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Economic performance assessment with optimized LQG benchmarking in MIMO systems

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***Abstract*— The objective of an economic performance assessment strategy is to quantitatively measure the effectiveness of a process in an economic framework. Such procedures typically involve the comparison of current operation with an appropriate benchmark to determine potential improvement through improved process control. In this work, a linear quadratic Gaussian (LQG) controller is used as a benchmark under conditions of uncertainty. By relating key process variables to a function describing the profitability of a process, the current and potential (with LQG control) modes of operation can be assessed in an economic framework. This work provides an approach to such an assessment for a MIMO system through economic optimization of an LQG controller weighting matrix, and illustrates results in the form of a case studies.**

I. Notation

K	steady state gain matrix
c_u	economic performance coefficient vector of process inputs
c_y	economic performance coefficient vector of process outputs
n_u	number of process inputs
n_y	number of process outputs
P	profitability of operation
$\bar{u}$	mean process input vector
u_i	i^{th} process input variable
u_{min}	process input lower limits
u_{max}	process input upper limits
$\bar{y}$	mean process output vector
y_i	i^{th} process output variable
y_{min}	process output lower limits
y_{max}	process output upper limits
z_{α_u}	z-coefficient corresponding to input constraint violation of with probability $1-\alpha$
z_{α_y}	z-coefficient corresponding to output constraint violation of with probability $1-\alpha$
α_u	probability of an acceptable input
α_y	probability of an acceptable output
λ	LQG weighting vector $[\lambda_u \ \lambda_y]$
λ_{min}	minimum LQG weight
λ_{max}	maximum LQG weight
λ_u	LQG input weighting vectors
$\lambda_{u,i}$	LQG weighting parameter for i^{th} input
λ_y	LQG output weighting vectors
$\lambda_{y,i}$	LQG weighting parameter for i^{th} output
$\Delta\lambda$	incremental testing resolution of λ
σ_u	input standard deviations
σ_y	output standard deviations

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II. Introduction

The ability to quantitatively determine the effectiveness of a controller, or a system of controllers, is critical to the management of complex operations. It is generally accepted that a reduction in process variability through improved control can lead to an improved product [1][2][3] so the existence of a relationship between controller performance and financial benefit is logical. Economic performance assessment (EPA) is a model-based tool that quantitatively measures this relationship by providing an assessment of controller performance in an economic framework. The resulting measurement can be used to identify poor controller performance, analyze potential investments, or choose between control strategies [4]. EPA has been an area of interest common to both industry and academia, especially over the past two decades [5].

The speed or ease of assessment is especially important when dealing with large facilities in industries including petroleum, mining, and pulp & paper, where tens of thousands of controllers are used in day-to-day operations. A detailed analysis of each controller would be a highly inefficient use of resources. Therefore, EPA strategies tend to focus on quick but effective analysis of raw data, which is typically readily available for such applications. The intention is to provide a reliable estimate of performance that may be used for financial proposals or to justify further investigation using more rigorous methods [4]. Initial work in the field of performance assessment implied the existence of a financial benefit to improved performance, but did not attempt to quantify it directly. Instead, a controller performance metric was usually a quantitative comparison of current operating conditions against a benchmark control strategy.

Astrom [6], Harris [1], and Marlin, Stanfelj and MacGregor [7] propose reference to a minimum variance (MV) controller performance as a benchmark for controller assessment. Many other algorithms based on slight modifications to MV benchmarking emerged in the early 1990s, either for ease of applicability or to address specific cases. These include works by Shah, Huang and Kwok [8], Desborough and Harris [9], Tyler and Morari [10], and Tsiligiannis and

Svoronos [11]. Other notable works from the 90's based on MV benchmarking include work by Eriksson and Isaksson [12], and Miao & Seborg [13], among others. Lynch and Dumont [14], Martin, Turpin and Cline [15], and Latour [16] provide examples of industrial application of such strategies.

However, the use of MV benchmarking has several downfalls. The most notable of these is the impracticality of implementation due to a lack of constraints on control action, which is assumed to be potentially infinite. MV control also provides the best possible feedback regulatory control, but does not provide a good benchmark for servo control applications [12]. Finally, MV is not realizable (infinite control impracticalities aside) for non-square systems where the number of control variables exceeds the number of manipulated variables [8].

