

An Hysys Simulation of a Dynamic Process using Linear Offset Free MPC with an Empirical Model

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Abstract

Objectives: In advanced process control, especially model predictive control (MPC), a model is needed to calculate the input (manipulated variable) to the plant to track the set-point. The model used for MPC is usually empirical model, usually a state space model in the open literature, identified by system identification. The problem is that the empirical model is never completely accurate to represent the plant, a reason that brings about an offset in set-point tracking by MPC. In addition, in the presence of disturbance, the accuracy becomes much worse. **Method:** In this work, we recommend state estimation for the state prediction according to measured output at each iteration calculation to obtain an equal output prediction with output measurement from the plant. **Findings:** It was found out that integrating MPC and Kalman filter could facilitate linear offset free MPC. **Application:** The success of this approach is demonstrated using an integrated MPC and Kalman filter in Simulink-Matlab to control the dynamic Depropanizer process in Hysys.

Keywords: Kalman Filter, Linear Offset Free MPC, Matlab-Hysys Interface

1. Introduction

Model predictive control (MPC) is a control strategy which deals with finding a sequence of control move by using a predictive model to repeatedly solve an online optimization performance index problem at any instant over a finite prediction horizon. Thus, at any given instant, only the first control move of the optimum solution is applied and process is continually repeated.

In practical applications, MPC is required to achieve set point with disturbances and model plant-mismatch present. Thus, disturbances and model plant-mismatch are the reason of giving offset when the process is controlled with MPC. In order to deal with offset in MPC control, the disturbance model is added to the prediction model and state observer is designed to estimate the disturbance state. This solution is the standard way and has been used in¹⁻⁴ to reject disturbances and track the set points with zero offset.

Linear state space prediction model is often used in the open literature to formulate optimization problem in MPC⁵. When using state space model in MPC, the reason that offset occurs is due to the error in state estimate as error results in the predicted output; though the predicted output is equal to the reference, the measured output is different.

Thus, integrating Kalman filter with MPC to correct the state plant model according to measured output from the real plant because Kalman filter is the best possible method to estimate state of a process⁶. When the state is corrected, the predicted output is asymptotic equal to measured output thereby eliminating the offset. Until recently, some studies have demonstrated well performance of MPC in conjunction with Kalman filter⁷⁻⁹. In these articles, MPC utilized mechanistic process models, so nonlinear Kalman filter (extended Kalman filter or unscented Kalman filter) is employed to estimate process states because the mechanistic

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models are usually nonlinear model. So far, the performance of integrating MPC with Kalman filter based on empirical model is still an open issue. Therefore, this work demonstrates the performance of control of the Depropanizer dynamic process simulation in Hysys by using integrating MPC with Kalman filter based on empirical model.

2. Problem Statement

Consider a common discrete state space model for a process given as:

$$\begin{aligned} x_{k+1} &= Ax_k + Bu_k \\ y_{k+1} &= Cx_{k+1} \end{aligned} \quad (1)$$

where $x \in R^{n_x}$ is the state vector, $u \in R^{n_u}$ is the manipulated vector and, $y \in R^{n_y}$ is the algebraic controlled vector. The matrices A, B and C are often called process matrix, input matrix and output matrix respectively and can be determined by system identification while the state is estimated based on measured variables.

Definition 1: MPC is used to find the approximate inputs based on prediction model (discrete state space model) by optimizing the control law function:

$$J = \sum_{k=1}^{n_y} \|W_s (r_{k+1} - y_{k+1})\|_2^2 + \sum_{k=1}^{n_u} \|W_r (u_k - u_m)\|_2^2 \quad (2)$$

where n_y is the prediction horizon and n_u is the control horizon ($n_u \leq n_y$), $r_{k+1} \in R^{n_y}$ are the set points, $u_m \in R^{n_u}$ is the measured input at each transition, $\|\cdot\|_2^2$ is square of two-norm of a vector defined as: $\|x\| = x^2 + \dots + x^2 \cdot W_s$ and W_r are positive weights, since W_r is a regularization term which penalizes the control moves.

Assumption 1: y_{k+1} will be reachable set-points in some transition by minimization of (2). Figure 1 shows that the measured output, y_m , is in offset with y_{k+1} because of model-plant mismatch and disturbances.

The offset can be removed by the estimation of the correct state model. The proposed method imposes convergence of measured outputs, y_m to asymptotic set-points.

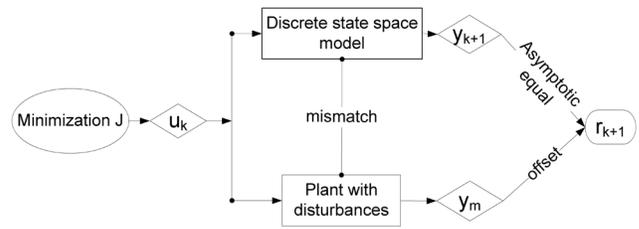


Figure 1. Offset with Normal MPC.

