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MODEL PREDICTIVE STATISTICAL PROCESS CONTROL - HANDLING STEP UPSETS

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Abstract: A feedback-based model predictive control (MPC) approach to product quality improvement that incorporates multivariate statistical techniques has been developed [1]. The objective of the approach is to use existing process measurements to help reduce the variability of product quality when its online measurement is not feasible. The approach is model based and it uses principal component analysis to compress selected process measurements into scores. One or more manipulated setpoints are chosen and varied to control the scores in order to counteract the effect of stochastic process disturbances on product quality. The approach assumes that the selected process measurements correlate with product quality, and that the stochastic disturbances that cause product variability are stationary. When implemented on the Tennessee Eastman process the approach resulted in a 44% reduction in the variability of the product quality. In this paper the issue of how to handle non-stationary step upsets is addressed. A steady state model predictive control approach is used in conjunction with the dynamic score control to overcome the problems caused by the step disturbances. *Copyright © 2000 IFAC*

1. BACKGROUND

Statistical process control (SPC) aims at improving processes and products. In chemical processes the two most widely used SPC approaches are principal component analysis (PCA) [2] and partial least squares (PLS) [3]. Kresta et al [4] and Wise and Gallagher [5] have discussed the application of PCA and PLS in the process industries. Both PCA and PLS calculate linear combinations of raw variables, called scores. This paper discusses a model predictive control approach to SPC in which continuous feedback of score information is used. The control objective is to reduce the variability of product quality by changing the setpoints of one or more control loops in a plant. The measured variables used for feedback are a linear transformation of the process scores calculated from a PCA model.

The issue of reducing the variation in product quality when stationary stochastic upsets enter a process has been addressed in the earlier paper [1]. Often one does not have either an on-line analyzer or a soft sensor for determining product quality. One then has to rely on taking samples to a laboratory and waiting for them to be assayed, typically on the order of 8 hours or longer. It is this case that is addressed here. The methodology in [1] made use of data based multivariate statistical process models within a feedback control system. It is well known that one has to be very careful when such models are incorporated into a feedback system [6]. If normal process operating data are used for model development, then the data have a correlation structure. The resulting model can be extrapolated by feedback to a region in which the underlying correlation structure is no longer valid, and therefor the model should not be used. To avoid this problem, either some plant testing must be conducted, or the database used for model development must be rich enough that it can be used in feedback control

Chen, Mc Avoy, and Piovoso [7] discussed the use of PCA models in what Piovoso and Kosanovich [8] termed score control. In reference [7] a lagged PCA model was developed and model predictive control was used to force the PCA scores toward the origin. Application of the approach to a binary distillation tower and the Tennessee Eastman process [9] was discussed. It was found that the score controller resulted in a significant reduction in the variability of the product quality in both examples. A more recent paper [1] also uses a model predictive score controller built on top of an existing plant control system. An advantage of such an architecture is that it can be turned off and then the system reverts to that which was originally present. In [7] the score control was used in addition to a feedback quality controller that employed a composition analyzer. In the more recent paper [1] a score based approach that does not require an online analyzer was presented. The method, which is outlined below, was applied to the Tennessee Eastman process and it resulted in a significant reduction in product quality variability, namely 44%. The disturbance considered was a stationary upset, labeled IDV(8) in [9]. However, when score control is used and step upsets occur, poor transients result. An approach to overcome this problem is the focus of this paper, and it is discussed after a review of the results in [1] is given.

2. REVIEW OF MODEL PREDICTIVE CONTROL IN THE SCORE SPACE

In the earlier approach [1] it is assumed that the plant is running under an existing control system and that it is subjected to stationary stochastic disturbances. Since the process operation is stationary, no net steady state adjustment is made to the manipulated setpoints. In the methodology the disturbances do not have to be measured directly. Rather the effect of the disturbance is inferred through the use of existing measurements. To reduce the product variations the following steps are carried out:

Step 1. A group of real time measurements, **x**(t), and a group of setpoints to be manipulated, **s**(t), are selected.