Alternative performance assessment methods have been proposed based on optimal H_2 control [17], model predictive control (MPC) [18][19][20], and linear quadratic gaussian (LQG) control [4][21][22][23]. On a related note, Bauer and Craig [24] provides useful results from a web based industrial survey on the state of economic assessment capabilities in advanced process control applications.

The major contribution of this work is an extension to the work by Zhao *et. al.* [4] in the form of an economically optimized LQG weighting matrix in the multiple inputs, multiple outputs (MIMO) LQG assessment algorithm. Section 2 provides additional background on stochastic performance optimization. Notation is listed in section 3. Section 4 outlines model identification strategies. Section 5 covers the two stages of EPA. A case study is presented in section 6. Finally, conclusions are presented in section 7.

III. Stochastic economic performance optimization

The *back-off* approach to constraint handling has proven to be an effective way of dealing with the inherently stochastic nature of any process [25][26][27]. Back-off refers to the size of the offset between the variable set point and upper or lower operating limit. This offset allows for the customization of failure probability by specifying back-off according to the known variability distribution.

In most cases it is desirable to keep a process set point as close as possible to a constraint while maintaining an acceptably-low level of constraint violation [28]. For this reason, management of the stochastic nature of a process is a critical component of a successful control strategy. By reducing variance through improved process control, the set point can be moved closer to a limit while maintaining the same probability of failure, as shown in Fig. 1. This set point shift may result in an improved product, which can be related to profitability through an economic performance function.

Stochastic economic performance optimization generally involves the development of a control strategy that allows for the highest economic output under conditions of inherent uncertainty [4]. This optimization procedure varies in difficulty depending on the size of the problem, starting from a fairly straight forward procedure for single input, single output (SISO) systems and becoming increasingly difficult for increasingly complex MIMO systems, especially in the absence of obvious input-output controller pairings.

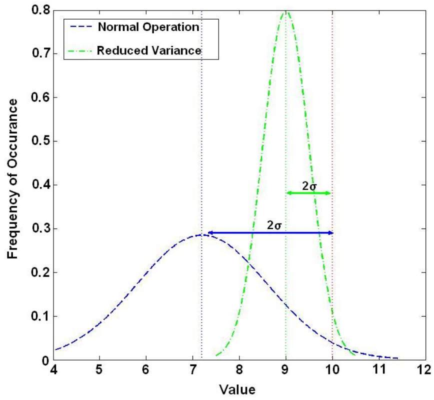

Fig. 1. Mean shift towards constraint due to reduced variance

For this work it is assumed that all stochastic components are in the form of Gaussian white noise. The assumption of Gaussian process noise inherently implies the exclusive use of soft constraints. In practice, many process variables (especially inputs) are subjected to hard constraints due to limits on the physical operating range. For more information on controller stability and feasibility while subject to a mix of hard constraints see the work of Haneveld & van der Vlerk [29] and Qin & Badgwell [30]. The focus of this work, however, is a high level assessment of current and potential process performance, and will not therefore make a distinction between hard and soft constraints, as would be recommended during the process of controller design.

IV. Model Identification

Strong motivation from industry necessitates quick and easy implementation of economic performance assessment methods. It is therefore desirable to make use of existing operational data while analyzing performance for two main reasons: the experimental collection of data can be time consuming and/or disruptive to a process, and operational data is usually readily available in an industrial setting.

First order transfer function process models will likely suffice for quick analysis, although more thorough models should be investigated for controller redesign. The use of simple, first order models makes the extraction of the steady state gain matrix fairly straight forward. For this work, the MATLAB System Identification Toolbox was used to generated first order transfer function matrices capturing system behaviour based on sets of operational data.

V. Economic performance assessment

A metric of performance is required for the meaningful assessment of a system control strategy, and basing that metric on economics is an intuitive choice for industrial application. A cost function is a function that puts system operation in an economic framework by relating costs to each observed state. A linear cost function in the form of (1) is a reasonable choice [4] that allows the appropriate weighting of variable priority through cost vectors c_u and c_y.

The cost vectors in c_u and c_y can be chosen to represent a monetary gain or loss associated with a one unit shift in the mean operating condition over a given period of time. A basic understanding of plant economics is required for this step. For most applications, several of these parameters will be equal to zero, implying no direct relationship of those respective variables with overall plant profitability.

$$P = c_y^T \bar{y} + c_u^T \bar{u} \tag{1}$$

The use of (1) as the objective function in a optimization procedure allows for quick and easy calculations, and establishes a convex basis for the problem. In this work, an objective function of this form is used for two economic optimization steps: set point shift, and LQG benchmarking with set point shift.

