2011 American Control Conference
on O'Farrell Street, San Francisco, CA, USA
June 29 - July 01, 2011

Data-driven LQG Benchmaking for Economic Performance Assessment of Advanced Process Control Systems

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Abstract— **In this paper, a data-driven subspace approach for economic performance assessment of the advanced process control (APC) systems is presented. The method introduces LQG tradeoff curve to estimate potential of reduction in variance, which is directly obtained from subspace matrices using closed loop data. To exploit feasible economic performance of the APC systems, the proposed approach considers the uncertainties induced by process variability and evaluates the economic performance through solving stochastic optimization problem. Results of the performance evaluation provide a guideline for the control system tuning to realize the potential improvement in profitability of process. The application of the proposed method is illustrated by its benefits evaluation on a simulated example.**

I. INTRODUCTION

With the widespread implementation of advanced process control (APC) applications in oil, gas and chemical industries in the last two decades, it has become evident that the economic analysis of selected APC technologies is an important task of control engineers for decision making on any control upgrading project, because of their high design and implementation cost [6]. Thus, recently economic performance assessment (EPA) of advanced process control has become one of the most active areas of research in the field of control engineering, and there have been a group of EPA techniques and relevant case studies have been reported in the literature, and a particular informative and revealing review of EPA for APC applications is provided in [10].

The interest in EPA of process control can be traced back to the work of Astrom [17] and Harris [18] who proposed that the minimum variance benchmark can be identified by using normal closed-loop data. Martin presented a general framework for economic justification of advanced process control applications [7]. A statistics-based approach for analysis of potential variance reduction and the associated benefits under various improved control operations is developed in [4]. In order to better investigate the potential performance improvement of the process control in terms of variance, a profit index has been developed that links the variation of the quality process variable to economic performance quantities [10]. Latour proposed an optimization based approach to benefit calculation of process control named CLIFFTENT, which introduces an integral operator into economic performance assessment problem [5] and also provides a heuristic way of determining the optimal operating points and the best performance. Further extension and modifications to the CLIFFTENT approach have been proposed by Zhou et al.[8] who formulated the EPA problem into a constrained optimization problem. According to steady state process model and backoff idea, Xu et al. [1] developed an optimization based approach for the economic performance evaluation of MPC by calculating benefit potentials through variability reduction of process variables or constraints tuning. Further development of this approach was presented in Huang et al. [2], [3], in which the probabilistic approach and Bayesian inference were utilized for decision making on constraints tuning to achieve optimal MPC performance. An innovative technique for economic assessing APC performance has been proposed in the work of Zhao et al. [11]. By incorporating the LQG benchmark into performance evaluation framework, the variance based performance assessment was transferred to economic performance assessment for APC systems.

The LQG benchmark as an alternative benchmark has been proposed for performance assessment of control systems with consideration of the control action constraints [6]. A drawback of this benchmark is the requirement of a perfectly known process model, which has to be obtained through process identification under the open or closed loop condition. However, process test for process identification may not always feasible or may be expensive in practice [12], [13]. The success of subspace identification has inspired an alternative approach to assess the economic performance of process control systems [16].

In this paper, a data-driven LQG benchmark based approach to assess the economic performance of APC systems is proposed. Firstly, the LQG benchmark obtaining from closed loop data is introduced to estimate the potential variance reduction of process variables. Secondly, a stochastic optimization approach to benefits analysis of process control is developed. The proposed approach considers the uncertainties induced by process variability and evaluates the economic performance of advanced process control strategies through solving the stochastic optimization problems, and the main results are illustrated through a simulation example.

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II. Obtaining LQG benchmark from closed-loop data

Subspace methods provide a numerically robust approach to conventional identification methods, which also give a alternative for LQG controller design and performance assessment since it does not require an explicit process model. LQG benchmark has been proven to be a realistic benchmark for assessing constrained control systems since LQG tradeoff curve represents the optimal performance limit in terms of the best achievable input and output variances [15]. The LQG objective function is define as:

$$J(\lambda) = E(y_t^2) + \lambda E(u_t^2) \tag{1}$$

Obtaining LQG tradeoff curve from subspace matrices is briefly reviewed in this section following the approaches of [12] and [13].

