Model-based and data-driven model-reference control: a comparative analysis

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Abstract— In the scientific literature, two main approaches have been proposed for control system design from data. In the "model-based" approach, a model of the system is first derived from data and then a controller is computed based on the model. In the "data-driven" approach, the controller is directly computed from data. In this work, the above approaches are compared from a novel perspective. The main finding of the paper is that, although from the standard perspective of parameter variance analysis the model-based approach is always statistically more efficient, the data-driven controller might outperform the model-based solution for what concerns the final control cost.

I. INTRODUCTION

The use of data as an alternative to physical knowledge to design fixed-order controllers, *e.g.* PID, has attracted more and more interest throughout the years, since it is often cheaper and less time-consuming.

In the "model-based" approach, a model of the plant is identified from data and used to compute the fixed-order controller satisfying some user-defined requirements. As an example, in model reference control, the identified model is used to design a controller that minimizes the model reference criterion, either algebraically or through optimization, and a controller-order reduction step is performed (if needed) before implementation. However, this controller is not necessarily optimal when connected to the plant, and the control performance is limited by modeling errors.

In the "data-driven" controller tuning approach, the controller is directly derived from input/output (I/O) data. These techniques have been proposed to avoid the problem of under-modeling and to facilitate the design of fixed-order controllers, both iteratively [7], [8] and non-iteratively [1], [5] [15]. Specifically, in non-iterative approaches, stability can be guaranteed [15] and, since the controller parameter estimation problem is convex for most interesting controller structures, the global optimum can be found. Various application examples (*e.g.*, [4], [3]) have shown that critical control problems can be dealt with by using a data-driven method. However, it can be debated whether similar results can be obtained if the same amount of data is available for system identification and a model-based controller is designed.

In the context of system identification, it has been shown that an indirect approach consisting of two optimization steps

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is statistically efficient [14]. As a matter of fact, according to the invariance principle of maximum likelihood (ML) estimators, an estimator of a function of the model parameter estimates is asymptotically efficient if the model parameter estimate is statistically efficient. Translating these results to the specific case of controller tuning, arguments have been put forward in favor of model-based approaches [6]. In fact, based on the translation of the previous results to controller estimation, it can be argued that an efficient model-based approach in this sectionis optimal and will therefore achieve equivalent or better results than data-driven approaches that are not statistically efficient.

Analysis of the accuracy of controller estimates is limited both for data-driven and model-based approaches and a quantitative comparison confirming the argument given above is lacking. One of the problems in performing such an analysis is that the achieved performance of model-based controller tuning methods strongly depends on the modeling technique that is used. If an identified parametric model is used, the control performance depends on the identification approach and the resulting amount of under-modeling. Furthermore, the order of the controller depends in general on the order of the identified model. In practice, bounds on the modeling error can be defined, but the exact amount of under-modeling will be unknown and problem dependent.

In this paper, a model-based controller tuning approach based on the invariance principle of ML estimators is proposed that allows for a comparison of the asymptotic variance of the controller parameter estimate with the accuracy achieved by data-driven approaches. A high-order model is identified using ML estimation (in this step the modeling error can be assumed negligible) and the controller parameters are estimated using an L_2 approach, under the assumption that the control objective is achievable. According to the arguments set out above, this approach achieves the Cramér-Rao lower bound [6]. Moreover, this method can fairly be compared to non-iterative data-driven control (in this work, the Correlation-based Tuning, CbT [15], will be accounted for) as both approaches are based on convex optimization only.

According to [6], it is already known that, in terms of variance, the model-based approach yields the best performance. However, since from the perspective of control design, *variance analysis is only an intermediate step* towards the evaluation of the methods, in this paper, the real final objective, that is the control cost achieved by the designed controller, is assessed.

Specifically, it is here shown that the expected value of

the final control cost is biased and the bias depends not only on the variance of the controller parameters, but also on some parameters. It might therefore happen that for large but finite number of data, a data-driven approach achieves a lower control cost than a statistically efficient model-based approach.

The remainder of the paper is as follows. Preliminaries and notation are given in Section II. The model-based and data-driven methods used in the paper for fixed-order model-reference design are described in Section III. The main results on accuracy analysis are presented in Section IV. A simulation example is used in Section V to illustrate the theoretical observations on the benchmark system introduced in [10]. Finally, Section VI concludes the paper.

