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Moving Horizon Estimation and Control of an Experimental Process

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Keywords: Parameter Estimation, Moving Horizon, Experimental Process, Mixed Integer Programming

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Abstract

A horizon-based method is presented for use in control and estimation of a dynamic process. Process measurements are used to solve a Mixed Integer optimization process online for estimating disturbance levels. The estimated disturbances are then used to update a Model Predictive Control (MPC) algorithm. The method is applied to two case studies: an experimental multivariable process and a carbon dioxide absorber simulation.

Keywords: Disturbance Estimation, Model Predictive Control, Moving Horizon, Mixed Integer Programming, Distributed Computing.

Introduction

Horizon-based control has become an established method for use with difficult industrial process control applications. Moving horizon methods efficiently use process models to effectively control multi-variable systems and process constraints. It has been shown that model predictive control can benefit from the use of state estimation. Various methods using horizon-based estimation show that accurate estimates can be developed for process systems. The work presented in this paper demonstrate the integrated use of horizon-based estimation and control on two complex systems: an experimental four-tank system and a mini-plant simulation system.

There are many advantages in the use of a moving horizon formulation for both disturbance estimation and process control. The methods are very similar, in that at every time step an optimization problem is solved using a finite amount of measurement data and a model of the process. The estimation procedure attempts to solve for the past disturbances that best reconcile the given historical data. The control problem uses the process model to solve for the optimal control moves for the system. Horizon-based formulations allow for the addition of mathematical constraints to the optimization problem. Horizon-based formulations can also readily handle multivariable systems.

The estimation formulation currently used takes advantage of step response models to capture the influence of unmeasured disturbances on the modeled process outputs. Assuming that a limited number of disturbances are present over a single optimization window, propositional logic constraints can be added to the optimization formulation. These constraints include binary decision variable representing the presence or absence of a disturbance. Depending upon the objective function chosen, this results in either a Mixed Integer Linear Program (MILP) or a Mixed Integer Quadratic Program (MIQP). The disturbance estimate can potentially be used to improve controller response. Also, the use of an explicit estimation scheme which detects and isolates disturbances allows for the added potential for supervisory correction of disturbances, if possible.

The proposed architecture requires that the two optimization problems be solved at each sampling time: one to reconcile past disturbance effects on measurements and one to predict optimal control moves for a known future trajectory. In addition to the optimization problems to be solved, a separate application must handle data moving to and from the process in question, whether it is a high fidelity simulated model or an actual physical process. Currently, the most difficult computational problem is the estimation process. The use of a mixed integer formulation results in problems that can be difficult to solve in real-time. By taking advantage of prior solutions, exploiting the formulation structure, and distributing the computational load to multiple machines, the estimation problem can be handled in a timely manner. This allows the use of accurate disturbance estimates when solving the control problem.

Two case studies are considered for application of moving horizon estimation and control. A four-tank experimental laboratory apparatus (similar to the system presented in [11]) is considered. This multivariable system can exhibit a multivariable right-half or left-half plane zero, depending upon the valve settings for a given operating condition. This system is automated by a Bailey DCS system running Freelance using a Dynamic Data Exchange (DDE) interface to connect to MATLAB and SIMULINK. The system has two manipulated variables, two measured variables (both controlled), six unmeasured disturbances, and time constants on the order of 45 seconds. A high fidelity simulation of a CO2 absorption/desorption process is also considered, as modeled by [4]. The simulation and modeling is carried out using Aspen Dynamics and Aspen Custom Modeler with a DDE interface to MATLAB. This system has one manipulated variable, ten measured variables (one controlled), sixteen unmeasured disturbances, and time constants on the order of 800 seconds.

Related Work

There are many different methods for combined estimation and control of a chemical process. Presented below is a partial listing of some relevant work.

Moving horizon control has been effectively used in the process industries for many years, particularly the petroleum industries. Model Predictive Control solves an optimization problem at discrete time steps to minimize the error between the process measurements and a reference. A method for basic MPC using linear models with Kalman Filter based state estimation is presented in [17]. Methods for MPC have also been proposed using nonlinear models of a system to solve a nonlinear optimization problem at each time step [2] as well as extensions for use of nonlinear estimation techniques [13].

Parameter estimation and disturbance estimation can both be treated as a general state estimation problem. Kalman filtering has been used extensively to solve linear estimation problems. Nonlinear estimation techniques have also been applied. The Extended Kalman Filter (EKF) has met with much success [18, 22]. Other types of Principal Component Analysis (PCA) can also be used for determination of the state of a process [6, 5]. Moving horizon methods can produce results similar to those of Kalman Filtering. An overview of nonlinear estimation is found in [12]. Work with linear moving horizon methods [18, 19] as well as nonlinear moving horizon methods [1, 15, 16] have show the effectiveness and usefulness of moving horizon approaches.

In some cases, disturbances affect a system in deterministic, stepwise manners. This type of effect can be considered similar to a fault detection and diagnosis problem. Fault diagnosis infers the use of qualitative rules. Parameter estimation can be treated as a moving horizon optimization problem. The combination of estimation and diagnosis results in a problem that can be formulated and solved using Mixed Integer (MI) optimization methods. Mixed Integer Quadratic Programming (MIQP) formulations have been proposed in [20, 21]. A Mixed Integer Linear Programming (MILP) formulation and efficient solution methods have been discussed by [7]. Both MIQP and MILP of formulations expresses qualitative rules about a system as constraints involving integer variables.