3. State Estimation by Kalman Filter

Matrices A, B, C in (1) become fixed once identification of the model of the MPC has been accomplished; so y_{k+1} calculated using equation (1) will be different from measured output, y_m at time k+1 because of incorrect state estimate. Getting y_m asymptotically equal to y_{k+1} can only be through state estimate of vector x_{k+1} ; to get the corrected state x_{k+1} discrete-time Kalman filter is employed for the state estimation algorithm for the corrected x_{k+1} .

Summarized below is the discrete-time Kalman filter equations in ⁶:

Priori estimate state:

$$x_k^- = Ax_{k-1}^+ + Bu_{k-1} \quad (3)$$

Priori covariance:

$$P_k^- = AP_{k-1}^+ A^T + Q \quad (4)$$

Kalman gain:

$$K_k = P_k^- C^T (CP_k^- C^T + R)^{-1} \quad (5)$$

Posteriori state estimate:

$$x_k^+ = x_k^- + K_k (y_{m|k} - Cx_k^-) \quad (6)$$

Posteriori covariance:

$$P_k^+ = (I - K_k C) P_k^- \quad (7)$$

Where x_k^- denotes as priori estimate state when estimate x_k with all of measurements up to time k-1, x_k^+ denotes as a posteriori estimate state when all measurements up to time k available for estimate x_k , Q is process noise covariance matrix, R is measurement covariance matrix. The transpose of matrix A, C is defined as A^T , C^T respectively.

Kalman filter will give optimal state estimation x_k^+ to substitutes x_k in equation (1), so y_{k+1} will asymptotic equal to y_m .

4. Model Predictive Control

Assume that the discrete state space model (1) is gotten by system identification from real plant.

We rewrite (2) as:

$$J = W_S \left\| r * ones(ny, 1) - \underline{y}_{k+1}^{ny} \right\|_2^2 + W_R \left\| \underline{u}_k^{nu} - u_m \cdot ones(nu, 1) \right\|_2^2 \tag{8}$$

Where

$$\underline{y}_{k+1}^{ny} = \begin{bmatrix} y_{k+1} \\ y_{k+2} \\ \vdots \\ y_{k+ny} \end{bmatrix}; \underline{u}_k^{nu} = \begin{bmatrix} u_k \\ u_{k+1} \\ \vdots \\ u_{k+nu-1} \end{bmatrix};$$

$$r * ones(ny, 1) = \begin{bmatrix} r^1 \\ \vdots \\ r^{ny} \end{bmatrix}; u_m * ones(nu, 1) = \begin{bmatrix} u_m^1 \\ \vdots \\ u_m^{nu} \end{bmatrix};$$

The predictive output vector:

$$\underline{y}_{k+1}^{ny} = P x_k + H \underline{u}_k^{ny} \tag{9}$$

Where:

$$P = \begin{bmatrix} CA \\ CA^2 \\ \vdots \\ CA^{ny} \end{bmatrix}; \begin{bmatrix} CB & 0 & 0 \\ CAB & CB & \\ \vdots & \vdots & \ddots \\ CA^{ny-1}B & CA^{ny-2}B & CB \end{bmatrix}$$

MPC controller will optimize J function (8) and getting vector \underline{u}_k^{ny} as root, but taken only in the vector and sending as manipulated variables to the real plant.

5. Integrate Model Predictive Control and Kalman Filter

x_k^+ in (6) substitutes x_k in (9) at each iteration of MPC calculation:

$$\underline{y}_{k+1}^{ny} = P x_k^+ + H \underline{u}_k^{ny} \tag{10}$$

So, y_{k+1} in vector \underline{y}_{k+1}^{ny} will be priori output, y_{k+1}^- and u_k in vector \underline{u}_k^{ny} will be sent to real plant. After sufficient iterations, y_{k+1}^- will be asymptotically equal to output from real plant, y_m . Figure 2 illustrates how MPC integrate with Kalman filter to control a plant.

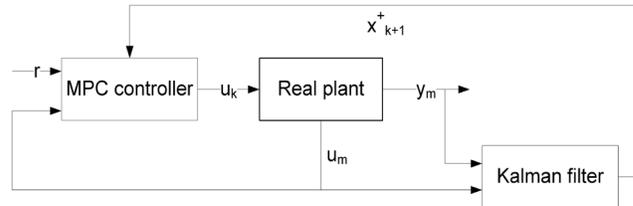


Figure 2. Integrating MPC with Kalman Filter.