A. Subspace Identification

A linear time-invariant system can be described in a state space representation form as

$$\begin{aligned} x_{t+1} &= Ax_t + Bu_t + Ke_t & (2)\\ y_t &= Cx_t + Du_t + e_t & (3) \end{aligned}$$

where the symbols are the input u_t, the output y_t, the sate x_t, the stochastic input e_t, the Kalman filter gain K and the zero-mean Gaussian white noise e_t. A, B, C and D are the matrices of the state space system with appropriate dimensions. Based on the innovation form in (3), an extended state space model can be formulated as following the standard subspace notation, Equation (3) can be rewritten:

$$\begin{aligned} y_f &= \Gamma_N x_f + H_N u_f + H_N^s e_f & (4)\\ &= L_w W_p + L_u u_f + L_e e & (5) \end{aligned}$$

where

$$y_p = \begin{bmatrix} y_0 & y_1 & \cdots & y_{j-1} \\ y_1 & y_2 & \cdots & y_j \\ \cdots & \cdots & \cdots & \cdots \\ y_{N-1} & y_N & \cdots & y_{N+j-2} \end{bmatrix} \tag{6}$$

$$y_f = \begin{bmatrix} y_N & y_{N+1} & \cdots & y_{N+j-1} \\ y_{N+1} & y_{N+2} & \cdots & y_{N+j} \\ \cdots & \cdots & \cdots & \cdots \\ y_{2N-1} & y_{2N} & \cdots & y_{2N+j-2} \end{bmatrix} \tag{7}$$

$$u_f = \begin{bmatrix} u_N & u_{N+1} & \cdots & u_{N+j-1} \\ u_{N+1} & u_{N+2} & \cdots & u_{N+j} \\ \cdots & \cdots & \cdots & \cdots \\ u_{2N-1} & u_{2N} & \cdots & u_{2N+j-2} \end{bmatrix} \tag{8}$$

$$x_f = \begin{bmatrix} x_N & x_{N+1} & \cdots & x_{j-N+1} \end{bmatrix} \tag{9}$$

$$e_f = \begin{bmatrix} e_N & e_{N+1} & \cdots & e_{j-N+1} \end{bmatrix} \tag{10}$$

The indices p and f stand for the past and future. Γ_N is the extended observability matrix, H_N and H_N^s are the lower triangular Toeplitz matrices corresponding to the deterministic input u_k and the unknown stochastic input e_k, respectively [13].

B. Obtaining LQG tradeoff curve from closed-loop data

Consider a regulatory finite-horizon LQG control objective function defined as

$$J = E\left\{ \sum_{k=1}^{N} \left[y_k^T y_k + u_k^T (\lambda I) u_k \right] \right\} \tag{11}$$

The optimal control criterion can also be written as

$$J_{LQG} = \widehat{y}_f^T \widehat{y}_f + u_f^T (\lambda I) u_f \tag{12}$$

where

$$u_f = \begin{bmatrix} u_1 \\ u_2 \\ \cdots \\ u_N \end{bmatrix} \widehat{y}_f = \begin{bmatrix} \widehat{y}_1 \\ \widehat{y}_2 \\ \cdots \\ \widehat{y}_N \end{bmatrix} \tag{13}$$

are the future input sequences and the corresponding estimated future output sequences. Minimizing J, yields an optimal control law:

$$u_f = -\left(\lambda I_{N1} + L_u^T L_u\right)^{-1} L_u^T L_{e,1} e_0 \tag{14}$$

The corresponding optimal output expression:

$$\widehat{y}_f = \left[I - \left(\lambda I_{N1} + L_u^T L_u\right)^{-1} L_u^T \right] T L_{e,1} e_0 \tag{15}$$

Define the following two matrices:

$$\begin{bmatrix} \gamma_0 \\ \gamma_1 \\ \cdots \\ \gamma_{N-1} \end{bmatrix} \triangleq -\left(\lambda I + L_u^T L_u\right)^{-1} L_u^T L_{e,1} \tag{16}$$

and

$$\begin{bmatrix} \varphi_0 \\ \varphi_1 \\ \cdots \\ \varphi_{N-1} \end{bmatrix} \triangleq \left[I - L_u \left(\lambda I + L_u^T L_u\right)^{-1} L_u^T \right] L_{e,1} \tag{17}$$