Other fault detection and isolation methods are available for chemical engineers attempting to minimize process down time and industrial accidents. Rule-based diagnosis and root cause analysis has been presented in numerous sources [3]. A method for diagnosis based on digraph representations has also had some success [10, 14]. Many fault detection and isolation methods are adequate for dealing with faults on a purely qualitative level. In many cases one desires a more useful estimate of the current system state, so a combined moving horizon estimation technique with propositional logic constraints is desired.

Methodology

Control Formulation

To solve the control problem, at each time step an optimization problem is solved for a control move that minimizes the following objective function:

$$\min_{i = k...k+p} ||\Gamma_y \, (y(i) - r(i))||_2 + ||\Gamma_u \, \Delta u(i)||_2$$

where $r(i)$ is the reference at time i for the process measurements $y(i)$. The process inputs are given as $u(i)$ and $\Delta u(i)$ is the difference between $u(i)$ and

$u(i-1)$. The values for the process input beyond a point m in the horizon are assumed constant:

$$m(i+m) = m(i+m+1) = \ldots = m(i+p)$$

The values Γ_y and Γ_u are matrices that can be used to scale and weight process outputs and changes in process inputs. The Γ_y values can express preference for control of one measurement over another. The Γ_u values suppress chatter and extreme moves in the calculated process inputs.

The formulation takes advantage of a prediction of the future process outputs.

$$y(i) = y(i-1) + Mu(i) + M_d d(i) + f_d(y_m(k) - y(k))$$

Here, M is the impulse response matrix relating u to y. M_d is a model relating the disturbances d to the process outputs y. The model error, or disturbance term, at the current time step relating the actual measurement, y_m, to the modeled value $y(k)$ can be multiplied by filter f_d in order to reduce noise effects.

Estimation Formulation

Three different factors affect the estimation formulation objective function: the error between the measurement residuals and the model, the change in parameter estimates across a given window in time, and the change in parameter values from one time step to another. The current formulation solves the following problem:

$$\min_{i = k-h \ldots k} ||m_1(y(i) - \widehat{y}(i))||_2 + ||m_2 \Delta\Theta(i)||_2 + ||m_3 \Delta_T \Theta(i)||_2$$

where k is the current time, y_i is the process measurement vector at time i, $\widehat{y}(i)$ is the vector of process model estimates at time i, m_1 is a scaling vector for weighting and normalizing the measurements, m_2 is a scaling vector for weighting and normalizing the change in the parameter estimates in the given horizon window, m_3 is a scaling value for normalizing the change in parameter estimates across time, h is the length of the moving horizon, and Θ_i is the vector of parameter estimate at time i. The value for $\Delta\Theta(i)$ is given by:

$$\Delta\Theta(i) = \Theta(i) - \Theta(i-1)$$

Θ_{i-h} is the value of the parameter estimate θ_{i-h+1} from the previous horizon window. An impulse response formulation is used to calculate the response of the process model estimate, $\widehat{y}(i)$ to changes in the system parameters, Θ. An individual system parameter (or fault) may be described at time i as $\Theta_j(i)$. The value for $\Delta_T\Theta(i)$ is shown as:

$$\Delta\Theta_T(i) = \Theta(i) - \Theta_{k-1}(i+1)$$

Here, parameter estimates from the previous horizon's optimization result are used to minimize the change in a parameter from one time step to another. The value is shifted in time so that the current estimate corresponds to the value in the previous estimation window.

The impulse response formulation for $\widehat{y}(i)$ is:

$$\widehat{y}(i) = \sum_{j=1}^{F} M_j\theta_j(i) + ... + M_j\theta_j(i)$$

where M_j are the impulse response coefficients for model j. The value F is the total number of disturbances modeled in the formulation. The index j represents the number of possible faults (or disturbances).

The formulation up to this point only includes continuous variables and few constraints. Solving this formulation without additional constraints typically yields an under specified problem that can match the measurement values with the estimated measurement values exactly. One may make the assumption that only a limited number of disturbances can affect the system during a single horizon. This leads one to use binary decision variables to represent whether or not a fault has occurred in the current horizon window. The following constraints are added:

$$|\theta_j(i)| \leq Mf_j \quad \forall i, \forall j$$

$$\sum_{j=1}^{F} f_j \leq S$$

for all fault parameters j and all horizon indices (times) i. The value M is a large number that ensures whenever $\theta_{j,n}(i)$ is nonzero, f_j switches from 0 to 1. S is the total number of faults that can occur in a horizon window. In the presented results, response to positive and negative changes in a parameter are treated as separate fault events.

MIQP Solution Method

To solve the MIQP estimation problem in real-time, various steps are taken to minimize the time needed for calculation [8]. The type of constraints in this propositional logic problem allow significant improvement in the solution time. In a situation where F disturbances are possible and the system is constrained to allow only a single disturbance, $S = 1$, the problem reduces significantly. A small-scale quadratic programming problem can be solved for each of the F disturbances. Because the faults are mutually exclusive, this can easily be accomplished. This procedure must take into account the effect of previous solutions in order to be accurate. If fault Θ_1 were found to be optimal at time k , the objective function at time $k+1$ for all other disturbances must show a cost for changing the values for Θ_1 to zero across the horizon.