6. Case Study

In this session some results will be shown. Firstly, the process is described and then, the results of linking dynamic process simulation with Matlab-Simulink are presented.

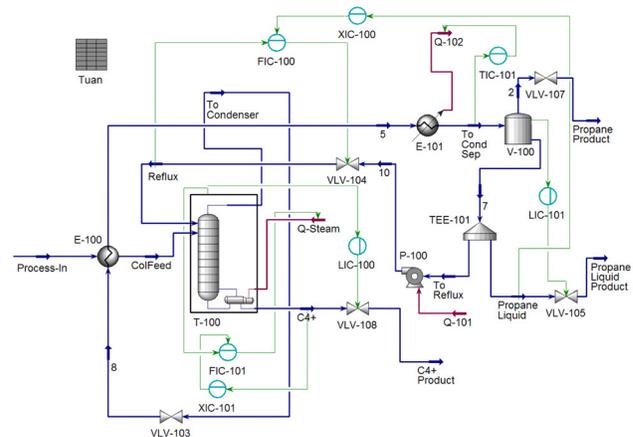


Figure 3. Dynamic Depropanizer Column Simulation.

6.1 Process Description

Figure 3 shows the dynamic simulation of the Depropanizer column process which was described in¹⁰. The controlled variables are purity of top and bottom products based on propane composition while manipulated variables are reflux flow rate and boil up flow rate, and disturbance is introduced by changing flow rate and propane compositions in feed stream. The integration MPC with Kalman filter is

designed in Simulink-Matlab to control the dynamic process simulation by using the Matlab-Hysys interface. The interface code is from the toolbox¹¹.

6.2 Results and Discussion

In this work, MPC controls the Depropanizer column in dynamic simulation in which the model is not known yet. So, the empirical model (state space model) is identified for a use in MPC controller. The empirical model is not a true replica of the real plant because we cannot get exact model through system identification.

Matrices A,B and C are identified according to procedure in¹⁰ for model (1):

$$A = \begin{bmatrix} 2.2077 & 0.1053 & 1 & 0 & 0 & 0 & 0 & 0 \\ -0.3009 & 2.2246 & 0 & 1 & 0 & 0 & 0 & 0 \\ -1.4570 & -0.2570 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0.7212 & -1.7152 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0.1268 & 0.2106 & 0 & 0 & 0 & 0 & 1 & 0 \\ -0.5622 & 0.5392 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0.1191 & -0.0591 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0.1363 & -0.0503 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}; B = \begin{bmatrix} 0.0005 & 0 \\ 0.0009 & -0.0005 \\ -0.0008 & 0 \\ -0.0015 & 0.0006 \\ 0.0004 & 0 \\ 0.0006 & 0 \\ -0.0001 & 0 \\ 0 & -0.0001 \end{bmatrix}; C = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

The set points are 0.88 and 0.09 for top and bottom product purity respectively which MPC is tracking simultaneously. The current values of those controlled variables are 0.9 and 0.07. After successful tracking those set points, the disturbance is introduced into the feed stream by changing propane mole fraction from 0.4133 to 0.3925 and flowrate from 192.6 m³/h to 193.8 m³/h as shown in Figures 4 and 5 respectively.

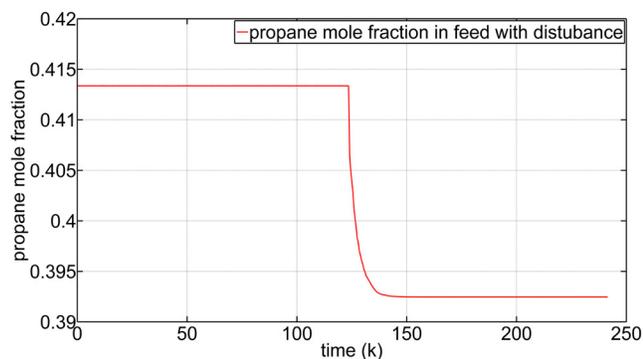


Figure 4. Disturbance in Feed Composition.

Figure 6 and Figure 7 shows the offsets that are present before and after introducing the disturbance according to the set points: 0.88 and 0.09, respectively. The reason that offset occurs before introducing disturbance is due to model-plant mismatch but after introducing disturbance is due to both model-plant mismatch and disturbance.