According to the principle of superposition, the optimal sequence of control inputs as

$$u_t^{opt} = \sum_{k=0}^{N-1} \gamma_k e_{t-k} \tag{18}$$

$$y_t^{opt} = \sum_{k=0}^{N-1} \varphi_k e_{t-k} \tag{19}$$

From above equations, we can calculate the LQG benchmark variances of the process inputs and outputs as

$$\text{var}\,[u_t] = \sum_{k=0}^{N-1} \varphi_i \text{var}\,[e_t] \varphi_i^T \tag{20}$$

$$\text{var}\,[y_t] = \sum_{k=0}^{N-1} \gamma_i \text{var}\,[e_t] \gamma_i^T \tag{21}$$

For obtaining the LQG tradeoff curve, define

$$u_{LQG} = trace\left\{\text{var}\,[u_t]\right\} \tag{22}$$

$$y_{LQG} = trace\left\{\text{var}\,[y_t]\right\} \tag{23}$$

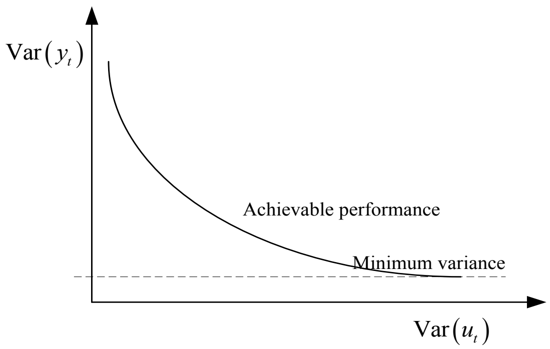

Fig. 1. LQG tradeoff curve

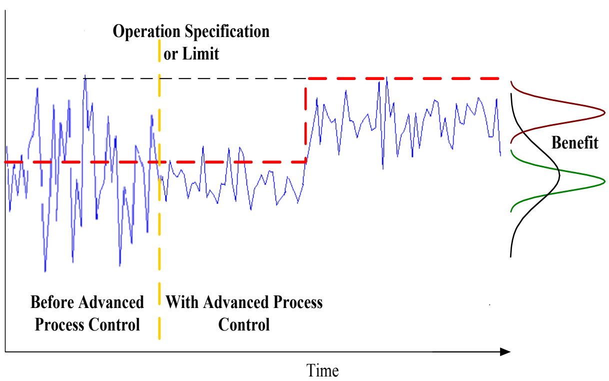

Fig. 2. Conventional approach to economic benefit estimation

By varying λ, various LQG control solutions of $E\left[y_t^2\right]$ and $E\left[u_t^2\right]$ can be calculated. Then the achievable performance limit for a linear system is given by a tradeoff curve which can be plotted from these solutions [11], as shown in (Fig.1).

III. Economic benefit analysis of advanced process control

It is assumed that improved process control strategies (such as APC strategies et al.) would result in a variance reduction of the key process variable [9], which in turn allows the process operating mean value to be shifted closer to the operation constraint without increasing the frequency of violation. The economic benefit is realized by from this new operation point, as shown in (Fig.2).

Thus, the economic performance assessment problem can be expressed in terms of determining the optimal operating condition for a given control system. Accordingly benefits calculation may be formulated as an optimization problem. In order to make ensure that the obtained operating point is practically feasible, the formulated optimization problem must incorporate the uncertainties in both process economic function and the constraints [8]. Therefore, performance estimation problem can be stated as stochastic optimization problem:

$$\max P = E\left[\vartheta\right] = \int_x \vartheta\left(x\right) f\left(x,\mu,\sigma\right) dx \quad (24)$$

$$g_1\left(x\right) \leq 0 \quad (25)$$

$$\Pr\left\{g_2\left(x\right) \leq 0\right\} \geq \alpha \quad (26)$$

where P is the profit objective function, $\vartheta(x)$ is the economic performance function (EPF), $f(x)$ is the probability density function (PDF). $\Pr\{\cdot\}$ is the operator of probability computation and α is the specified probability level. $g_1(x)$ represents the deterministic constraint, and $g_2(x)$ is the probabilistic constraint which should be satisfied at a defined probability level α.