Step 2. PRBS forcing is used on the setpoints to develop a database for modeling the process dynamics. The variation in the measurements is caused both by the unmeasured stochastic disturbances as well as by the PRBS forcing that is used to generate the database.

Step 3. The process measurements are compressed to scores using PCA.

Step 4. Orthogonal PCA [10] is used to focus on that part of the score space, **z**, that can be affected by manipulating the chosen setpoints.

Step 5. A dynamic model is fitted to the **z**,**s** data.

Step. 6 Model predictive control is used to calculate changes in **s** to force the predicted values of **z** to the origin. A key aspect of the formulation is the incorporation of a constraint that forces the sum of the changes in **s** to be zero. This constraint is used since it is assumed that the disturbance that is causing the process to move is a stationary disturbance. Thus, no net change in the setpoints is required.

This approach has been applied successfully to the Tennessee Eastman process, a detailed description of which is given in reference [9]. The process involves the production of two products, G and H, from four reactants, A, C, D, and E. In addition, there are two side reactions that occur and an inert, B, essentially all of which enters with one of the feed streams. A process diagram for the Tennessee Eastman process is shown in Fig. 1., including the control system that is being used to run the plant. The tuning parameters for the various loops shown are given [1]. In the original problem statement, an analyzer was used to measure the composition of the product stream. For the model predictive score controller it is assumed that this composition is not available online, but rather that it is measured offline in a laboratory. The product composition control objective is to maintain the G/H ratio in the product stream constant. As discussed by Mc Avoy and Ye [11], the ratio of the D and E feeds can be used to control the G/H ratio in the product. Since an online analyzer is not being used a fixed value for the D/E ratio of .813 is employed as a base case. The disturbance that was considered in [1] was a random change in the composition of the C feed, labeled IDV(8) in [9]. The response of the G/H ratio to IDV(8) resulting from the existing control system is shown in Fig. 2 as the dotted line. A 3-day period is simulated and for purposes of clarity only the responses for the first 24 hours are shown in Fig. 2. The remainder of the transients shows the same trends. Over the 3-day period the G/H ratio oscillates around a steady state value of 1.226, and it ranges from 1.167 to 1.280. The standard deviation of the G/H response is a measure of the product variability and its value over the 3 days is .0229. A model predictive control approach was used to reduce this standard deviation without using either a product analyzer or measuring the disturbance. The model predictive results are also shown in Fig. 2 where it can be seen that a significant reduction the product variability is achieved. How these results are produced is discussed next.

When score control was used, 5 process measurements were selected for feedback, and the D feed was manipulated. The measurements used were: A feed flow, reactor pressure, reactor temperature, separator level, and separator pressure. These measurements have 3 key characteristics in common. First, they are affected by the random upset in the C feed. Second, their response tends to lead the response of the G/H ratio in the product. Lastly, these variables are affected by the manipulated D feed setpoint. To develop a dynamic score model, a PRBS signal of ± 1% (±36.56 kg/h) was added to the D feed setpoint for a period of 10 hrs. During this period the random disturbance in the C feed also occurs. It can be noted that the variance of the change in the D feed was larger than that resulting from the PRBS forcing alone since the D/E ratio contributes to changing the D feed setpoint as well. The E feed responds to the random upset since it is used for reactor level control. The E feed then affects the D feed set point through the constant D/E ratio. A sampling time of 5 mins. was used. The 5 measurements as well as the D feed setpoint measurement were scaled to zero mean and unit variance. The 5 measurements were reduced to 2 scores using PCA, and the 2 scores explain 88.3 % of the variance in the 5 measurements. The scores were transformed into a scalar variable that can be affected by the D setpoint, z. Then the MATLAB Identification Toolbox [12] was used to develop a dynamic model between the D feed setpoint and z. A third order ARX model was identified using the instrumental variable option in the Identification Toolbox. Additional details are given in [1].

