# OPTIMIZATION OPPORTUNITIES IN PROCESS CONTROL FOR INDUSTRY/UNIVERSITY RESEARCH

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*Abstract*

The Measurement and Control Engineering Center (MCEC), a National Science Foundation Industry/University Cooperative Research Center (I/UCRC), is a cooperative venture among Oklahoma State University, The University of Tennessee, Oak Ridge National Laboratory, the National Science Foundation, and numerous industrial partners. Current research efforts include two projects where opportunities for optimization in process control are being explored. One project, Control to Economic Optimum, is developing a control and optimization algorithm that addresses the profit maximization motive behind industrial operations and dictates economically optimal dynamic profiles for manipulated variables. In the Experimental Batch Optimization project, new techniques are being developed for experimental optimization of batch recipes in real-time.

*Keywords*

Optimization, batch recipe, profit maximization

## Introduction

The main objective of this paper is to show the opportunities for economic optimization of dynamic processes in process control. Traditional industrial applications of process control economically optimize assuming steady state behavior, ignoring the dynamic nature of many processes.

## Control to Economic Optimum

### *Background*

A control system is designed to maintain the process in a profitable state of operation, respecting safety, stability and quality constraints of the process. To produce a product of uniform quality, process control must compensate for effects of disturbances and hold the product quality constant (Buckley, 1964). There is a dual optimization approach in the conventional control approach. First setpoints for each controlled variable are calculated from a design condition, typically the steady state. Then the controller calculates a manipulated variable profile which minimizes squared deviation from setpoint, a non-economically motivated objective. As the plant continually changes from one state to another, its optimal conditions change; thus the basic motive of maximizing profit is addressed only at particular conditions. In recent decades, the Online Optimization (OO) concept was implemented in the control process. Using the OO strategy, the optimizer periodically (on an hourly scale) updates the setpoints for the process according to a predefined objective function, (technical or economic). The OO concept is used widely (Ayala, 1997) and provides a better profit compared to conventional control algorithms (Lauks, et al. 1992). However, OO concept still uses the steady state process consumption.

*Motivation*

The power of the computer presently challenges the current control methods in following ways:

- The ultimate objective of control is to maximize profits, not to minimize the variance from setpoints.
- A steady state assumption is rarely valid due to the continual transient nature of continuous processes.
- Process changes between setpoints update periods and old setpoints are off optimum, but the outdated values are still used.

This suggests a modification in the control objective function to incorporate process economics. The optimizer should dynamically dictate the next most profitable operating point and also the most economically optimum path to that point. The main flow of the CEO (Control to Economic Optimum) algorithm can be seen in Figure 1.

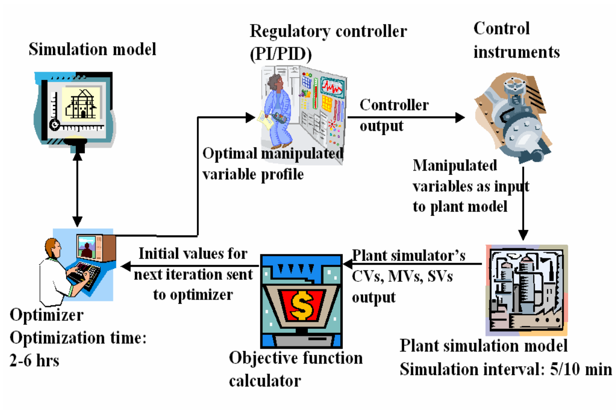



*Figure 1. Control to Economic Optimum flow chart*

*Formulation of Objective Function*

The aim of the process is to maximize the total profit during the period considered, the objective function is adjusted as:

$$Profit = \int (Product\ Revenue - Operation\ Cost) * dt \quad (1)$$

The optimizer will provide optimal manipulated variable profiles, which will be implemented into the process.

*Case Study*

The binary distillation column is chosen as the process studied, which has 15 trays and one feed flow. Two models involved in the case study, one is the full range model modified from Luyben's (Luyben, 1992) binary distillation column model, which is used as the plant model and receives the input from the second model, the simulator/optimizer; the other model is the key of the study, the simulator/optimizer, which predicts the optimal control variable profile in the 2 hours prediction horizon, (480 sampling points are used.) and output them to the plant model. (The software is MATLAB/Optimization Toolbox).

In order to differentiate these two models, the simulator/optimizer was developed by reduced order model, using the orthogonal collocation method (Stewart et al. 1985).

Since the process is usually in a transient state, overhead product removal rate (D), bottoms product removal rate (B), reflux rate (R) and vapor boilup rate (V) are not constant; the above formulation can be divided into small temporal stages which need to be integrated, the objective function is written as:

$$Profit = \Sigma( V_D*D_i + V_B*B_i - C_R*R_i - C_V*V_i) * \Delta t_i \quad (2)$$

$V_D$, $V_B$ are the values of the distillate and bottom product respectively, and $C_R$, $C_V$ are the cost of reflux and vapor boiled up respectively; the summation is over the prediction horizon.