II. PRELIMINARIES

A. The approximate model reference control problem

Consider the stable linear SISO plant $G(q^{-1})$, where q^{-1} denotes the backward shift operator. Specifications for the controlled plant are given as a reference model $M(q^{-1})$. In the following, it is assumed that $M \neq 1$. The backward shift operator will be omitted in the sequel for convenience. The control objective is to design the controller $K(\rho)$, parameterized through ρ, such that the closed-loop system resembles the reference model M. This can be achieved by minimizing the two-norm of the difference between the reference model and the achieved closed-loop system:

$$J_{mr}(\rho) = \left\| M - \frac{K(\rho)G}{1 + K(\rho)G} \right\|_2^2 \qquad (1)$$

A discussion on the choice of M can be found in [2]. Here, the controller structure is chosen linear in the parameters,

$$K(q^{-1}, \rho) = \beta^T(q^{-1})\rho, \quad \rho \in \mathcal{D}_K \subseteq \mathbb{R}^{n_\rho} \qquad (2)$$

where the set $\mathcal{D}_K$ is compact and $\beta(q^{-1})$ is a vector of size n_ρ of linear discrete-time transfer operators (in general an orthogonal basis). Only the cases where $K(\rho)$ is stable or it contains an integrator if $M(1) = 1$ will be considered. The ideal controller K^* can be defined by G and M as

$$K^* = \frac{M}{G(1 - M)}, \qquad (3)$$

that always exists since $M \neq 1$. Notice that K^* might be of very high order, it might not stabilize the plant internally and it might be non-causal.

Notice that the model reference criterion (1) is non-convex with respect to ρ. An approximation that is convex for linearly parameterized controllers (2) can be defined using the reference model, as follows. The ideal sensitivity function is given by

$$\frac{1}{1 + K^*G} = 1 - M.$$

Note that this function is causal (as well as the reference model M) independent of the causality of K^*. Recalling (3), the model reference criterion (1) can be expressed as:

$$J_{mr}(\rho) = \left\| \frac{K^*G - K(\rho)G}{(1 + K^*G)(1 + K(\rho)G)} \right\|_2^2 \qquad (4)$$

Approximation of $1/(1 + GK(\rho))$ by $1 - M$, the ideal sensitivity function, leads to the following approximation of the model reference criterion:

$$J(\rho) = \left\| \frac{K^*G - K(\rho)G}{(1 + K^*G)^2} \right\|_2^2 = \qquad (5)$$

$$= \left\| (1 - M)[M - K(\rho)(1 - M)G] \right\|_2^2. \qquad (6)$$

The quality of this approximation of $J_{mr}(\rho)$ is discussed in [1]. Notice that, with the selected parameterization, $J(\rho)$ is a quadratic function of ρ and its global optimizer can be easily found using the least squares techniques.

The optimal controller is defined as $K_o = K(\rho_o)$ with

$$\rho_o = \arg \min_{\rho \in \mathcal{D}_K} J(\rho) \qquad (7)$$

In practice, if the controller order is fixed according to (2), the objective is not necessarily achievable and $K^* \notin \{K(\rho)\}$, $K_o \neq K^*$ and $J(\rho_o) > 0$. To allow for analysis of the accuracy of the estimated controller parameters, it is assumed that

A1 The objective can be achieved, *i.e.* $K^* \in \{K(\rho)\}$. Therefore, it holds that $K_o = K(\rho_o) = K^*$ and $J(\rho_o) = 0$.

B. System identification

Assume that a set of input, $r(t)$, and output data, $y(t)$, with data length N is available from an open-loop experiment. Suppose that the output is generated as:

$$y(t) = G(q^{-1})r(t) + v(t) \qquad (8)$$

where $v(t)$ is the measurement noise.

From the point of view of system identification, many different approaches can be employed to identify the system dynamics. In this paper, an FIR model $\hat{G}$ of G will be identified, as the optimization is convex and does not require any prior knowledge on the system structure, except for the length of its impulse response (that however can be inferred from data, if the energy of noise is low).