Decomposing the MIQP solution into multiple small scale QP problems allows for the use of computing power in parallel. The separate QP optimization problems can be solved using computational processes on separate CPUs, potentially even in different machines. The QP solution processes can also be warm started by using the solutions from the previous time step to warm start the QP calculation.

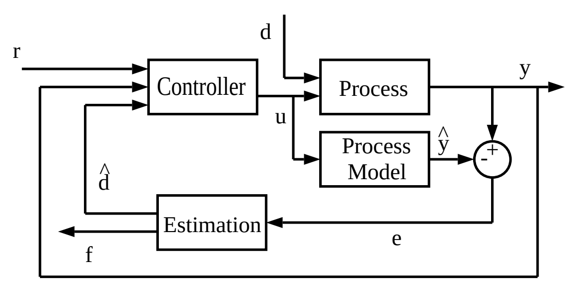

Figure 1: Proposed control system schematic

Application and Results

This section describes two separate case studies. The first case study is a four-tank experimental apparatus. This system has two measurements and two manipulated variables with up to 4 external unmeasured disturbances. The second case study is a CO_2 absorber simulation. This system has ten measurements, one manipulated input, and up to sixteen unmeasured disturbances. Control and estimation results from both case studies will be presented.

Figure 2 shows a general schematic for configuring the system. Each box in the diagram represents a separate physical computer or apparatus. The four-tank process is controlled by a Bailey Process Station apparatus, which can then be controlled by a PC. In Figure 2, each line is a flow of information and each block of text represents a computational process. Information travels between physical entities using TCP/IP and between processes on a PC using a Dynamic Data Exchange (DDE) protocol. For the computational processes, the indented text represents a subroutine of the process. MATLAB code has been developed to allow direct use of CPLEX and LOQO applications for solving LP, QP, and mixed integer problems. Independent MATLAB processes can pass and receive messages from a Java based application, allowing for non-blocking (continuous) operation of both processes. The Parallel Matlab Interface (PMI) toolbox also allows for communication between MATLAB processes, but receiving messages becomes a blocking task and the structure is parent-child instead of peer-to-peer.

Experimental Four-Tank Process

An interacting four-tank process has been implemented at the University of Delaware [9]. This process is currently used in both the elective multidisciplinary undergraduate control laboratory and the advanced graduate control course. The design is inspired by the benchtop apparatus described in [11]. A simple

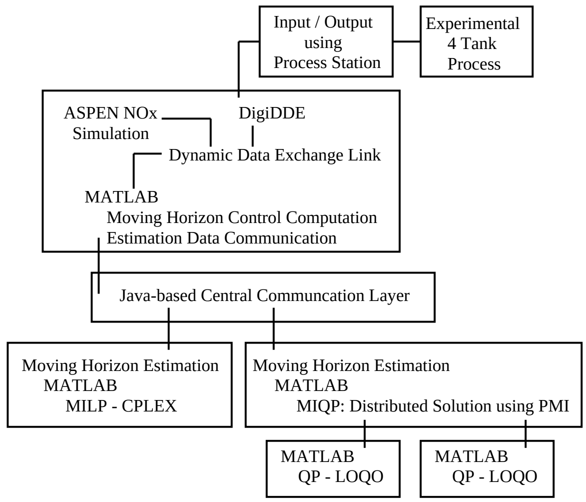

Figure 2: Schematic of the control system

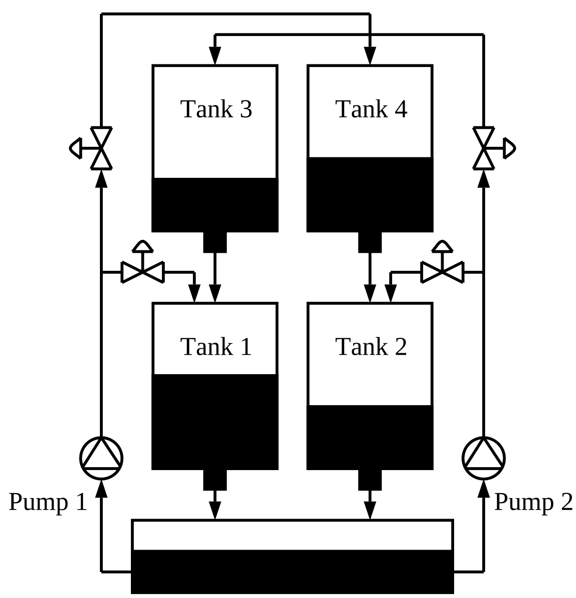

Figure 3: Schematic of the experimental process

schematic is shown in Figure 3. Two voltage-controlled pumps are used to pump water from a basin into four overhead tanks. The two upper tanks drain freely into the two bottom tanks, and the two bottom tanks drain freely into the reservoir basin. The liquid levels in the bottom two tanks are directly measured with pressure transducers. As can be seen from the schematic, the piping system is configured such that each pump affects the liquid levels of both measured tanks. A portion of the flow from one pump flows directly into one of the lower level tanks where the level is monitored. The rest of the flow from a single pump is diverted into an overhead tank, which drains into the other monitored tank. By adjusting the bypass valves on the system, the amount of interaction between the two pump flow rates (inputs) and the two lower tank level heights (outputs) can be varied. For this work, it is assumed that an external unmeasured disturbance flow may also be present which drains or fills the top tanks. The original work of [11] employed tanks with volume of $0.5L$ whereas the present work uses $19L$ (5 gallon) tanks for a more realistic experimental process.