In this optimization objective function, the independent variables, or the decision variables are the $R_i$ and $V_i$. By choosing the best profiles of $R_i$ and $V_i$, the process can be maintained at the best profit condition over the study horizon.

As a preliminary study, eight decision variables (DVs) (four for R and V each) are used in this case study. The first set of decision variables is located at 5 minutes to accommodate computation time in the controller. Other three sets are located at 15, 30, 60 minutes respectively. The result from this case was compared with the conventional PI controller (which controls the top and bottom product concentrations). The cumulative profit was compared on an 8 hours plant operation. See Figure 2.

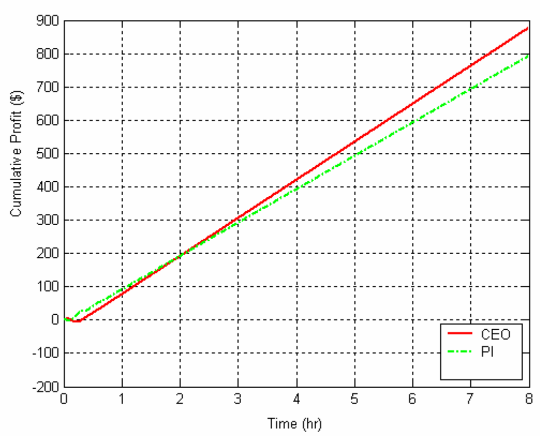



*Figure 2. Cumulative profit comparison*

In the current study, the products are regarded as the intermediates or raw materials for next unit operation. The purpose of doing this is to test how the economic consideration will affect the process operation and the profit. When the product purity has the requirement to meet the range of the specification, just add the quality penalty term in the objective function. An alternative is using the Taguchi-based method (Taguchi, et al, 1989) to control the quality.

Figure 3 and Figure 4 show the predicted and plant "real" concentrations profiles of the top and bottom products for the given location of the DVs. The next step of this research will focus on the comparison between the dynamic oriented CEO and steady state oriented Online Optimization, since they are optimizers, while the usage will be totally different. Process disturbances and random operational parameters' changes will be incorporated to model the real industrial environment.

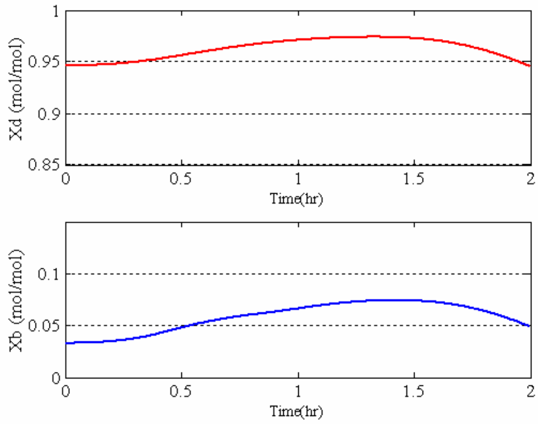



*Figure 3. Predicted top and bottom products concentrations profiles*

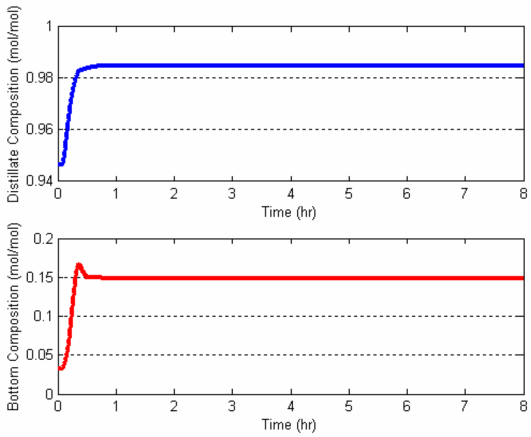



Figure 4. Plant "real" top and bottom products concentrations profiles

As the next step of this study, the disturbances will be introduced into the process, considered disturbances are feed flow rate changes, feed composition changes, and other non major random disturbances.

## Experimental Batch Optimization

### *Introduction*

Optimization of batch processes has been the focus of many studies (Love, 1988) and the use of in-situ spectroscopic measurements for characterizing batch process has received significant attention in the past few years (Dekkers, 1991). We believe the combination of these two technologies can develop the generic approach to optimizing batch processes.

In one experimental optimization of a batch process, the parameters of a simple unstructured, un-segregated model were dynamically adjusted to maintain an accurate representation of the process (Iyer, et al. 1999). Once the model parameters were adjusted, the batch was re-optimized, whereby inaccuracies in the model were taken care of by on-line data reconciliation and model parameter adjustment. Although that work cited focused on a fermentation process, the approach is perfectly general and is easily applicable to any batch process that can be modeled.