Next, model predictive control was implemented, and the results achieved by this controller are also shown in Fig. 2. As can be seen the G/H ratio oscillates around a steady state value of 1.226. The maximum G/H value is 1.260 and the minimum is 1.195 over the 3 days simulated. The standard deviation of the G/H response is .0128 over the 3 days, which is a reduction in the product quality variability of 44% compared to the constant D/E policy. This result is excellent and it is achieved by using measurements that are already available. It can be noted that the MPC tuning parameters used were not optimized. Thus, even better performance might be achievable through optimization of these tuning parameters. Although the results shown in Fig. 2 are encouraging, the algorithm has a problem if non-stationary step upsets occur. After discussing the problem, and approach to overcoming it is presented.

3. HANDLING STEP UPSETS

A key assumption that is made in formulating the model predictive score control is that the stochastic disturbances encountered are stationary in nature. If a step disturbance enters the process, then continued use of the model predictive SPC controller can cause problems. Figure 3 shows the responses produced by the SPC controller compared to a controller that uses a fixed D/E ratio when a step disturbance occurs in the composition of the C feed stream in addition to the random IDV(8) disturbance. The step disturbance is labeled IDV(1) in [9]. The step upset results in the plant being brought to a new, non-zero steady state operating point in terms of the z score variable. When the model predictive SPC controller tries to bring the process back to $z^{sp}=0.$, its action results in a very slow transient in G/H compared to the constant D/E controller. As can be seen in Fig. 3 the dynamic score controller does reduce the variability of the G/H ratio significantly, but the desired G/H setpoint of 1.226 is not achieved. Table 1 gives G/H results averaged over 500 minute intervals. The score controller produces an average G/H ratio of 1.193 even during the period from 1000 to 2500 minutes. By contrast the constant D/E policy produces a G/H value that is much closer to setpoint, 1.226, during the same period. In order to bring G/H back to setpoint it is necessary to change the D/E ratio setpoint when the score controller is used, and a steady state approach to this calculation is discussed next.

To overcome the problem a steady state MPC controller is used on top of the dynamic score controller to change the D/E ratio every time a lab assay is obtained. The steady state controller is calculated by solving the following optimization problem:

$$\frac{\min}{(\Delta(d/e))_k}[(\hat{g}/h)^2 + w * \Delta(d/e)_k^2]$$

$$subject\ to: \quad (\hat{g}/h) = m\,\Delta(d/e)_k + \Delta(g/h)_k \tag{1}$$

where $(\hat{g}/h)$ is a deviation between the predicted value of G/H and 1.226, $\Delta(g/h)_k$ is the deviation between the measured G/H value at time k and 1.226, $\Delta(d/e)_k$ is the difference between the deviation variable (d/e)≡(D/E-.813) at time k and the same variable at time k-1, and w is a scalar weight. For the Tennessee Eastman process the stoichiometry is such that 1 mole of G is produced by 1 mole of D and 1 mole of H is produced by 1 mole of E. Thus, the deviation in G/H, g/h, can be modeled as directly proportional to the deviation in D/E, d/e and the proportionality constant, m, can be calculated from the steady state values of G/H and D/E as 1.50. Equation 1 can be solved analytically to give:

$$\Delta(d/e)_k = -\frac{[m * \Delta(g/h)_k)]}{[m^2 + w]} \tag{2}$$

Figure 4 shows the responses produced by the addition of the steady state G/H controller on top of the SPC controller. For Fig. 4 the disturbances used are IDV(1) plus IDV(8), and w is 2. It is assumed that G/H is measured every 8 hours and the sample used is a composite 8 hour sample which results in the average value of G/H over the time period being determined. As can be seen the addition of the steady state controller improves the response of the SPC controller, which in turn reduces the variability of the product quality. Table 2 gives G/H results averaged over 500 minute intervals for the constant D/E and steady state D/E plus score controllers. The addition of the steady state D/E controller produces an average G/H ratio of ~1.232 during the period from 1000 to 2500 minutes, which a significant improvement compared to using just the score controller. A comparison of Figs. 3 and 4 shows that the score controller with the steady state adjustment greatly reduces the variability in the product G/H ratio compared to the constant D/E approach. It takes the steady state controller approximately 16 hours to eliminate the effect of the IDV(1) step upset. From 1000 min. to 2500 mins. the standard deviation of G/H produced by the constant D/E controller is .022, while the proposed approach produces a standard deviation of .0124, which is a 43% reduction in variability. Figure 5 shows how the D/E setpoint is manipulated by the steady state controller to achieve the results shown in Fig. 4. It is straightforward to show that using d/e given by eqn. 2 results in no steady state offset in g/h. Equation 2 shows that $\Delta(d/e)|_k$ only equals 0. when $\Delta(g/h)|_k$ is 0, which happens when the measured G/H value is at setpoint. The Tennessee Eastman example which is used here for illustration involves only a single manipulated variable. It is straightforward to use a multivariable approach in which several setpoints are manipulated. It is also straightforward to extend eqn. 1 so that optimum values can be calculated for all the manipulated setpoints so that step upsets can be handled effectively.

4. CONCLUSIONS

This paper has presented a steady state approach to adjusting setpoints for a recently published model predictive SPC controller. The model predictive SPC controller reduces product quality variability for stationary stochastic upsets, but it has a problem when step upsets occur. It has been shown that the addition of the steady state controller overcomes the problem caused by step upsets. The approach has been illustrated on the Tennessee Eastman testbed process.

5. LITERATURE CITED

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Table 1. Comparison of Constant D/E and Score Controllers for IDV(1) + IDV(8)

Time Period min.	Constant D/E Policy	Score Controller
0 - 500	1.211	1.188
501 - 1000	1.231	1.173
1001 - 1500	1.224	1.193
1501 - 2000	1.223	1.193
2001 - 2500	1.230	1.193

Table 2. Comparison of Constant D/E and Score + Steady State MPC Controllers for IDV(1) + IDV(8)

Time Period min.	Constant D/E Policy	Score Controller with Steady State Update
0 - 500	1.211	1.188
501 - 1000	1.231	1.190
1001 - 1500	1.224	1.232
1501 - 2000	1.223	1.235
2001 - 2500	1.230	1.228