Generally, the economic objective of process is to maximize the product profitability with the minimum cost. Thus, economic performance function can be expressed in terms of those quality process variables, which are the main profit factors contributing to the benefits of the process control systems. Accordingly, EPF is expressed as a linear function in this paper:

$$\vartheta = \sum_{i=1}^{p} c_y^{(i)} y_i - \sum_{j=1}^{m} c_u^{(j)} u_j \quad (27)$$

where u_j, y_i are the ith input variable and jth output variable, and c_y , c_u are economic (or cost) coefficient vectors of output and input variables, which are assumed to be known. Since the process variables are assumed to be normally distributed in this work, profit function can be obtained as follows

$$profit = P = \sum_{i=1}^{p} c_y^{(i)} \bar{y}_i - \sum_{j=1}^{m} c_u^{(j)} \bar{u}_j \quad (28)$$

A robust approach for dealing with constraints under uncertainty is to frame the problems into probability constraints, which are usually stated as following:

$$\Pr\left\{y_{i,\min} \leq y_i \leq y_{i,\max}\right\} \geq \alpha_i, i = 1,\ldots,p \quad (29)$$

Inequality (29) is the form of individual probabilistic constraint (IPC), where each individual constraint in IPC problem is satisfied at a specified probability level α_i, Incorporating the probabilistic constraints into performance evaluation problem helps to make a robust decision on the economic quantification of a given process control, based on a desired tradeoff between profitability and reliability.

Since the process constraints are linear in process variable, and output variables are assumed to follow a Gaussian distribution, the constraint (29) can be recast as the deterministic form

$$y_{i,\min} - \Phi^{-1}\left(1-\alpha_i\right) \times \sigma_{yi} \leq \bar{y}_i \quad (30)$$

$$y_{i,\max} - \Phi^{-1}\left(\alpha_i\right) \times \sigma_{yi} \geq \bar{y}_i \quad (31)$$

Where Φ^{-1} is the inverse function of the Gaussian distribution function, its value is only dependent on the specified confidence level.

Generally, constraints enforced on the input variables are usually considered as the hard constraints, constraint violation is not allowed in practice. Thus, a more conservative manner is taken to define probability level for the process constraints on input variables.

$$u_{j,\min} + 3 \times \sigma_{uj} \leq \bar{u}_j \quad \leq \quad u_{j,\max} - 3 \times \sigma_{uj} \quad (32)$$

where σ_{yi} and σ_{uj} are the standard deviation of input and output variables.

The LQG benchmark is used for estimating the available process variability change, σ_{yi} and σ_{uj}, in this paper. The LQG tradeoff curve in terms of variances are obtained directly from subspace matrices using closed-loop data with certain external excitations, as previous section mentioned. The way to determine LQG tradeoff curve in terms of equalities can be referred to the work [11].

A. Economic Performance Evaluation

Economic profit function should be evaluated by maximizing the profit function, subject to the probability constraints enforced on the process variables and the equalities related to process variances. Based on previous analysis, the problem formulation of optimal operation is described as follows.

Given an $p \times m$ system, having steady-state process gain matrix K. $(\bar{y}_{i0}, \bar{u}_{j0})$ is defined as the current operating point and $(\bar{y}_i, \bar{u}_j)$ is the optimal operating point. Then the steady state optimization problem is :

$$\max_{\bar{u}_j, \bar{y}_i; \sigma_{uj}, \sigma_{yi}} P = \sum_{i=1}^{p} c_y^{(i)} \bar{y}_i - \sum_{j=1}^{m} c_u^{(j)} \bar{u}_j \quad (33)$$

subject to

$$\begin{aligned} \Delta \bar{y}_i &= \sum_{j=1}^{m} [K_{ij} \times \Delta \bar{u}_j] \\ \bar{y}_i &= \bar{y}_{i0} + \Delta \bar{y}_i \\ \bar{u}_j &= \bar{u}_{j0} + \Delta \bar{u}_j \end{aligned} \quad (34)$$