A nonlinear model given by [11] has been modified to accommodate the addition of disturbance flows into and out of the various tanks, d_i. This model is given in the following equations:

$$\begin{aligned}
\frac{dh_1}{dt} &= -\frac{a_1}{A_1}\sqrt{2gh_1} + \frac{a_3}{A_1}\sqrt{2gh_3} + \frac{\gamma_1 k_1}{A_1}\nu_1 - \frac{k_{d_1} d_1}{A_3} \\
\frac{dh_2}{dt} &= -\frac{a_2}{A_2}\sqrt{2gh_2} + \frac{a_4}{A_2}\sqrt{2gh_4} + \frac{\gamma_2 k_2}{A_2}\nu - \frac{k_{d_2} d_2}{A_3} \\
\frac{dh_3}{dt} &= -\frac{a_3}{A_3}\sqrt{2gh_3} + \frac{(1-\gamma_2)k_2}{A_3}\nu_2 - \frac{k_{d_3} d_3}{A_3} \\
\frac{dh_4}{dt} &= -\frac{a_4}{A_4}\sqrt{2gh_4} + \frac{(1-\gamma_1)k_1}{A_4}\nu_1 - \frac{k_{d_4} d_4}{A_4}
\end{aligned}$$

Although this fundamental model is a reasonably accurate description of the system dynamics, many of the parameters are not available *a priori*, which requires the estimation of several model parameters. The tank areas A_i can be measured directly from the apparatus. Using tank drainage data, the cross sectional outlet areas a_i can also be determined. The steady-state operating point of $\nu_1 = 55\%$ and $\nu_2 = 55\%$ were used for subsequent results. The system valves were set for the bypass values γ_i such that the operating point exhibits inverse response ($\gamma_1 + \gamma_2 < 1$). Time constants, T_i, for the linearized system model are on the order of 40 seconds.

a_1, a_2	$2.3\, cm^2$	k_1	$6.81\, cm^3/s$
a_3, a_4	$2.3\, cm^2$	k_2	$6.94\, cm^3/s$
A_1, A_2, A_3, A_4	$730\, cm^2$	g	$981\, \frac{cm}{s^2}$
$\nu_1(0)$	55%	γ_1	0.102
$\nu_2(0)$	55%	γ_2	0.202
$h_1(0)$	$11.3\, cm$	$h_2(0)$	$16.4\, cm$
$h_3(0)$	$8.9\, cm$	$h_4(0)$	$10.9\, cm$
y_{1bias}	-1.8	y_{2bias}	-6.0

Table 1: Model parameters

A suitable test input sequence to generate data for the estimation of the remaining parameters. In this case, they elected to identify the parameters of the original nonlinear model, requiring the solution of a nonlinear optimization problem. The problem was formulated to minimize the 2-norm of the difference between the nonlinear model and actual measurements, searching over six parameters. Using dynamic data from the experiment, the optimization routine found the optimal pump gains k_i, gamma values γ_i, and measurement bias y_{ibias} as depicted in Table 1. A similar routine could be employed to model the characteristics of the disturbance introduced by the submersible pumps, k_{d_i} , but this was not done. The models used for estimation are based on a first-principles model without first-hand knowledge of the physical parameters.

Linear step response models are derived from the nonlinear process model, assuming a step in the inputs of 5% and a sample time of 5 seconds, using 60 coefficients. Aggressive controller tuning can result oscillations or unstable behavior. The controller was tuned with $m = 2$ and $p = 40$. The values for Γ_y were [1 1] and for Γ_u were [.1 .1]. This tuning results in acceptable setpoint tracking as well as disturbance rejection. The inverse response of the system imposes a bound on the performance of the system.

m	2 samples	p	40 samples
Γ_y	[1 1]	Γ_u	[0.1 0.1]
m_1	[10 10]	m_2	[3.5 3.5 0.9 0.9 0.6 0.6]
m_3	[1.7 1.7 0.4 0.4 0.3 0.3]	h	30 samples

Table 2: Control and estimation algorithm parameters

Six faults are identified for this system: four flows into or out of the tanks in addition to bias changes on the process inputs. Linear response models were determined for the disturbance flows, assuming a level of disturbance that would result in an open-loop change of approximately $5\,cm$ in the process measurements. The input bias models are taken from the models used for the MPC control calculation. Process measurements are available every second. These values are filtered to provide measurements every five seconds. The tuning parameters m_1, m_2, and m_3 are given in Table 2. These values are chosen such that the system can distinguish between the first-order type response of the lower tanks and the second-order response of the upper tanks, assuming that the disturbance is a step disturbance. Other types of disturbances such as ramps and pulses can be estimated, but in some cases the system recognizes an incorrect fault.

Figure 4 shows actual process measurements during four different disturbances. This figure also shows the process residuals for the system. The output values of the nonlinear process model are compared to the actual process measurements for calculation of the process residuals.