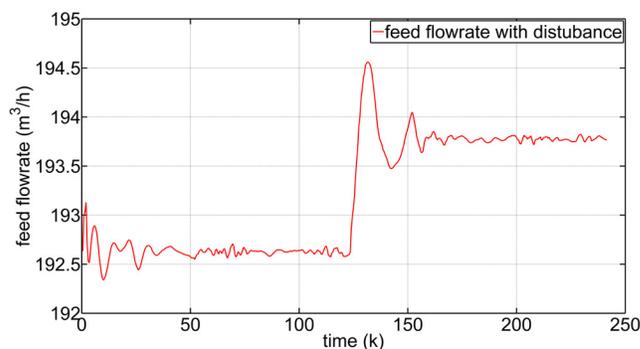


Figure 5. Disturbance in Feed Flow Rate.

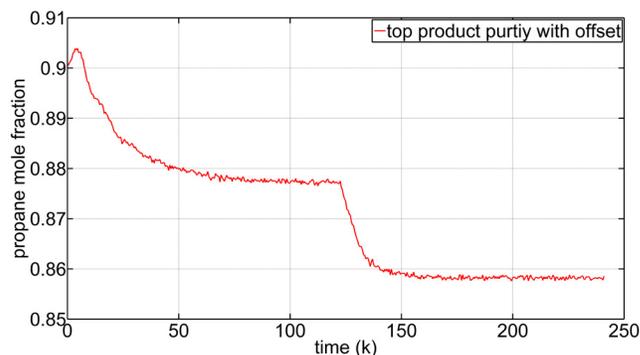


Figure 6. Top Product Purity without Kalman Filter.

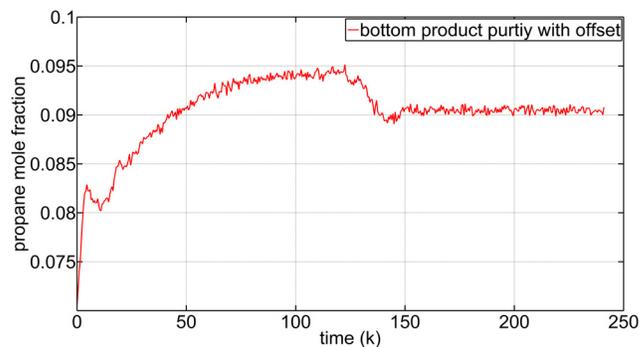


Figure 7. Bottom Product Purity without Kalman Filter.

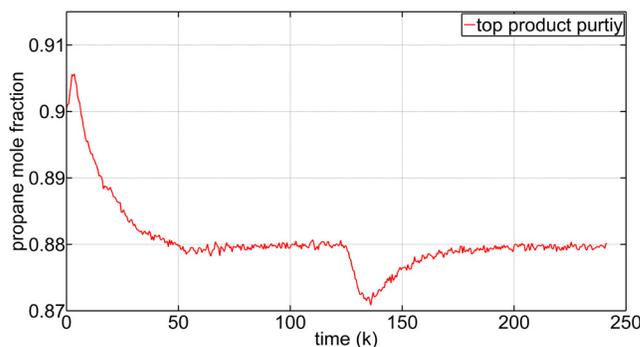


Figure 8. Offset Free Top Product Purity.

The introduction of the disturbance results in 'erratic' behaviour but later start to track the set point as shown in Figures 8 and 9.

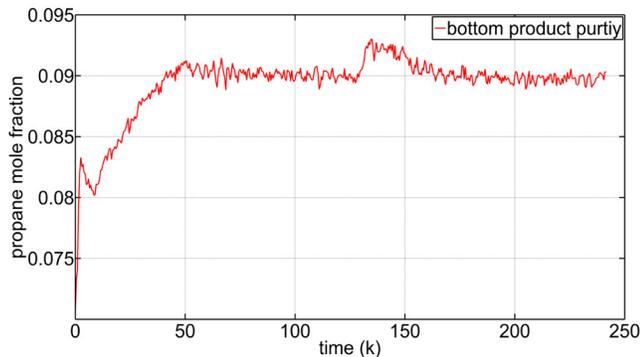


Figure 9. Offset Free Bottom Product Purity.

Considering figures 8 and 9, it is obvious that the integration of Kalman filter with MPC achieves an offset free even in the presence of model plant-mismatch and disturbance. This is because at every instant of iteration, Kalman filter calculates the estimate of the state of model which makes prediction output be equal to measurement output for every small change in manipulated input; at the end, prediction output, measurement output and set point are all equal.

7. Conclusion

MPC and Kalman filter are successfully integrated based on the achievement of the desired outcome of the application on the case study; specifically, it satisfactorily regulate propane mole-fraction. The International Conference on Fluids and Chemical Engineering (FluidsChE 2017) is the second in series with complete information on the official website¹² and organized by The Center of Excellence for Advanced Research in Fluid Flow (CARIFF)¹³. The publications on chemical engineering allied fields have been published as a special note in volume 3¹⁴. Host being University Malaysia Pahang¹⁵ is the parent governing body for this conference

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