$$y_{i,\min} - \Phi^{-1}(1-\alpha_i) \times \sigma_{yi} \leq \bar{y}_i \leq y_{i,\max} - \Phi^{-1}(\alpha_i) \times \sigma_{yi} \quad (35)$$

$$u_{j,\min} + 3 \times \sigma_{uj} \leq \bar{u}_j \quad \leq \quad u_{j,\max} - 3 \times \sigma_{uj} \quad (36)$$

$$\sigma_Y = f(\sigma_U) \quad (37)$$

$$\sigma_Y^2 = \sum_{i=1}^{p} w_i \sigma_{yi}^2 \quad (38)$$

$$\sigma_U^2 = \sum_{j=1}^{m} r_j \sigma_{uj}^2 \quad (39)$$

$$\begin{aligned} \sigma_{uj} &\geq 0 \\ \sigma_{yi} &\geq 0 \end{aligned} \quad (40)$$

where $i = 1, \cdots, p$ and $j = 1, \cdots, m$; $(\Delta y_i, \Delta u_j)$ is the variable change, which must satisfy the steady state relation (36) [1]. Then the solution of this optimization problem yields an optimal operating condition and the optimal economic performance that can be expected. We will discuss the economic performance calculations under different operation scenarios [11]:

- **Base case operation:** In this case, only evaluation of performance objective function by replacing $(\bar{y}_i, \bar{u}_j)$ with the current operating point $(\bar{y}_{i0}, \bar{u}_{j0})$ in (36), which is denoted as P_0. It is a value to be compared with improved performance for the calculation of economic potentials.
- **Existing variability case:** It is the evidence that the performance degrades with time in any control system [5]. Thus, existing controller may not be optimally tuned in the most cases. By shifting operating point only, and no action is taken to reduce the variability of the quality variables in this case, The resultant optimal operating point is denoted as $(\bar{y}_{Si}, \bar{u}_{Sj})$, and corresponding objective function as P_S.
- **Maximum achievable performance:** Performance improvement not only results from the shift in setpoint, but also from the reduction in variance through improved control operation [6]. With variability reduction on the quality variables due to tuning of control system, which will further move the mean value closer to the specification limit and thus gives rise to increased economic benefit. The optimal operating point in this case is denoted as $(\bar{y}_{Ri}, \bar{u}_{Rj})$, and corresponding economic performance is defined as P_R, which can be calculated via the solution of defined performance evaluation problem.

Now economic benefit improvement due to control system upgrade can be investigated by comparison of performance for different process operation conditions, and two economic benefit benefits, the existing benefit potential (ΔP_S) and the maximum available economic benefit (ΔP_R), can be determined accordingly.

$$\Delta P_S = P_S - P_0 \quad (41)$$

$$\Delta P_R = P_R - P_0 \quad (42)$$

Compared ΔP_R with ΔP_S, the following inequality holds $\Delta P_S \leq \Delta P_R$.

A large value of ΔP_S means that the calculated operating point in the existing variability scenario is much closer to specification limit that current value, and the controller tuning through simply mean shifting for controller may lead to better economic performance. While ΔP_R represents the maximum achievable profitability improvement that can be obtained by reducing the variability through LQG control.

IV. CASE STUDY

In this section, a simulation example is performed to demonstrate the effectiveness of the proposed approach to the benefits analysis problem of the APC systems. The process considered in this case study is a chemical pilot plant with implementing of the advanced process control strategy, which was presented in [14]. The process has three manipulated variables (electrovalve for flow (u_1), electrovalve for level (u_2) and fan speed (u_3)), three controlled variables (flow sensor(y_1), level sensor (y_2) and temperature sensor

