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Comparison of Linear and Nonlinear Model Predictive Control for Optimization of Spray Dryer Operation

Lars Norbert Petersen *,** **Niels Kjølstad Poulsen** * **Hans Henrik Niemann** *** **Christer Utzen** ** **John Bagterp Jørgensen** *

* *Department of Applied Mathematics and Computer Science, Technical University of Denmark, Kgs. Lyngby, Denmark, (e-mail: {lnpe,nkpo,jbjo}@dtu.dk)*
** *GEA Process Engineering A/S, Søborg, Denmark, (e-mail: christer.utzen@gea.com)*
*** *Department of Electrical Engineering, Technical University of Denmark, Kgs. Lyngby, Denmark, (e-mail: hhn@elektro.dtu.dk)*

Abstract: In this paper, we compare the performance of an economically optimizing Nonlinear Model Predictive Controller (E-NMPC) to a linear tracking Model Predictive Controller (MPC) for a spray drying plant. We find in this simulation study, that the economic performance of the two controllers are almost equal. We evaluate the economic performance with an industrially recorded disturbance scenario, where unmeasured disturbances and model mismatch are present. The state of the spray dryer, used in the E-NMPC and MPC, is estimated using Kalman Filters with noise covariances estimated by a maximum likelihood (ML) method.

Keywords: Model Predictive Control, Optimization, Spray Drying, Simulation

1. INTRODUCTION

Spray drying is a process that turns a liquid product into a free-flowing powder. The most efficient and dominating type of spray dryer is the multi-stage dryer, which combines drying in several stages: Spray drying at the top of the dryer chamber, drying in an integrated static bed at the bottom of the chamber and drying in an external vibrating fluidized bed. Spray drying is a highly energy consuming process. The pressure of environmental issues and demands for better product quality drives the need for innovations within process efficiency and quality control (Govaerts et al., 1994). The key product qualities in spray drying are the bulk density, the particle size distribution and the residual moisture. Research shows that the powder residual moisture content predominate all the other physical parameters. Hence it is of considerable importance to control the moisture content in the powder while minimizing the energy consumption.

The main challenge in controlling the spray dryer is to use a minimum of energy (hot air) to bring the residual moisture in the powder below the specification and to avoid that the powder stick to the walls of the chamber. This is a challenge, as the operation of the spray dryer must continuously be adjusted to variations in the feed and the ambient air humidity. The conventional PID control approach is simple, but known to be insufficient at controlling the moisture and the powder may turn sticky inside the dryer during high ambient air humidities. This motivates more advanced control methods in the presence of feed and ambient air variations.

1.1 Process Description

A multi-stage dryer (MSD$^{\mathrm{TM}}$) consist of a spray chamber (SD), a static fluid bed (SFB) and two vibrating fluid bed (VFB) stages. Fig. 1 illustrates the stages of the spray dryer as well as the hot air and the powder in- and outlets. The hot inlet air is fed into the upper section of the drying chamber around the high pressure nozzles. The nozzles disperse the liquid feed into droplets. The heat is transferred from the hot air to the droplets, which makes most of the water evaporate. The dried product then enters the SFB where it is further dried by hot air from below. Next, the powder is transported to the VFBh and VFBc stages for gentle drying and is cooled to the temperature desired for handling and storage.

1.2 Control

For a long time, linear tracking Model Predictive Control (MPC) has been the preferred advanced control methodology in the process industries. MPC is popular for its flexibility, performance and ability to handle constraints (Darby et al., 2009). Often MPC is combined with an economically optimizing RTO layer (Darby et al., 2011). Recent advances within process optimization focus on optimizing the higher-level objectives, such as economics, directly in the control layer. A popular framework is the economically optimizing Nonlinear Model Predictive Controller (E-NMPC). The discrete-time NMPC problem may be solved using single-shooting (control vector parametrization), multiple shooting (Bock and Plitt, 1984), or the simultaneous method. The multiple-shooting

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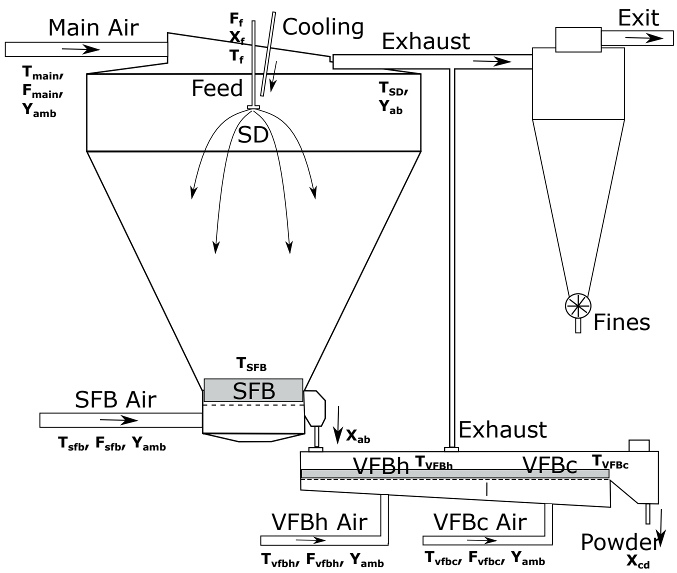

Fig. 1. Diagram of the spray dryer. Sprayed droplets and hot air are mixed in the top. The droplets dry into powder and are dried further in the SFB and VFBh stages and cooled in the VFBc stage.

algorithm is a popular choice, as it has good stability properties and can use state-of-the-art ODE/DAE solvers (Capolei and Jørgensen, 2012). The explicit singly diagonally implicit Runge-Kutta (ESDIRK) method is an example of such a DAE solver with sensitivity computation capabilities. The method is a special implicit Runge-Kutta method that is computationally efficient for particularly stiff systems, both A- and L-stable, and often has an embedded error estimator (Kristensen et al., 2004a). The ESDIRK method is also well suited in combination with a continuous-discrete extended Kalman filter (EKF) for state estimation (Jørgensen et al., 2007).