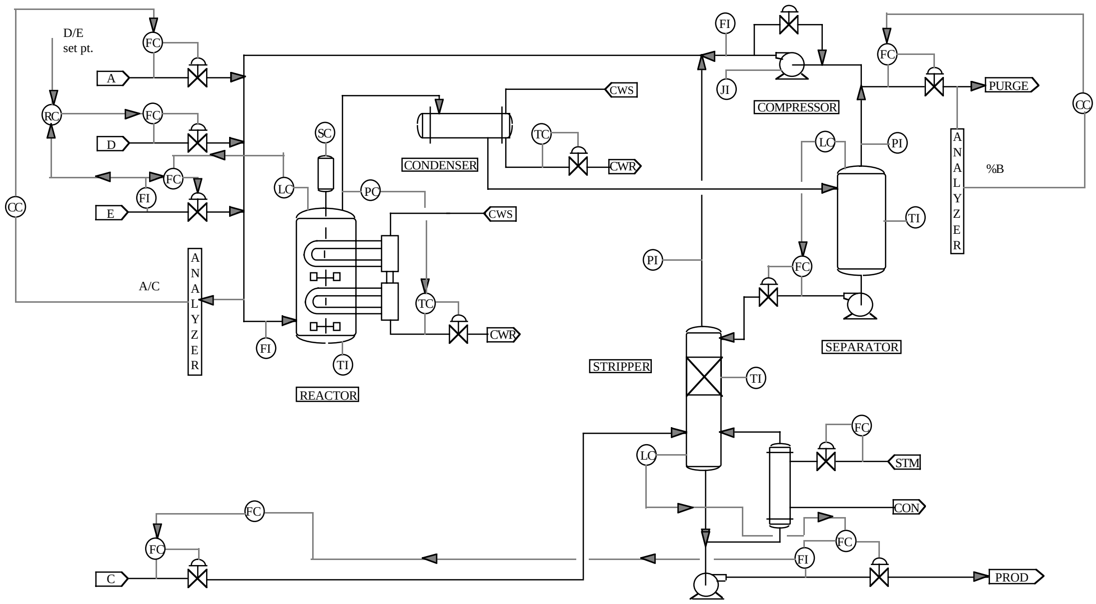

Figure 1. Schematic of Tennessee Eastman Process

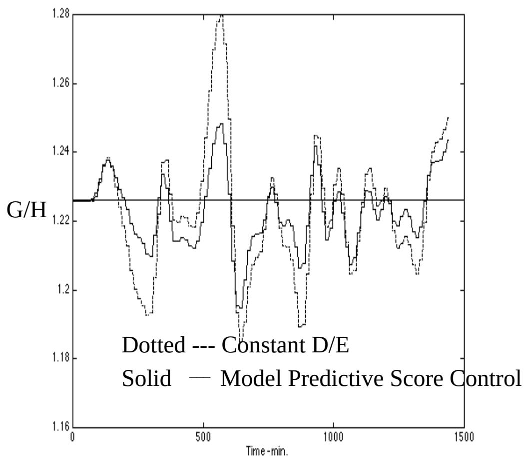

Figure 2. Comparison of Constant D/E policy and Model Predictive Score Control

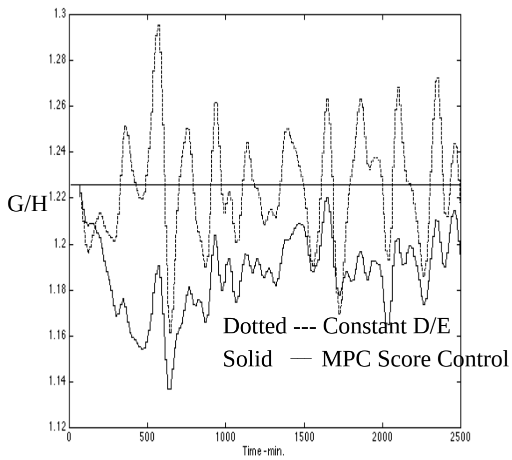

Figure 3. Plot of G/H ratio in Product for IDV(1) + IDV(8)

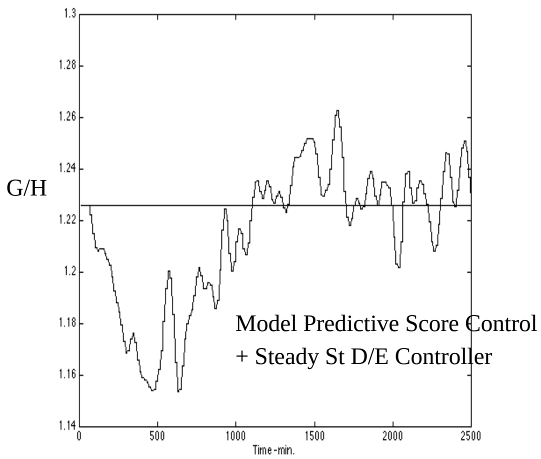

Fig. 4. Plot of G/H ratio in Product for IDV(1) + IDV(8)

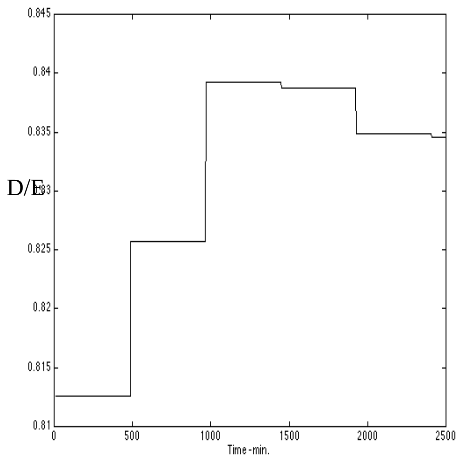

Fig. 5. Plot of D/E ratio for Score + SS MPC Control