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EVALUATION OF A MODEL BASED CONTROL STRATEGY FOR A NON-ISOTHERMAL SYSTEM WITH MULTIPLE INLETS AND OUTLETS

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Abstract. With the rising development of embedded technologies, the use of a controller with a traditional control strategy, such as a PID, can be replaced by advanced control methods. Advanced control methods guarantee greater efficiency in complex situations which enhances process security and final product quality. The present work investigated how model-based control methods performed in a laboratorial tank system scenario. For this purpose, a theoretical and stochastic model was developed which was based on mass, energy, momentum, and analysis of the data collected. After validation, a model-based control strategy with a generic and then optimal approach was applied off-line, with ISE tuning. To solve the model, an explicit Runge-Kutta's method and parameter optimization with PSO method was used. Finally, the influence of data reconciliation processing on control development was investigated. It was concluded that both model-base strategies were more efficient regarding the stability and proximity of the controlled variable to the setpoint, especially when the data reconciliation was present.

Keywords: Model Based Predictive Control, Data Reconciliation.

1 Introduction

The increasing industrial competitiveness requires a high quality and operational cost reduction of the processes. In this sense, the industrial processes need to be controlled in an efficient manner. So, besides the implementation of robust control techniques, for example, the model based predictive control (MPC), data reconciliation can be used to adjust measures and parameters, providing a steady and secure operation.

MPC is a powerful, well developed and consolidated control technique. It is based on three control strategies: prediction in several steps, optimization over time horizon, L. Wang [1], and data reconciliation for adjustment of measures provided by the sensors and process parameters, minimizing the deviations between the corrected and observed plant values, G. Fadda *et al* [2].

In the present study, the implementation of the MPC control technique is done offline on a pilot scale plant with temperature and level control. The system operates in a non-isothermal manner. The theoretical model was developed based on mass and energy balances. The data reconciliation was in excellent accordance with the experimental data model.

2 Methodology

The system considered in the projects is described in Fig. 2.

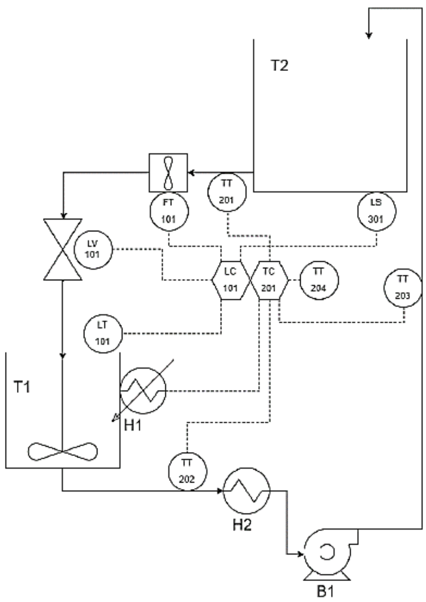

Figure 1. P&I diagram of the pilot plant.

The system was modeled using the equations based on the mass and energy balances of tanks 1 and 2, which leads to the Eq. (1-4).

$$\frac{dT_{o1}}{dt} = \frac{Q_R + \rho Cp F_{o2}(T_{o2} - T_{o1})}{\rho Cp A_1 h1}. \tag{1}$$

$$\frac{dT_{o2}}{dt} = \frac{F_{o1}(T_{i2} - T_{o2})}{V_2}. \tag{2}$$

$$\frac{dh1}{dt} = \frac{F_{o2} - F_{o1}}{A1}. \tag{3}$$

$$\frac{dV_2}{dt} = F_{o1} - F_{o2}. \tag{4}$$

The system variables are:

Table 1. Variables description.

Variable	Status	Description
h1	Measured	Level of Tank 1
V2	Not measured	Volume of Tank 2
To1	Measured	Outlet Temperature of Tank 1
To2	Measured	Outlet Temperature of Tank 2
Ti2	Measured	Inlet temperature of Tank 2
Fo2	Measured	Outlet flow of tank 2
Fo1	Not measured	Outlet flow of tank 1
Cp	Known	Specific Heat of Water at 25°C (4.186 J/Kg°C)
ρ	Known	Density of Water at 25° C (996.7 kg/m³)
A1	Known	Transverse section area of Tank 1 ($7.62*10^{-2}$ m²)
Qr	Known	Provided Heat (1500W)

The data collection of the system was done at 4.5s interval. For the data reconciliation, three different robust functions were selected, according to the Eq. (5-7).

$$\frac{1}{2}\frac{\left(x^{measured} - x^{reconciliated}\right)^2}{\sigma^2}. \tag{5}$$

$$c_c^2 ln\left(1 + \frac{\left(x^{measured} - x^{reconciliated}\right)^2}{(\sigma c_c)^2}\right). \tag{6}$$

$$-ln\left((1-p_{NC})exp\left(\frac{-1}{2}\frac{\left(x^{measured} - x^{renconciliated}\right)^2}{\sigma^2}\right) + \frac{p_{NC}}{b_{NC}}exp\left(\frac{-1}{2}\frac{\left(x^{measured} - x^{reconciliated}\right)^2}{(\sigma * b_{NC})^2}\right)\right). \tag{7}$$

Eq. (5-7) are, respectively, Least-squares (LS), Cauchy and Contaminated Normal (CN) robust functions. The values of Cc, p_{NC}, b_{NC} are the tuning parameters of the functions and are found in França *et al* [3].