A. Set Point Shift

Before addressing issues of controller performance, there are usually steps that can be taken to improve the economics of operation based on the establishment of ideal steady state conditions under the current control strategy [4]. Process set points may be set further from constraint limits than is required according to back-off analysis. Financial benefits through improved product may be attainable simply by finding the minimum back-off, and moving the set points there. Implementation of this step is quick, easy, and requires no capital investment.

The steady state gain matrix (K) and variability vectors (σ_y, σ_u) can be readily extracted from process data. Constraint violation tolerance vectors ($1-\alpha_y, 1-\alpha_u$) and cost function parameters (c_y, c_u) can be obtained from process engineers. For more information on how to calculate z-coefficients ($z_{\alpha_y}, z_{\alpha_y}$) based on a given constraint violation probability, see [4]. Solution of the minimum back-off set points can then be calculated using the following optimization procedure, outlined by equations (1)-(4), as developed by Zhao *et. al.* [4].

$$\underset{\bar{u},\bar{y}}{\text{Maximize:}} \qquad P = c_y^T \bar{y} + c_u^T \bar{u}$$

Subject to:

$$\bar{y} - \bar{y}_o = K(\bar{u} - \bar{u}_o) \tag{2}$$

$$y_{min} + z_{\alpha_y/2}\sigma_y \leq \bar{y} \leq y_{max} - z_{\alpha_y/2}\sigma_y \tag{3}$$

$$u_{min} + z_{\alpha_u/2}\sigma_u \leq \bar{u} \leq u_{max} - z_{\alpha_u/2}\sigma_u \tag{4}$$

Since (1), (2)-(4) are all linear with respect to the optimization variables $\bar{u}$ & $\bar{y}$, the above optimization problem is convex and can be solved using a variety readily available methods.

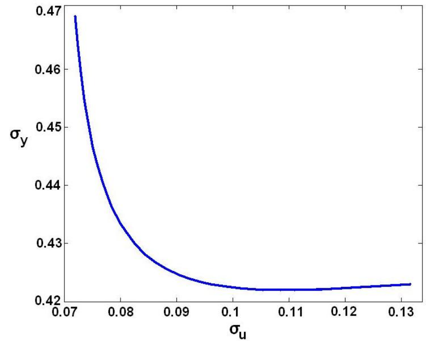

Fig. 2. Typical LQG input-output standard deviation tradeoff curve over a range of λ

B. LQG benchmark with set point shift

Once set points are optimized based on current controller performance, the EPA turns to controller assessment with the objective of reducing or redistributing variability through implementation of an optimized control strategy. By doing so, it may be possible to shift set points further towards constraints, as depicted in Fig. 1. LQG control is one benchmarking method that has grown in popularity since first proposed for this purpose by Huang and Shah [23].

An LQG controller works by formulating a set of control laws based on the minimization of the objection function (5), where $\lambda = [\lambda_u \ \lambda_y]$ is a tuning parameter vector used to balance control effort with output variance. When λ_u is empty, a MV controller is produced. When λ_y is empty, no control action is applied. By varying the values of λ over a feasible range, a tradeoff curve between σ_y and σ_u, such as that shown in Fig. 2, is produced [31] with asymptotes of $\sigma_y = \sigma_{y,MV}$ and $\sigma_u = \sigma_{u,min}$.

$$J(\lambda) = \sum_{i=1}^{n_y}(\lambda_{y,i}E(y_i^2)) + \sum_{j=1}^{n_u}(\lambda_{u,i}E(u_i^2)) \tag{5}$$

These input-output variance tradeoff curves represent a lower bound on attainable variability through feedback control, where each point along the curve corresponds to specific controller weights λ_u, λ_y. Therefore, these functions can be used to systematically choose values of λ_u, λ_y corresponding to ideal ratios of σ_y:σ_u. These ratios can be expressed in the form of (6). By transferring uncertainty from constraint-limited variables to variables not operating at minimum back-off levels, it is usually possible to shift steady state operating conditions to more economically advantageous points. As opposed to the case of MV benchmarking, this method results in solutions that are feasible using feedback control.