Figure 5 shows the estimated values for these four different disturbances. The input bias disturbances should track the solid lines at a normalized level of four units. The flow rate disturbances were never modeled exactly, so the actual level of the disturbance is unknown. A solid line at the normalized level of two

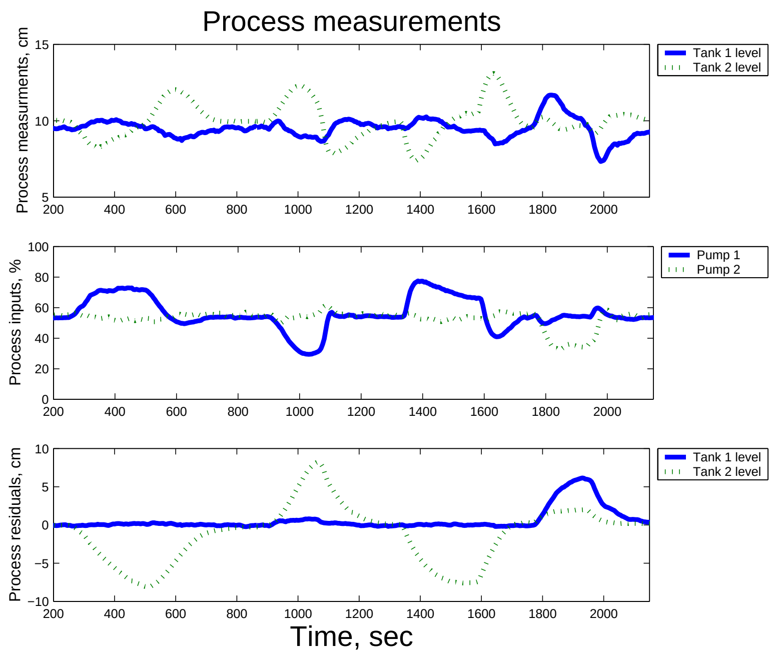

Figure 4: Experimental process measurements

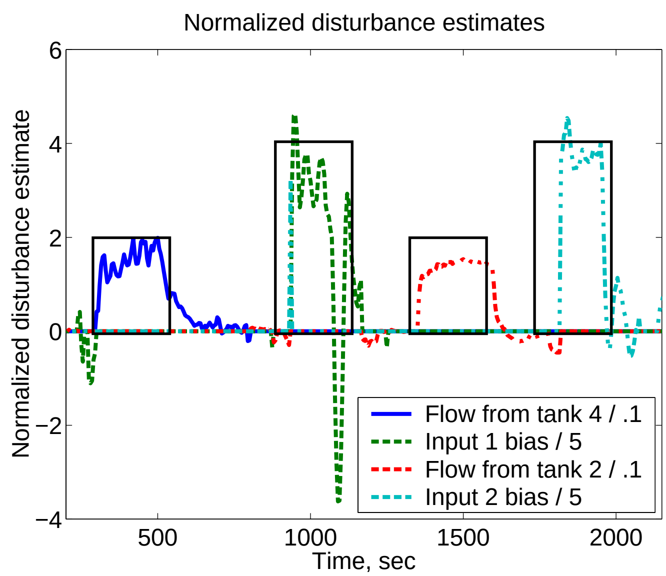

Figure 5: Estimated disturbance levels for different faults

shows the times at which the flow disturbances were applied to the system. Note that in some cases the incorrect fault was initially detected. After more information was available, the correct fault was determined.

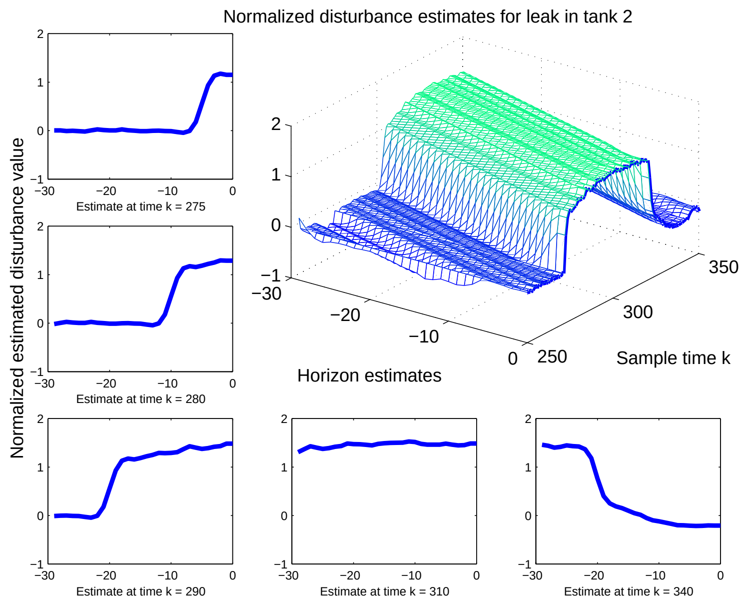

Figure 6: Disturbance estimates for leak in tank 2

Figures 6 and 7 show the horizon estimates for two different faults as a function of time. The small inset graphs on these figures show the optimal horizon estimates at different times. The estimated from 6 are much smoother than those of 7. The weights on the change of the disturbance were developed so that both faults could be distinguished, even though both faults are very similar in nature. A step-like leak in tank 2 appears as a first-order change in the residuals. A leak in tank 4 appears as a second-order change in the process residuals. The disturbance models for both faults can be used to account for the other fault. As a result, it can become difficult to develop weighting parameters to distinguish between these two faults.