In this project, we propose to use techniques similar to the ones cited above; however, the control schemes will utilize traditional process measurements like temperature augmented with *composition profiles* estimated by multivariate calibration models and self-modeling curve resolution (SMCR) from in-situ spectroscopic measurements (Gemperline, 1999).

The batch recipe being taken under consideration here is the production of aspirin (acetylsalicylic acid, ASA). The process being modeled in this project is shown in Figure 4.

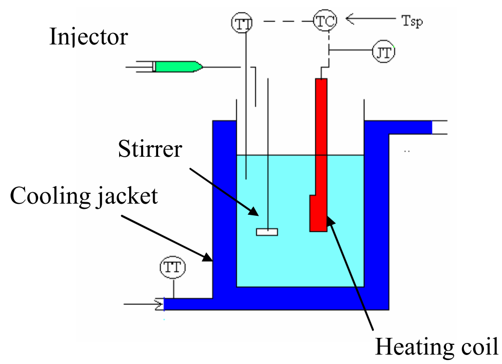



*Figure 4. Drawing of a single reactor setup*

### *Experimentation*

After the Reactor is filled with salicylic acid (SA), acetic anhydride (AA) is injected in an impulse to the reactor. The reactions that take place are as follows:

$$SA + AA \rightarrow ASA + HA \quad (k_1) \qquad (R1)$$

$$W + AA \rightarrow 2HA \quad (k_2) \qquad (R2)$$

In Reaction 1 SA reacts with AA to give, ASA and acetic acid (HA). Reaction 2 is an undesired side reaction, which occurs between the water (W) present in the solvent and the added AA and gives HA.

Because of wavelength range limiations, concentration of only SA and ASA can be estimated. This is done by the use of fiber optic UV/vis spectrometer. The spectrum data is used by the computer to generate the concentration profile of the reagents using SMCR.

*Model Development*

Model equations were developed based on traditional mass and energy balances. The experiment is conducted isothermally; therefore, the rates of reactions are not functions of temperature.

Four parameters ($k_1$,$k_2$,$C_{wo}$ initial water concentration, and $C_{AAin}$ AA concentration added) were optimized to match the model to experimental data. The model has been tested to be internally consistent.

*Results and Discussion*

Figure 5 shows a very close match between the SA concentration predicted by the model and the measured concentration.

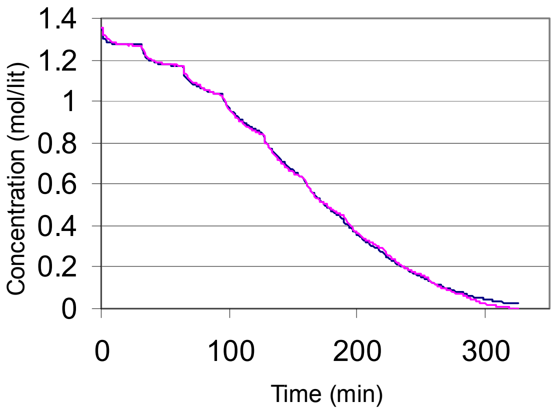
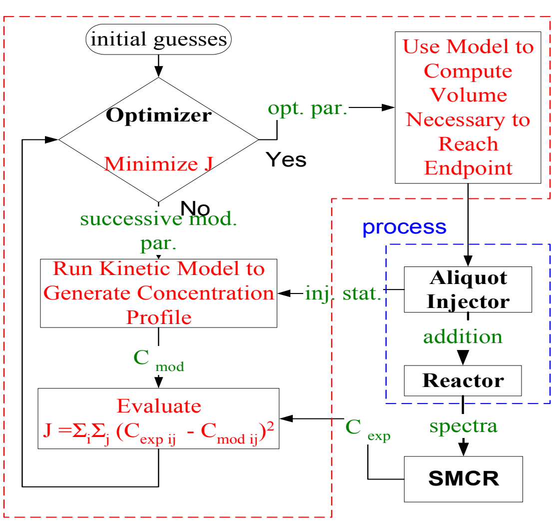



*Figure 5. Plot of SA concentration as a function of time*




SMCR: Self Modelling Curve Resolution
$C_{mod}$: model predicted concentration
$C_{exp}$: comcentration obtained from SMCR

*Figure 6. Command Flow Diagram*

The next implementation step will be to use the adjusted model to predict the optimal addition schedule for the remainder of that particular batch.

Figure 6 shows the strategy that will be used to re-optimize the batch recipe.

## Conclusions

The power of today's computer opens opportunities to use optimization within several process control functions. Summaries of two industrially sponsored projects are presented.

## Acknowledgements

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