$$\sigma_y = f(\sigma_u) \tag{6}$$

The relationship in (6) can be applied as an additional constraint on the optimization problem outlined in Section 4.1. The results is the following LQG tradeoff-based stochastic algorithm, as presented by Zhao *et. al.* [4].

$$\underset{u,y,\sigma_u,\sigma_y}{\text{Maximize:}} \quad P = c_y^T \bar{y} + c_u^T \bar{u}$$

$$\text{Subject to:} \quad (2), (3), (4), (6), \text{ and}$$

$$\sigma_u, \sigma_y \geq 0 \tag{7}$$

Optimizing the variance tradeoff is relatively straight forward for the SISO case, but becomes increasingly difficult as the size of the system increases. In a SISO system, λ is a single constant value, and is optimally chosen based on a single tradeoff curve. However, λ can take several forms when dealing with MIMO system.

Optimal performance is not necessarily achieved through minimization of variance for economically critical variables. Instead, all interactions between input and output variables must be explored. Ideal operation of a process almost always involves one or more variables operating at a process constraint, or at a minimum back-off from a constraint, but these are not necessarily the most (directly) economically significant variables. In order to further increase the economic output, the variability of these constrained parameters must be reduced, thus allowing the critical operating set points to be moved closer to the constraint.

For example, a filtering process may be described by a 2x2 system with two inputs: slurry and vapour stream inlet flow rates; and two outputs: a filtrate production rate, and an internal pressure. Even though the filtrate production rate is the economically significant output with the highest cost function parameter, the process may be constrained by a maximum pressure. Therefore, a reduction in pressure variability could allow operation at a higher pressure, which may increase the rate of filtration. The point is that even though pressure is an economically insignificant variable, it may be the focus of an improved control strategy in an economic framework.

For MIMO systems, Zhao *et. al.* [4] propose the use of a weighted summation of input and output variances to generate the LQG tradeoff curve with an objective function of the form (8), where λ is a constant. However, determining the appropriate weighting elements for summation may be difficult, as they will not necessarily be the same as the parameters of the cost function. As mentioned above, optimal cost benefit is not always achieved through reduction of the most economically significant variables. The method proposed by Zhao *et. al.* [4] allows for limited customization beyond the cost function, as λ is a single constant even for large MIMO systems.

$$J_{LQG}(\lambda) = \sum_{i=1}^{p} w_i \sigma_{yi}^2 + \lambda \sum_{j=1}^{m} r_j \sigma_{uj}^2 \tag{8}$$

Gu *et. al.* [18] proposes a similar solution by incorporating input and output weighting matrices directly into the LQG objective function for MIMO cases. Again, however, it is proposed that the economically optimal weighting of inputs and outputs LQG objective may not necessarily reflect the weighting of those variables according to the cost function. In order to improve economic performance, a control strategy must target constrained process variables, which may or may not be directly economically significant. The weighting functions for controller design and cost function should be chosen separately. This work proposes an iterative optimization procedure where each iteration involves the selection of one value in the LQG weighting vectors λ_u and λ_y in (5) according to the following procedure:

1) vary one element 'i' of λ over an appropriate range while testing the system in closed-loop to obtain a LQG tradeoff curve for every σ_u-σ_y pairing in the form of (6).
2) perform the optimization procedure described in section 5B using (1), (2)-(4), (6), (7) to determine the ideal value of $\lambda(i)$
3) repeat until each element in λ has been optimally chosen

The nature or order of (6) will determine both the accuracy of solution and the difficulty of the optimization procedure. For the simplest optimization procedure the relationship between σ_u and σ_y can be approximated as linear, but this yield inaccuracies in the solution as Fig. 2 is clearly not linear. Higher order approximations for (6) will result in more accurate control, but will also require more robust optimization techniques. Alternatively, the observed sets of σ_u and σ_y during step 1) may be used in to iteratively solve for each optimal value of lambda. In this case, the iterative procedure would be revised as follows:

1) select λ and perform a closed-loop test to determine σ_u and σ_y
2) perform the optimization procedure described in section 5A using (1), (2)-(4) and the observed values σ_u and σ_y to determine the optimal profitability
3) repeat 1) - 2) while varying one element 'i' of λ over an appropriate range
4) select the value of $\lambda(i)$ corresponding to the highest profitability observed in 2)
5) repeat until each element in λ has been optimally chosen