The Model Predictive Control algorithm can be extended to included the

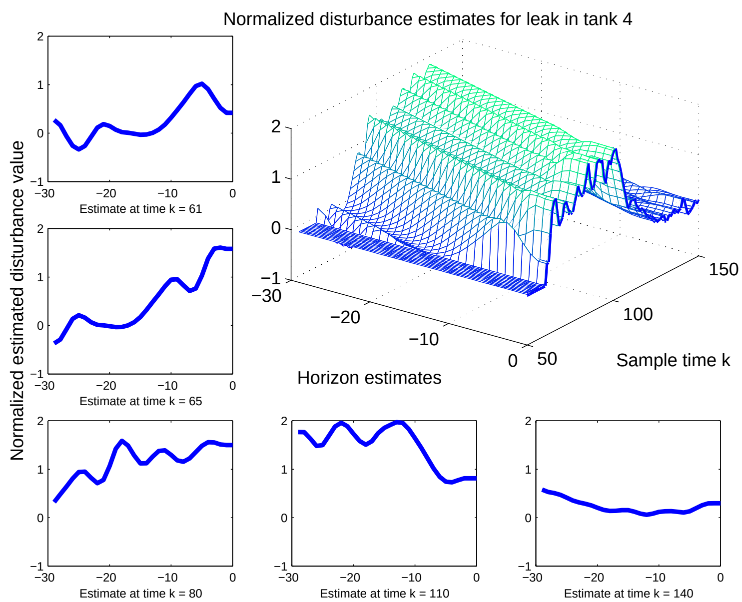

Figure 7: Disturbance estimates for leak in tank 4

effects of a measured disturbance on the process. In cases where a disturbance measurement is not available, an estimation method can be used calculate the level of the disturbance. This can be considered a soft sensor. The disturbance estimate is treated as a measured disturbance. In Figure 8, a simulation of the four-tank system is shown where the MPC algorithm rejects the disturbance of a leak in tank four without a measured disturbance update. In this simulation, the 2-norm of the process error is 9.9.

In Figure 9 the same disturbance hits the system, but the value of the estimated disturbance is used for control. The disturbance estimate is filtered with a first-order filter of the form:

$$y(k) = (\lambda - 1)y(k-1) + \lambda u(k)$$

where $\lambda = 0.15$. The 2-norm of the process error in this case is 5.7. This is a significant improvement over the case without a disturbance update. Figure 10 shows a simulation of the run using the non-filtered estimate. The 2-norm of this run is 4.0, but the control moves are erratic.