Some progress has been made towards improving the control of spray dryers. Govaerts et al. (1994) reports a black-box model combined with a cascade PID controller as well as a physics based soft-sensor. A linear MPC and an E-NMPC for a spray dryer is presented in Petersen et al. (2014a) and Petersen et al. (2014b). Shabde and Hoo (2008) synthesizes PI controllers for control of the residual moisture content and the particle size.

1.3 Content & Organization

The aim of this paper is to compare the application of E-NMPC and linear tracking MPC for a multi-stage dryer in an industrially recorded disturbance scenario. The optimal control problem in the E-NMPC is solved using the multiple-shooting method combined with an interior point optimization algorithm (IPOPT). The ESDIRK3(4) method, with sensitivity capabilities, is used for state integration of the stiff model. The linear MPC is based on Petersen et al. (2014a) with an RTO layer for calculation of the set-points.

The paper is organized as follows. Section 2 provides a brief description of the spray dryer model. Section 3 presents the EKF used for state estimation and the E-NMPC optimization problem. Section 4 describes the linear tracking MPC. In Section 5 we present a simulation to show the benefit of optimizing the operation and compares the performance of the E-NMPC to the MPC. Conclusions are given in Section 6.

2. SPRAY DRYER MODEL

2.1 Model

The model, described in Petersen et al. (2015), is used for simulation as well as for prediction in the MPCs. It is derived from first engineering principles and describes drying of maltodextrin DE-18 in a small-scale industrial spray dryer. The deterministic model is augmented by two stochastic terms. We have a system of the form

$$x_{k+1} = F(x_k, u_k + w_{\mathrm{u},k}, d_k + w_{\mathrm{d},k}, \theta) \tag{1a}$$

$$y_k = h(x_k) + v_k \tag{1b}$$

The state and measurement noise covariances are $w_{\mathrm{u},k} = N_{\mathrm{iid}}(0, R_{\mathrm{u}})$, $w_{\mathrm{d},k} = N_{\mathrm{iid}}(0, R_{\mathrm{d}})$ and $v_k = N_{\mathrm{iid}}(0, R_{\mathrm{v}})$. The three noise-terms are assumed to be independent and the noise variances, R_{u}, R_{d} and R_{v}, are based on manual inspection of the estimation data. The noise variances are used for simulation and are unknown to the state estimator. $F(\cdot)$ is the state integration of $dx(t)/dt = f(x(t), u(t), d(t), \theta)$. $h(\cdot)$ is the measurement equation. θ are the model parameters. The state vector, x, the manipulated input vector, u, the disturbance vector, d, and the measurement vector, y, are

$$x = [T_{\mathrm{SD}}\ T_{\mathrm{SFB}}\ Y_{\mathrm{ab}}\ X_{\mathrm{ab}}\ T_{\mathrm{VFBh}}\ T_{\mathrm{VFBc}}\ Y_{\mathrm{cd}}\ X_{\mathrm{cd}}]^T \tag{1c}$$

$$u = [F_{\mathrm{f}}\ T_{\mathrm{main}}\ T_{\mathrm{sfb}}\ T_{\mathrm{vfbh}}\ T_{\mathrm{vfbc}}]^T \tag{1d}$$

$$d = [X_{\mathrm{f}}\ T_{\mathrm{f}}\ F_{\mathrm{main}}\ F_{\mathrm{sfb}}\ F_{\mathrm{vfbh}}\ F_{\mathrm{vfbc}}\ T_{\mathrm{amb}}\ Y_{\mathrm{amb}}]^T \tag{1e}$$

$$y = [T_{\mathrm{SD}}\ T_{\mathrm{SFB}}\ Y_{\mathrm{ab}}\ T_{\mathrm{VFBh}}\ T_{\mathrm{VFBc}}\ X_{\mathrm{cd}}]^T \tag{1f}$$

The controlled variables, y, are the stage air temperatures T_{SD}, T_{SFB}, T_{VFBh} and T_{VFBc}, the absolute air humidity, Y_{ab}, and the powder residual moisture content, X_{cd}. The manipulated variables, u, are the feed flow, F_{f}, the inlet main air temperature, T_{main}, the inlet SFB air temperature, T_{sfb}, and the VFB air temperatures, T_{vfbh} and T_{vfbc}. The disturbance variables, d, are the feed concentration, X_{f}, the feed temperature, T_{f}, and the inlet air flows rates. The ambient air temperature and the air humidity, T_{amb} and Y_{amb}.

2.2 Cost of Operation

We will judge the control performance by the profit/cost of operating the spray dryer. The profit is the value of the product minus the raw material and energy costs

$$p(\cdot) = p_{\mathrm{p}} F_{\mathrm{s}}(1 + X_{\mathrm{cd}}) - p_{\mathrm{f}} F_{\mathrm{s}}(1 + X_{\mathrm{f}}) - p_{\mathrm{H}} \Delta H \tag{2}$$

p_{p} is the unit value of the product, p_{f} is the unit cost of feed material, p_{H} is the unit energy cost, and ΔH is the total energy supplied to the dryer. The energy efficiency of operation and the product flow rate are computed as described in Petersen et al. (2015).

2.3 Constraints

The maximum capacity of the feed pump limits the feed flow. The inlet temperatures must be higher than the