon content of the furnace atmosphere in order to maintain the final carbon concentration at the surface of the part, at a specified value. Important process variables include furnace temperature, furnace atmosphere composition, carburizing time and the carbon potential of the atmosphere. In order for carburizing to occur, the carbon potential of the atmosphere must be greater than the carbon potential of the component's surface. How much greater will affect the rate of carburizing.

Whether an endothermic atmosphere or a manually regulated nitrogen-methanol atmosphere is used, there is typically a large degree of variability in the composition of the furnace atmosphere. Traditional carbon potential control strategies assume that there is a fixed level of carbon monoxide (CO) in the furnace and base the value on assumed fixed gas flows and compositions entering the furnace. In fact, there can be large variations in the level of CO in the furnace atmosphere. Poor control or regulation of inlet gas flows or changes in natural gas compositions can cause this variation.

A multivariable control strategy is well-suited for this type of process. Inlet gas flows, furnace temperature and pressure can be used as manipulated variables to directly control carbon potential and maintain a fixed atmosphere composition. Disturbances, such as natural gas composition changes, can be accounted for and rejected easily by the controller. In addition, the target value of carbon potential can be calculated by the controller based on the desired component quality or the desired final case depth. Models between furnace parameters and case depth can be used by the controller to take action before disturbances affect the quality of the parts. Economic data (gas and energy costs) can be used to obtain the most cost effective combination of gas flows and temperature setpoints that still maintain desired component properties.

Similar benefits as discussed previously can be obtained for the carburizing process. These include reduced cost, consistent part quality and a reduction or elimination of furnace sooting—a major problem in many carburizing processes.

C. Sintering

Powder metallurgy is used to press metal powders into useful shapes which are then sintered under a high temperature, controlled atmosphere into finished products. Final quality parameters include close dimensional tolerance, strength, wear resistance, density and hardness. Important process variables include nature and composition of the metal powder blends plus the temperature and composition of the sintering atmosphere. Variances in the sintering process can lead to final dimension and strength properties to be out of specification. Desired surface and bulk carbon levels plus wear properties will not be obtained if there are large variations in the composition of the sintering atmosphere.

Various types of atmospheres can be used for sintering (endothermic, dissociated ammonia, nitrogen/hydrogen). Each type features unique challenges in controlling the process. Changes in the atmosphere composition or the introduction of impurities into the atmosphere make it very difficult to maintain the desired carbon potential or reducing potential. Producing consistently sintered products with desired properties is therefore extremely challenging.

As with brazing and carburizing, these challenges can be addressed with a multivariable, predictive control strategy. Manipulated variables, such as inlet gas flows, can be used to maintain the desired atmosphere composition. The controller can quickly react to reject disturbances, such as leaks in the system or changes in feedstock composition. The benefits are the same as before: reduced cost, improved quality, consistent performance and reduced maintenance.

IV. Summary

Heat treating processes are highly non-linear and interactive, featuring complex dynamics and transport phenomena. Final part quality parameters are difficult to measure and control online. Controlling key process parameters and eliminating variation in the process are critical to obtaining consistent product quality. Multivariable, predictive control strategies can be used to provide this control while simultaneously optimizing the process. Typical benefits include improved part quality and consistent performance, reduced furnace cycle times, improved potential control, reduction in atmosphere consumption, early warning of some furnace maintenance issues and reduced sooting. The techniques describes in this paper are applicable to many heat treating processes. Examples in brazing, carburizing and sintering were presented but extension to other applications can easily be made.

Process Control and Optimization Theory -- Application to Heat Treating Processes
Jake Fotopoulos, Lead Process Controls Engineer, Air Products and Chemicals, Inc.

References

Air Products and Chemicals, Inc. "Introduction to Furnace Brazing" Air Products Website. Available from http://www.airproducts.com/NR/rdonlyres/4F8170B9-E45A-4923-B064-716DAC8E038D/0/3300018.pdf.

Bowe, D., K. Berger, J. Marsden and D. Garg "Optimization of Nitrogen/Hydrogen Sintering Atmosphere Composition for Carbon Steel" Journal of Powder Metallurgy 31:1 (1995) p. 29.

Luyben, W.L. Process Modeling, Simulation and Control for Chemical Engineers. McGraw-Hill (1990).

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

Plicht, G., J. Frey, R. Edwards and T. Reusch "Accelerated and Improved Carburizing" Metallurgia 70:1 (2003) p. 8.

Plicht, G. "Harder, Faster, Better – Improved Carburizing through Advanced Control" Air Products Website. Available from http://www.airproducts.com/NR/rdonlyres/0CA5AB66-DDBA-41A0-98A0-277E2C2D2C34/0/carburisingarticle.pdf.

Ray, W.H. Advanced Process Control. McGraw-Hill (1981).

For More Information

Air Products and Chemicals, Inc.
7201 Hamilton Boulevard
Allentown, PA 18195
Tel 800-654-4567
Fax 800-272-4449
Email: gigmrktg@airproducts.com

tell me more
www.airproducts.com

Pub. No. 330-06-038-US