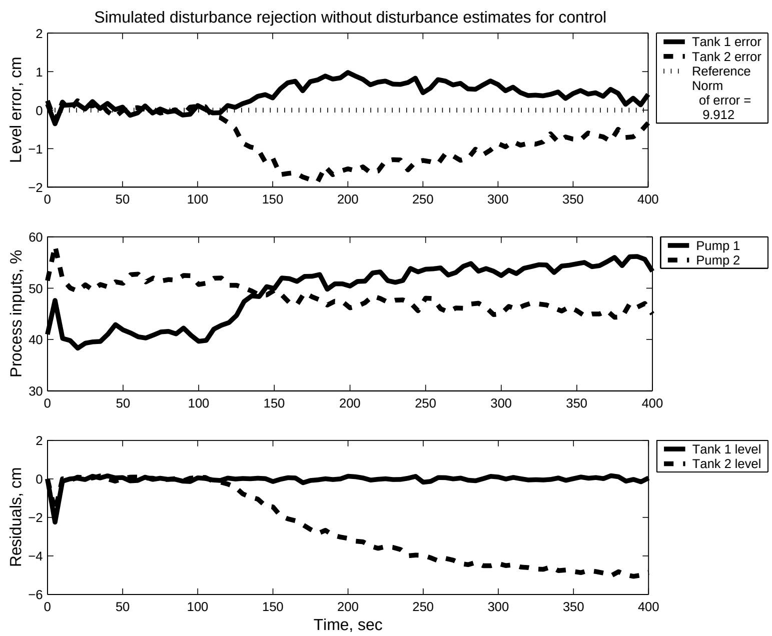

Figure 8: Closed-loop simulation without using estimates for control

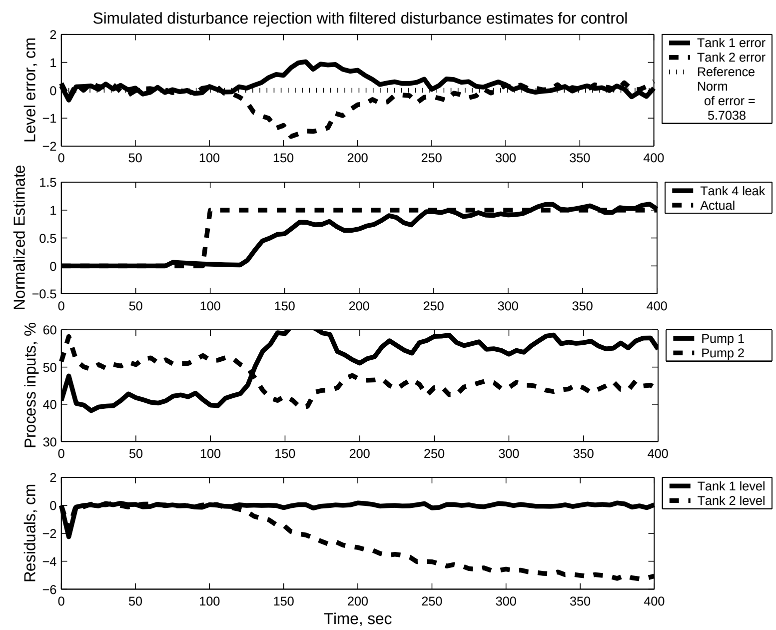

Figure 9: Closed-loop simulation using filtered estimates for control

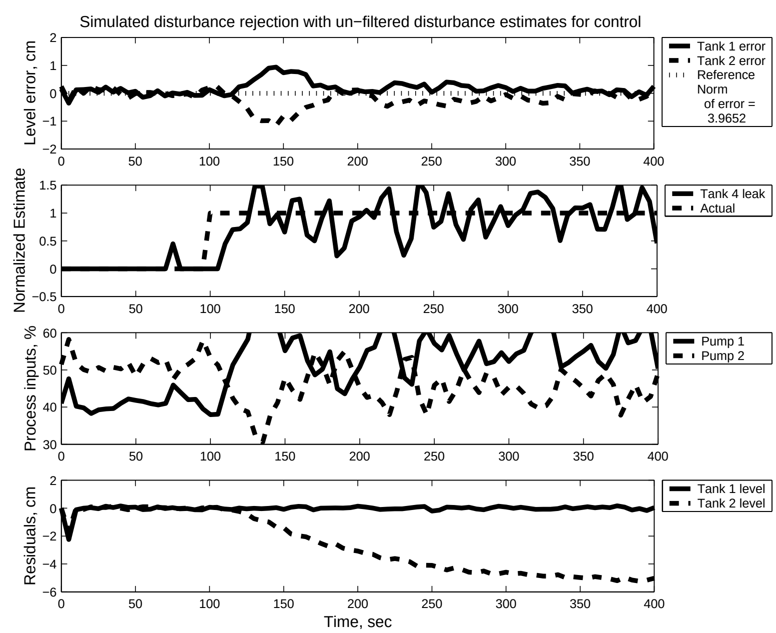

Figure 10: Closed-loop simulation using estimates for control

CO_2 Processing Simulation

The CO_2 case study simulated here is taken from the work of [4]. The simulation considers mass and energy balances, vapor-liquid equilibrium data, chemical reactions, and mass transfer relations. Monoetanolamine (MEA) is used in the system to react with the CO_2 in the with are considered in the simulation model. The controlled variable is the CO_2 concentration in the product vapor stream leaving the condenser. The manipulated variable is the reboiler steam flow rate. Disturbances include the feed CO_2 concentration, the feed CO_2 flow rate, the steam quality to the reboiler, the condenser duty, and variations in the MEA concentration.

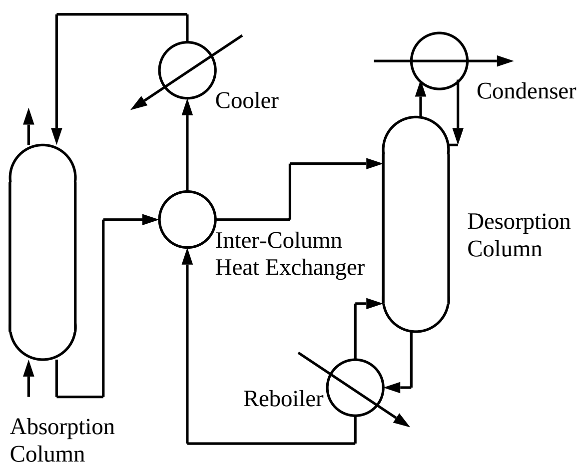

Figure 11: CO_2 Simulation Schematic

The following assumptions are made in the modeling of the absorber-desorber system.

- The absorbtion column is adiabatic
- The absorbtion column has no pressure drop
- Plug flow gas phase throughout the the columns

- Well mixed liquid phase on each tray
- The gas phase is pseudo steady state
- The gas phase is neglected in energy balance
- There are no radical temperature gradients exist throughout the column
- Liquid and gas phase temperatures are equal
- Constant physical properties for the columns
- The MEA in desorption column is non-volatile, no MEA in product stream
- No heat loss in the columns
- No accumulation of mass on desorption trays
- The condenser condensate contains no CO_2
- Condenser model is assumed steady state

Using the Aspen simulation model, linear disturbance models were developed for the six different faults. A sample time of 60 seconds was used, and 60 coefficients were use in the step response models. Table 3 shows the parameters used in the control and estimation problems. In figure 12, the controlled and manipulated variables for a step disturbance in the steam flow rate are shown for two cases. In the first case, the estimated disturbance is not used by the control algorithm. In the second case, the estimated disturbance is used in the control move calculation. Use of the disturbance estimate clearly improves control performance in the simulation environment.

Figure 13 shows the residuals for the eight different process measurements. The measurements selected include the absorber top tray mole fraction, the absorber top tray gas leaving mole fraction, the absorber bottom tray gas mole

m	2 samples	p	40 samples
Γ_y	[1]	Γ_u	[0.1]
m_1	$10 * [11111111]$	m_2	$0.8 * [11111]$
m_3	$0.2 * [111111]$	h	30 samples

Table 3: Control and estimation algorithm parameters for CO_2 case study

fraction, the reboiler temperature, the desorber top tray mole fraction, the top tray desorber temperature, the desorber bottom tray mole fraction, and the desorber bottom tray temperature. As stated, a linear model for the effect of the manipulated variable (steam flow rate) on the measured outputs is compared to the actual process measurements for calculation of process residuals.