For the solution of the Non Linear Dynamic Data Reconciliation problem, the SQLSQP optimizer from scipy.optimize in python was selected for the problem optimization.

The integration of the system consisting of Eq. (1-3) was done using 4th order Runge-Kutta method, using two intermediate points in each time collection interval. A five points data horizon was selected for both data reconciliation and model simulation.

3 Results

With the data reconciliation using three robust functions, LS, CN and Cauchy, the data was collected by disturbing the outlet flow of tank 2 by a step, corresponding to a valve opening of 85%. The following data treatment is presented in Fig.1-3.

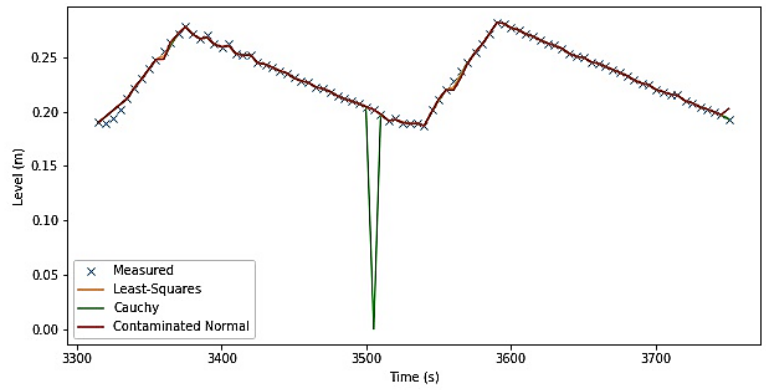

Figure 1. Tank level versus time.

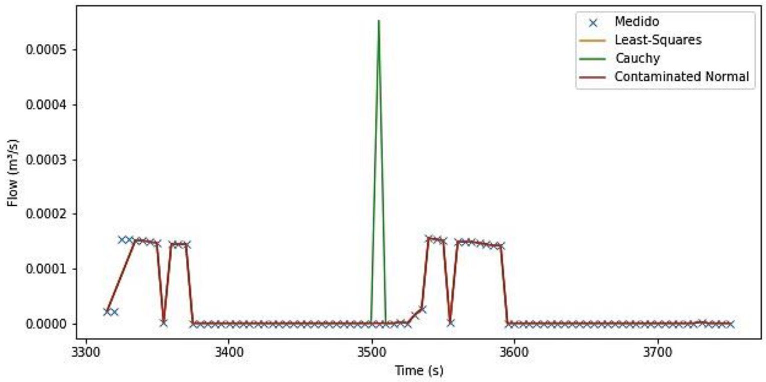

Figure 2. Outlet flow tank 2 versus time

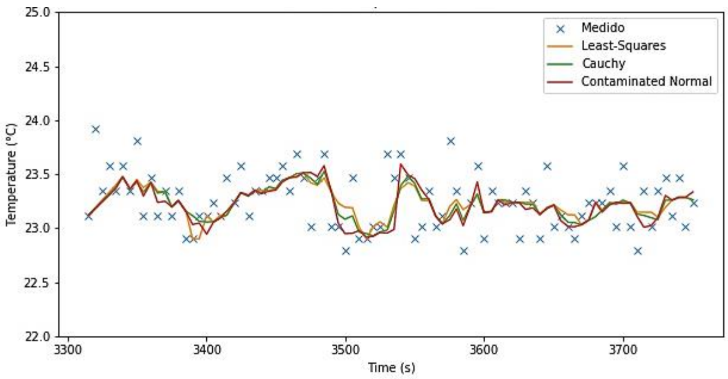

Figure3.Outlet temperature tank 1.

As can be observed in Fig. 3, the data reconciliation results in a smaller variance of the points when compared to the experimental data, corroborating with Liebman *et al*[4]. It can be observed in Fig. 2 that the application of the method leads to excellent accordance with the experimental data, also showing the accordance of the three robust functions by the absence of data outliers.

The robust functions showed a similar result. The subsequent analysis of the iteration number in the SLSQP optimizer shows that the Cauchy method lead to a superior computational performance, with exception to one point visible in Fig. 1-2.

Table 2. Comparison of robust estimators.

Robust Function	Number of Iteration	Number Function Evaluations	Objective Function Value
Least Squares	95	3747	2.4464e-03

Cauchy	96	3719	2.2315e-03
Contaminated Normal	101	3882	2.3625e-03

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