Every value of the weighting vector λ in these methods corresponds to a weighting of control effort on a single input or output parameter. The most influential elements of λ should be established first. An approximate order of significance can be determined through a preliminary screening procedure, where priority is given to variables with the lowest value of (9). Due to the iterative nature of these methods it should be noted that the computational expense is increased by a factor of $n_{inputs} + n_{outputs}$ in the first case, and $(n_{inputs}+n_{outputs})(\lambda_{max}-\lambda_{min})/(\Delta\lambda)$. Alternatively, if it is available, the MATLAB MPC toolbox can be used to provide a sufficient approximation to the LQG problem, as recommended by Zhao *et. al.* [4].

$$min(|\bar{x} - x_{min} - z_{\alpha_x/2}\sigma_x|, |x_{max} - z_{\alpha_x/2}\sigma_x - \bar{x}|), \tag{9}$$

$$x \in u, y$$

Although values of the LQG weighting parameters λ_u & λ_y do not appear in the optimization problem, they implicitly determine the relationship between σ_u & σ_y. Since this procedure is intended as a method to assess economic performance, rather than finalize a controller design, it may not be necessary to explicitly determine the optimal values of λ_u & λ_y. However, if these controller parameters are desired it should be straight forward to determine them based on the optimized variables σ_u & σ_y.

VI. CASE STUDY

The performance assessment method, as described in the previous section, was applied to the simulated operation of a multi-stage, counter-current evaporator. For this study, the mean observed values of each variable during normal operation were assumed to be the current set point. All noise was approximated as Gaussian for the purposes of model generation and simulation. Finally, MATLAB's identification toolbox was used to generate first order transfer function models for unit operation from the processed data.

A. Multi-stage evaporator

1) Process description: A multi-stage, counter current evaporator, based on a mathematical model developed by Kaya and Sarac [32], was used for the first case study. Such units are applied in large scale industrial processes requiring significant changes in solution concentration where the solute and solvent have considerably different vapourization temperatures. Multiple stages are generally used to reduce waste heat, and therefore reduce energy consumption.

The unit investigated in this work consisted of four stages of evaporation set up in countercurrent operation. The solution is fed into stage four, and flows through each stage to stage one. The desired product is the concentrated liquid phase solution extracted from stage one. Pressurized steam is fed into stage one from a boiler unit. The evaporated solvent from stage one is used to heat stage two, the evaporated solvent from stage two is used to heat stage three, and the evaporated solvent from stage three is used to heat stage four.

Operation of the evaporator system is controlled by three critical manipulated variables: inlet flow rate, steam flow rate, and steam pressure. However, overall plant operation dictates that inlet flow rate is determined by upstream production rate. Although a limited amount of upstream solution can be stored momentarily, its average operating flow rate cannot be changed without major changes to overall plant operation. Therefore, inlet flow rate, although essential to the unit model, will not be a variable for optimization.

Operation is also dictated by two monitored disturbance variables: inlet stream heat content (or temperature), and inlet concentration. The two controlled variables of the process are product concentration and flow rate. A generalization of the process schematic can be seen in Fig. 3.

The only significant process constraints were upper limits on product and steam flow rates, steam pressure, and a range for product concentration. A minimum back-off of 1.5σ was desired for each constraint. The current controller is a simple PID control strategy with key controller pairings.

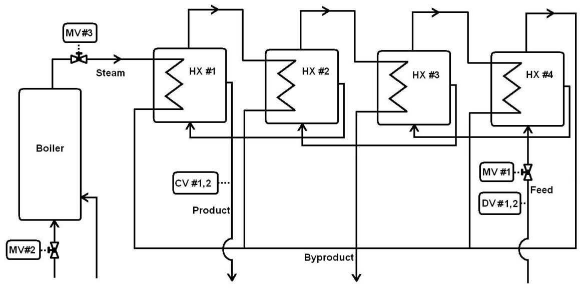

Fig. 3. Multi-stage, counter-current evaporator schematic

TABLE I
EVAPORATOR STEADY STATE PROPERTY VALUES

Variable	Current value	SP shift	LQG with sp shift [4]	LQG with sp shift (this work)
Product conc. (% TDS)	0.6907	0.6885	0.6852	0.6864
Product flow rate (kg/h)	21793	22168	24209	24284
Inlet flow rate (kg/h)	101000	101000	101000	101000
Steam flow rate (kg/h)	24487	24401	23774	23618
Steam pres. (bar)	1.3998	1.2638	1.2816	1.2795

The cost function for the evaporator involved a benefit associated with production rate and concentration, and a lesser cost penalty associated with steam flow rate and pressure. All other variables were considered cost-neutral.