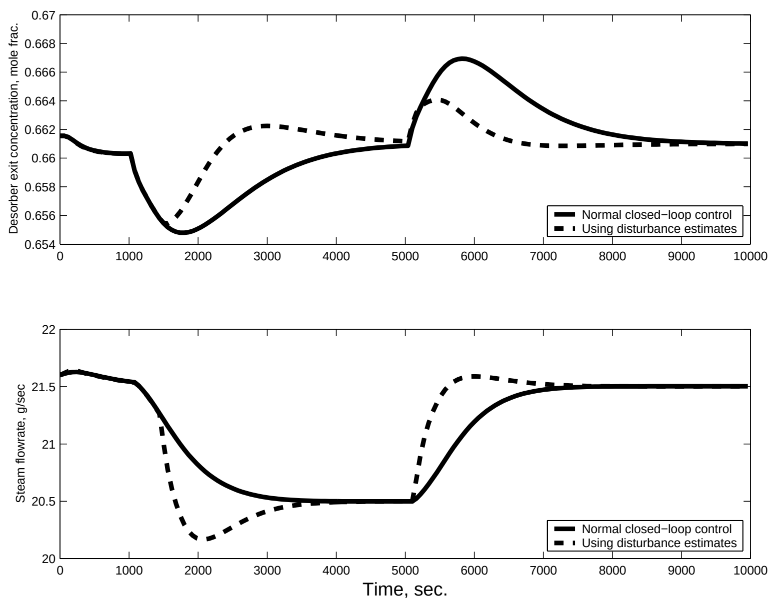

Figure 12: Controlled and manipulated variables for CO_2 absorber model, steam flow rate disturbance from t=1000 to t=5000 sec.

Figure 14 shows a typical horizon estimate for the system. In this case, there are small estimation errors at the onset of the disturbance. This can be attributed to model error due to nonlinearitites and initiall offset in the process residuals.

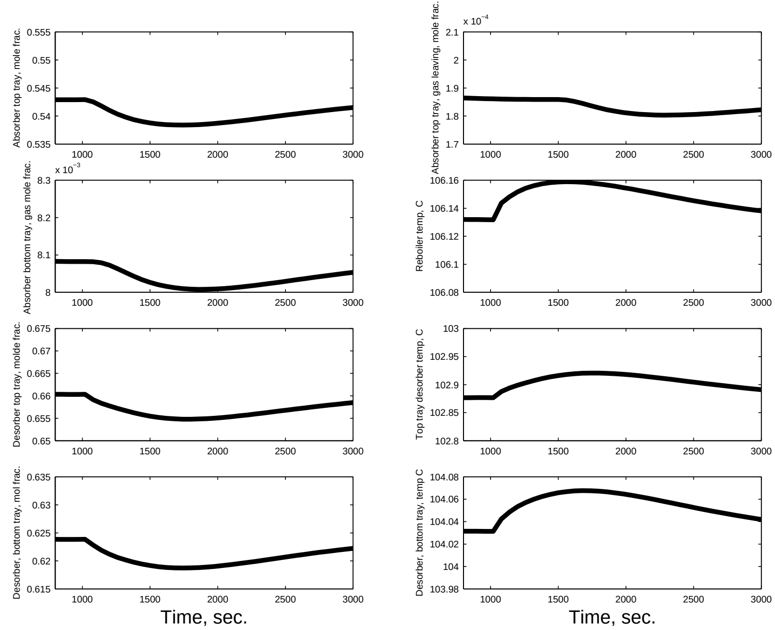

Figure 13: Process variables for steam flow rate disturbance

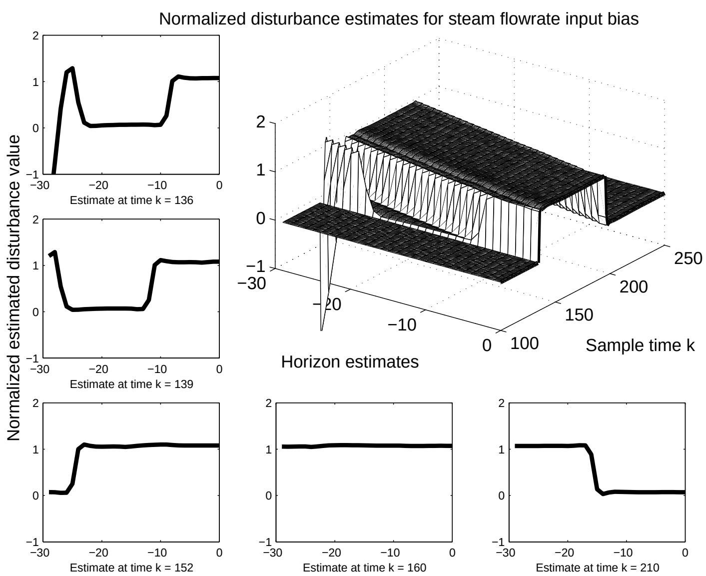

Figure 14: Horizon estimates for steam flow rate disturbance

Conclusions

In this paper a method for solving control and estimation problems has been demonstrated. The method uses a moving horizon controller in conjunction with a moving horizon propositional logic estimation method. The estimation method assumes that only a single, step-like, disturbance is present during a estimation period. As a result, the estimation method can distinguish between two faults that produce very similar process outputs. The estimation and control method has also been shown to be amenable to large scale application. In addition, the estimation computation can be distributed across multiple machines so that on-line estimates can be obtained quickly and efficiently.

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