Introduce the impulse response $g(t)$ of G and $\theta_o = [g(0) \ldots g(n - 1)]^T$, where n the length of the impulse response, such that $g(t) \approx 0$, $t \geq n$. Note now that (8) can be rewritten as $y(t) \approx \psi^T(t)\theta_o + v(t)$, where

$$\psi(t) = [r(t) \ldots r(t - n + 1)]^T.$$

An FIR estimate of G of length n is given by:

$$\hat{\theta} = \left[\frac{1}{N} \sum_{t=1}^N \psi(t)\psi^T(t) \right]^{-1} \frac{1}{N} \sum_{t=1}^N \psi(t)y(t). \qquad (9)$$

Assume now that

A2 The noise $v(t)$ is uncorrelated with $r(t)$.
A3 The noise can be represented as $v(t) = H_v e(t)$, where $e(t)$ is a zero-mean white noise signal with variance σ^2 and bounded fourth moments. H_v and H_v^{-1} are stable filters.

A4 $r(t)$ is persistently exciting of order n and $(1 - M)^2 G$ has no zero on the imaginary axis.

A5 The FIR model order is such that $n \geq n_\rho$.

The estimate (9) provides a unique solution, if **A4** is satisfied, given by $\hat{\theta} = \theta_o + \tilde{\theta}$, where

$$\tilde{\theta} = \left[\frac{1}{N} \sum_{t=1}^{N} \psi(t)\psi^T(t) \right]^{-1} \frac{1}{N} \sum_{t=1}^{N} \psi(t)v(t). \quad (10)$$

This estimate is consistent: $\lim_{N \to \infty} \hat{\theta} = \theta_o$, w.p.1, [11]. Moreover, if $v(t)$ is white, (9) is a maximum-likelihood (ML) estimator and the Cramér-Rao lower bound for the variance is achieved. When this is the case, the following principle (Theorem 5.1.1 [16]) holds, regarding all quantities derived from $\hat{\theta}$.

Invariance principle of maximum-likelihood estimation: Let $f : \Theta \to \Omega$ be a function mapping $\theta \in \Theta \in \mathbf{R}^n$ to an interval $\Omega \in \mathbf{R}^m$, with $m \leqslant n$. The invariance principle of ML estimation then states that, if $\hat{\theta}$ is a ML estimator of θ, then $f(\hat{\theta})$ is a ML estimator of $f(\theta)$.

III. MODEL REFERENCE CONTROL DESIGN FROM DATA

A. The correlation approach

Consider the scheme in Fig. 1, when $v = 0$ and the reference signal $r(t) = u(t)$, with $u(t)$ a white noise of unit variance. This scheme can be used to derive the optimal controller without using any explicit mathematical model of the process.
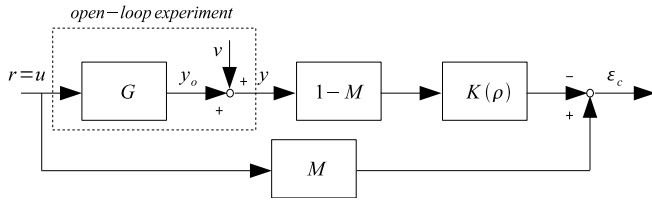

Fig. 1. Tuning scheme for Correlation-based Tuning

As a matter of fact, the most important observation at the basis of the CbT rationale is that, in the noiseless setting, the error signal $\varepsilon_c(t, \rho)$ can be directly computed from I/O data as follows:

$$\begin{aligned} \varepsilon_c(t, \rho) &= Mr(t) - (1 - M)K(\rho)Gr(t) \\ &= Mu(t) - (1 - M))K(\rho)y(t) \end{aligned}$$

and, assuming **A1** holds, the minimizer of the two-norm of $\varepsilon_c(t, \rho)$ is exactly K_o.

When data are noisy, the method resorts to the correlation approach to identify the controller. Specifically, an extended instrumental variable $\zeta(t)$ correlated with $u(t)$ and uncorrelated with $v(t)$ is introduced to decorrelate the error signal $\varepsilon_c(t)$ and $u(t)$. $\zeta(t)$ is defined as

$$\zeta(t) = [u(t + l), \ldots, u(t), \ldots, u(t - l)]^T, \quad (11)$$

where l is a sufficiently large integer. The correlation function is defined as

$$f_{N,l}(\rho) = \frac{1}{N} \sum_{t=1}^{N} \zeta(t)\varepsilon_c(t, \rho) \quad (12)$$

and the correlation criterion as

$$J_{N,l}(\rho) = f_{N,l}^T(\rho)f_{N,l}(\rho). \quad (13)$$

In [15], it has been proven that

$$\lim_{N,l \to \infty, l/N \to 0} J_{N,l}(\rho) = J(\rho), \quad (14)$$

for any sufficiently exciting input sequence, if data in $\zeta(t)$ are prefiltered by $L_c(q^{-1})$, defined as

$$L_c(e^{-j\omega}) = \frac{1 - M(e^{-j\omega})}{\Phi_u(\omega)}, \quad (15)$$

where $\Phi_u(\omega)$ denotes the spectral density of $u(t)$.