2) Economic performance assessment: Results are summarized in Table I. Financial results according to the given cost function are summarized in Fig. 4.

The first stage of performance assessment, the set point shift optimization, revealed a potential 2.15% increase in profitability without changes to the current control strategy.

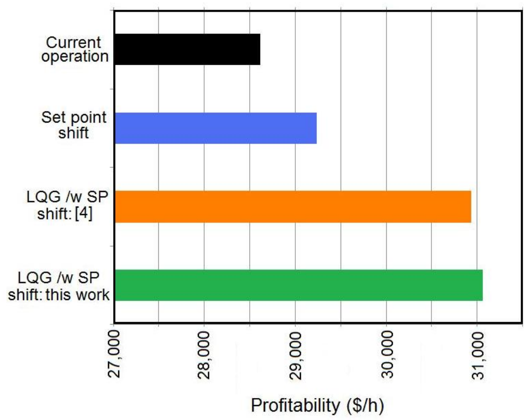

Fig. 4. Evaporator hourly profit based on current operation, set point shift, and LQG benchmarking methods with set point shift

The most notable change recommended during this step is a 0.1 bar decrease in steam pressure. Although this adjustment reduces the product concentration, it also increases the product flow rate due to a slight reduction in heat transferred, and consequently evaporation rate.

The performance assessment with LQG benchmarking using a cost function-based controller weighting, as recommended by Zhao *et. al.* [4], resulted in a 8.10% improvement over the current control method. However, by optimizing the controller weighting vector independently of the cost-function, a potential 8.53% improvement was revealed. The net difference between the two methods is $122.40/h, or $88,128/month. Although seemingly insignificant at first, this may be the difference between the approval of financing for a project, or the winning of a contract.

The difference between the two methods can be highlighted by examining variables such as product density. Product density is nowhere near operational limits, and therefore not limited directly by back-off from a constraint. Nonetheless, due to its high contribution to the cost function, the method in [4] focuses on reducing the variability of product density. The method presented in this paper, however, weights product density variability relatively low and focuses instead on constrained variables. The controller configuration in [4] is therefore not optimal for the current objective.

VII. Conclusions

Zhao *et. al.* [4] have made significant contributions to the field of controller assessment over the past decade. Their approach of using an LQG controller as a benchmark for performance assessment in an economic framework provides an accurate, relevant and realistic estimate of achievable performance through advanced process control. This work has modified the controller formulation method proposed by Zhao *et. al.* [4] for MIMO process assessment to achieve a more economically advantageous controller weighting strategy. Rather than using a cost function-based weighting matrix, an iterative approach is proposed to optimize each parameter within the weighting matrix concurrently with the input-output variability relationship. Although more computationally expensive, this new approach is especially useful for the assessment complex system control strategies in an economic framework.

References

[1] T.J. Harris. Assessment of closed loop performance. *Canadian Journal of Chemical Engineering*, 67:856–861, 1989.

[2] B. Huang and S.L. Shah. *Performance Assessment of Control Loops: Theory and Applications*. Springer, 1999. New York.

[3] T.F. Edgar. Control and operation: when does controllability equal profitability? *Computers and Chemical Engineering*, 29:41–49, 2004.

[4] C. Zhao, Y. Zhao, H. Su, and B. Huang. Economic performance assessment of advanced process control with lqg benchmarking. *Journal of Process Control*, 19:557–569, 2009.

[5] T.E. Marlin, G.W. Barton, M.L. Brisk, , and J.D. Perkins. Advanced process control: Project report and technical papers. Technical report, Warren Centre for Advanced Engineering, Sydney, 1987.

[6] K.J. Astrom. *Introduction to stochastic control theory*. Academic Press, 1970. New York.

[7] N. Stanfelj, T.E. Marlin, and J.F. MacGregor. Monitoring and diagnosing process control performance: the single-loop case. *Industrial & Engineering Chemistry Research*, 32:339–347, 1993.

[8] B. Huang, S.L. Shah, and E.K. Kwok. Good, bad or optimal? performance assessment of multivariable processes. *Automatica*, 33:1175–1183, 1997.