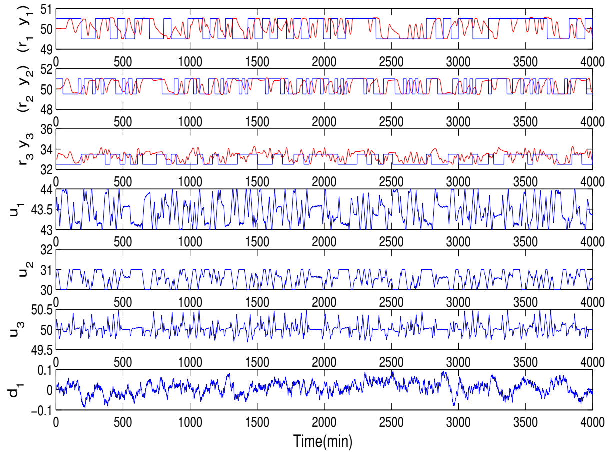

Fig. 3. Closed-loop system data

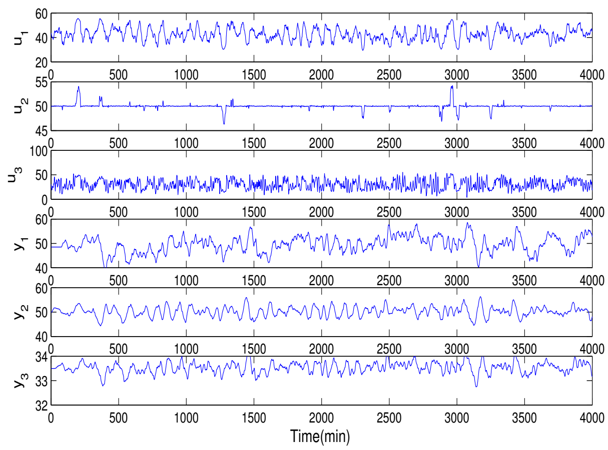

Fig. 4. Base case operation of simulated control process

(y_3)), and a disturbance variable (tank liquid temperature (d_1)). The process model is described by the following transfer functions

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} G_{11} & 0 & 0 \\ G_{21} & G_{21} & 0 \\ 0 & G_{32} & G_{33} \end{bmatrix} \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} + \begin{bmatrix} G_{n1} \\ 0 \\ G_{n3} \end{bmatrix} d_1 \tag{43}$$

where

$$G_{11} = \frac{2.3}{0.73s+1}e^{-3s} G_{21} = \frac{0.27}{s+1}e^{-3s} \tag{44}$$

$$G_{22} = \frac{-0.21}{s+1}e^{-6s} G_{32} = \frac{0.75}{15.3s+1}e^{-15s} \tag{45}$$

$$G_{22} = \frac{-0.95}{25s+1}e^{-11s} G_{n1} = \frac{0.6}{s+1} G_{n2} = \frac{1}{s+1} \tag{46}$$

Based on Matlab MPC toolbox, a designed MPC controller is implemented in the simulated distillation process. are the nominal steady state values. In the MPC design problem formulation, the constraints enforced on the manipulated and controlled variables are shown in [14].

According to [14], the economic incentive in this process is to maximize the flow of the product while keep the temperature closer to the lower limit in order to minimize the energy consumption. At the same time, possible overflows or underflows must be avoided. Since the satisfaction of the tank level (y_2) is more important than those of the flow (y_1) and temperature (y_3). Therefore, the output constraints need to be satisfied with the specified probability level $1-\alpha_1 = 90\%$ for y_1, $1-\alpha_2 = 95\%$ for y_2 and $1-\alpha_3 = 90\%$ for y_3. Meanwhile, the profit function takes the form as $P = 6.9\bar{y}_1 - 1.9\bar{u}_3$.

In order to calculate the LQG tradeoff curve based on the subspace matrices, closed-loop input/output data is obtained by exciting the system using the designed RBS signals of appropriate magnitude for the setpoints and random white noise of standard deviation 0.2 for the disturbance in Simulink. The closed-loop is plotted in Fig.3, and the obtained LQG tradeoff curve is shown in Fig.5.

By simulation on this MPC application, a set of 4000 samples are extracted from the base case operation with given constraints limits is shown in Fig.4. According to the benefits analysis procedure discussed in section 2, the resultant optimal operation condition, the calculated and verified economic benefits under different scenarios are summarized in Tab.I, which provide an indication of the potential improvement in profitability of process.

Based on the above results, the existing economic benefit and the best achievable benefit potential are calculated as $\Delta P_S = 15.8$ and $\Delta P_R = 66.1$ respectively, which means that 23.2% of maximum achievable benefit potential may be theoretically realized from moving the operating point towards the optimal one, while the reminder 76.9% of maximum economic potential is possible achieved by further reducing variability of controlled variables through further controller tuning.