The optimal controller is then defined as $K_{CbT} = K(\hat{\rho}_{CbT})$ with

$$\hat{\rho}_{CbT} = \arg \min_{\rho \in \mathcal{D}_K} J_{N,l}(\rho) \quad (16)$$

B. Model-based model reference control

If a model $\hat{G}$ of the system is available, a model reference controller $\hat{K}$ can be computed as $\hat{K} = M/[\hat{G}(1 - M)]$. However, in any model-reference method this might lead to a high-order controller that may destabilize the system if M is not minimum phase. $\mathcal{H}_2$ control theory can be used to compute a full-order model reference controller followed by a controller order reduction technique to compute a fixed-order controller. The accuracy of the final (fixed-order) controller is difficult to compute.

An alternative design of a fixed-order controller by minimization of the model reference criterion (1) approximated using the model $\hat{G}$ leads to a non-convex optimization approach. The quality of this controller estimate will depend on the initial values of the optimization variables and a fair comparison with data-driven approaches based on convex optimization is not possible. In this paper, the approximate control criterion (6) used in the data-driven approaches is therefore considered to develop a model-based approach that is comparable to the data-driven approaches.

Specifically, the approximate model reference criterion (6) can be approximated using the model $\hat{G}$ of the plant G, by minimizing $\left\| (1 - M)[M - K(\rho)(1 - M)\hat{G} \right\|$ over ρ. Since a parametric model is available, a simulated output sequence can be generated. This sequence can then be used to approximate the control criterion. This approach has also been used in model reduction, *i.e.* [14], [13].

In the following, a high-order parametric model $\hat{G}$ parametrized through $\hat{\theta}$ with an FIR structure is used together with the impulse excitation signal $\delta(t)$ to generate a simulated impulse response sequence, $y_{\hat{\theta}}(t) = \hat{G}\delta(t)$. This simulated output can be used to minimize the approximate model reference criterion

$$\hat{\rho}_{\hat{\theta}} = \arg \min_{\rho \in \mathcal{D}_K} J_{mb}(\rho, \hat{\theta}) \quad (17)$$

$$J_{mb}(\rho, \hat{\theta}) = \frac{1}{N_\delta} \sum_{t=1}^{N_\delta} \left(s(t) - K(\rho)(1-M)^2 y_{\hat{\theta}}(t) \right)^2, \quad (18)$$

where $s(t)$ is the impulse response of $(1-M)M$, i.e. $s(t) = (1-M)M\delta(t)$ and the number of generated samples $N_\delta \geq n$. The error can be written as:

$$s(t) - K(\rho)(1-M)^2 y_{\hat{\theta}}(t) = s(t) - \phi_{\hat{\theta}}^T(t)\rho, \quad (19)$$

where the regression vector $\phi_{\hat{\theta}}(t)$ is given by

$$\begin{aligned} \phi_{\hat{\theta}}(t) &= \beta(1-M)^2 y_{\hat{\theta}}(t) \\ &= \beta(1-M)^2 G\delta(t) + \beta(1-M)^2 \Delta G\delta(t) \\ &\triangleq \phi_o(t) + \tilde{\phi}_{\hat{\theta}}(t) \end{aligned} \quad (20)$$

and $\Delta G = \hat{G} - G$. The minimizer of (18) is given by

$$\hat{\rho}_{\hat{\theta}} = \left[\frac{1}{N_\delta} \sum_{t=1}^{N_\delta} \phi_{\hat{\theta}}(t) \phi_{\hat{\theta}}^T(t) \right]^{-1} \frac{1}{N_\delta} \sum_{t=1}^{N_\delta} \phi_{\hat{\theta}}(t) s(t) \quad (21)$$

From now on, let $N_\delta = N$ without loss of generality.