[9] L.D. Desborough and T.J. Harris. Performance assessment measure for univariate feedback control. *Canadian Journal of Chemical Engineering*, 70:1186–1197, 1993.

[10] M.L. Tyler and M. Morari. Performance monitoring of control systems using likelihood methods. In *Proceedings from the American Control Conference*, Seattle, WA, pages 1245–1249, 1995.

[11] C.A. Tsiligiannis and S.A. Svoronos. Dynamic interactors in multivariable process control-2, time delays and zeros outside the unit circle. *Chemical Engineering Science*, 44:2041–2047, 1989.

[12] P.G. Eriksson and A.J. Isaksson. Some aspects of control performance monitoring. In *Proceedings from the 3rd IEEE Conference on Control Applications*, Glasgow, Scotland, pages 1029–1034, 1994.

[13] T. Miao and D.E. Seborg. A monitoring strategy for flow and pressure control loops. In *2nd Asia-Pacific Conference on Control and Measurement*, Chongqing, China, 1995.

[14] C.B. Lynch and G.A. Dumont. Closed loop performance monitoring. In *Proceedings from the 2nd IEEE Conference on Control Applications*, Vancouver, Vancouver B.C., pages 835–840, 1993.

[15] G.D. Martin, L.E. Turpin, , and R.P. Cline. Estimating control function benefits. *Hydrocarbon Processing*, 69:68–73, 1991.

[16] P.R. Latour. Process control: Clifftent shows it's more profitable than expected. *Hydrocarbon Processing*, 75:75–80, 1996.

[17] B. Huang and S.L. Shah. The role of the unitary interactor matrix in the explicit solution of the singular lq output feedback control problem. *Automatica*, 33:2071–2075, 1997.

[18] Y. Gu, C. Zhao, H. Su, and J. Chu. A pragmatic approach for assessing the economic performance of model predictive control systems and its industrial application. *Chinese Journal of Chemical Engineering*, 17:241–250, 2009.

[19] C. Loeblein and J.D. Perkins. Structural design for on-line process optimization: 1. dynamic economics of mpc. *AIChE Journal*, 45:1018–1029, 1999.

[20] F. Xu, B. Huang, and S. Akande. Performance assessment of model predictive control for variability and constraint tuning. *Industrial and Engineering Chemistry Research*, 46:1208–1219, 2007.

[21] C. Zhao, H.Y. Su, and B. Huang. Economic control performance assessment with lqg benchmarking. In *Proceedings from the American Control Conference*, Seattle, WA, pages 11–13, 2008.

[22] B. Huang. A pragmatic approach towards assessment of control loop performance. *International Journal of Adaptive Control and Signal Processing*, 17:589–608, 2003.

[23] B. Huang and S.L. Shah. Limits of control loop performance: practical measures of control loop performance assessment. In *AIChE Annual Meeting*, Chicago, IL, 1996.

[24] M. Bauer and I.K. Craig. Economic assessment of advanced process control - a survey and framework. *Journal of Process Control*, 18:2–18, 2008.

[25] L.T. Narraway, J.D. Perkins, and G.W. Barton. Interaction between process design and process control: Economic analysis of process dynamic. *Journal of Process Control*, 1:243–250, 1991.

[26] J.C.C. Young, C.L.E. Swartz, and R. Ross. On the effects of constraint economics and uncertain disturbances on dynamic operability assessment. *Computers and Chemical Engineering*, 20:667–682, 1996.

[27] C. Loeblein and J.D. Perkins. Economic analysis of different structures of on-line process optimization systems. *Computers and Chemical Engineering*, 22:1257–1269, 1998.

[28] M.G. Forbes, M. Guay, and J.F. Forbes. Control design for first-order processes: shaping the probability density of the process state. *Journal of Process Control*, 14:399–410, 2004.

[29] W K Klein Haneveld and M H van der Vlerk. Integrated chance constraints: reduced forms and an algorithm. *Computational Management Science*, 3:245–269, 2006.

[30] S Joe Qin and Thomas A Badgwell. A survey of industrial model predictive control technology. *Control Engineering Practice*, 11:733–761, 2003.

[31] S. Boyd and C. Barratt. *Linear control design*. Prentice Hall, Eaglewood Cliffs, NJ, 1991.

[32] D. Kaya and H. I. Sarac. Mathematical modeling of multiple-effect evaporators and energy economy. *Energy*, 32:1536–1542, 2004.