The calculated benefit potentials can be verified by setting the optimal operating point obtained in different cases as the setpoint for corresponding low-level regulatory control loop with appropriate control upgrading. The realized benefit potentials are also list in Tab I. For the existing variability scenario, the verified potential is about 62.8% of calculated one. This indicates that the calculated existing benefit potential is indeed achieved in practice. The achieved benefit potential is verified as 52.1 by reducing the variability of process variables through tuning regulatory control loops, and it is also close to that of calculated one. The base case operation, optimal operation and the verified operation condition in terms of standard deviations are shown in Fig.5.

Fig.6 presents a typical simulation result for output y_1 under the base case and the variability reduction case operation. With the variance reduction of the y_1, the mean operating value is shift closer to its upper constraint limit, and thus give rise to increased economic benefit. Previous analysis and results once again shows that realized economic potentials agree with those calculated ones, and which demonstrates the feasibility of proposed approach for economic performance assessment of advanced process control strategies.

TABLE I

ECONOMIC PERFORMANCE ASSESSMENT RESULT OF PILOT PLANT

scenarios	optimal operation point						benefits value	economic potentials	
	u_1	u_2	u_3	y_1	y_2	y_3		calculated	verified
Base	37.1	49.6	27.5	41.7	43	32.9	235.7		
Existing	32.6	45.3	31.9	45.2	52	31.6	251.3	15.6	9.8
Maximum	39.2	50.1	42.1	55.3	49.6	32.2	301.6	65.9	52.1

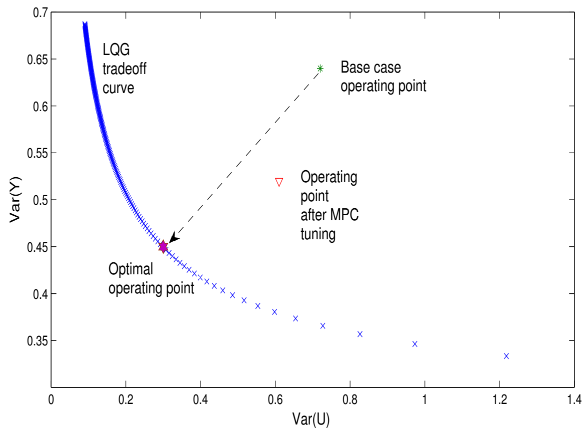

Fig. 5. Standard deviations of process under the different operation conditions

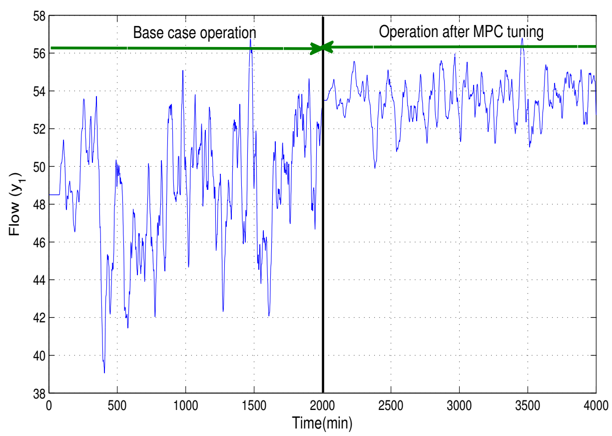

Fig. 6. Comparison of base case operation and improved control operation

V. CONCLUSION

An economic performance assessment algorithm based on the data-driven LQG benchmark is developed to evaluate the benefit potentials of APC strategies in this study. The optimal LQG benchmark variances are obtained directly from the subspace matrices using closed-loop data. Based on the LQG tradeoff curve as well as the inclusion of the process uncertainties into the performance evaluation problem, the economic potential and optimal operation condition can be obtained via solution of the formulated optimization problem. The proposed approach is illustrated by the application to economic performance assessment of a simulated model predictive control system.

VI. ACKNOWLEDGMENTS

The authors also thank NSFC and CSC for partially funding this work under grants NSFC-60804027, 61064003, PPP-20073086, 20096037 and FZU-022335.

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