Proposition 1: Assume that **A1-A5** are satisfied and let $N > n$. Then, if the FIR model $\hat{\theta}$ is estimated according to (9) and the controller parameters $\hat{\rho}_\theta$ according to (21),

$$\lim_{N\to\infty} \hat{\rho}_{\hat{\theta}} = \rho_o, \ \text{w.p.1}.$$

Proof: The noise-free signal $s(t)$ can be written as $s(t) = \phi_{\hat{\theta}}^T(t)\rho_o - \tilde{\phi}_{\hat{\theta}}(t)\rho_o$, the estimation error is given by

$$\hat{\rho}_{\hat{\theta}} - \rho_o = -\left[\frac{1}{N} \sum_{t=1}^{N} \phi_{\hat{\theta}}(t) \phi_{\hat{\theta}}^T(t) \right]^{-1} \frac{1}{N} \sum_{t=1}^{N} \phi_{\hat{\theta}}(t) \tilde{\phi}_{\hat{\theta}}^T(t) \rho_o. \quad (22)$$

Since $\lim_{N\to\infty} \hat{\theta} = \theta_o$, a continuous function of this variable $f(\hat{\theta})$ converges w.p.1 to $f(\theta_o)$ ([12], page 450). Consequently $\lim_{N\to\infty} \tilde{\phi}_{\hat{\theta}}(t) = 0$, w.p. 1, the regressor converges to the noise-free regressor, $\lim_{N\to\infty} \phi_{\hat{\theta}}(t) = \phi_o(t)$, w.p.1, and

$$\lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} \phi_{\hat{\theta}}(t) \phi_{\hat{\theta}}^T(t) = R_o, \quad \text{w.p.1}, \quad (23)$$

with R_o defined as

$$R_o = \lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} \phi_o(t) \phi_o^T(t). \quad (24)$$

This matrix has full rank since $N \geq n$ and **A4, A5** hold. It follows that $\lim_{N\to\infty}(\hat{\rho}_{\hat{\theta}} - \rho_o) = 0$, w.p.1. ∎

IV. Accuracy Analysis

In this section, the effect of noise will be assessed on the capability of the control design criteria of minimizing (6). It will be also shown that, from this point of view, *a criterion based on a ML estimator of the model is not always statistically better, in terms of the control cost* (6)*, than data-driven design*.

As a matter of fact, concerning CbT, the following result holds [15]:

Proposition 2: For large N, the expected value of the correlation criterion (13) is as follows.

$$\mathbb{E}[J_{N,l}(\rho)] \approx J(\rho) + \frac{\sigma^2(2l+1)}{2\pi N} \int_{-\pi}^{\pi} \frac{|1-M|^4 |K(\rho)|^2 |H|^2}{\Phi_u(\omega)} \, d\omega. \quad (25)$$

The same approach applied to model-reference control using model-based formula (21) gives the following bias for the control cost for large and finite N.

Proposition 3: For large N and n and small n/N, the expected value of the model-based cost function (21) is as follows.

$$\mathbb{E}[J_{mb}(\rho)] \approx J(\rho) + \frac{\sigma^2 n}{2\pi N} \int_{-\pi}^{\pi} \frac{|1-M|^4 |K(\rho)|^2 |H|^2}{\Phi_u(\omega)} \, d\omega. \quad (26)$$

Proof: Consider again the model-based control cost (18) and define $\Delta G = G - \hat{G}$. Since $\hat{y}_\theta(t) = \hat{G}\delta(t)$, where $\delta(t)$ is the discrete-time impulse, the control cost is given by

$$\begin{aligned} J_{mb}(\rho) &= \frac{1}{N} \sum_{t=1}^{N} \left(s(t) - K(\rho)(1-M)^2 \hat{y}_\theta(t) \right)^2 \\ &= \frac{1}{N} \sum_{t=1}^{N} \left(s(t) - K(\rho)(1-M)^2 G\delta(t) \right)^2 \\ &\quad + \frac{1}{N} \sum_{t=1}^{N} \left(K(\rho)(1-M)^2 \Delta G\delta(t) \right)^2 \\ &\quad + \frac{2}{N} \sum_{t=1}^{N} \left(s(t) - K(\rho)(1-M)^2 G\delta(t) \right) \\ &\quad \times \left(K(\rho)(1-M)^2 \Delta G\delta(t) \right) \end{aligned}$$

Notice that the first term of the sum is a (noiseless) consistent estimator of $J(\rho)$. Since the estimate of G is consistent, *i.e.* $\mathbb{E}[\Delta G] = 0$, then the expectation of $J_{mb}(\rho)$ becomes

$$\mathbb{E}[J_{mb}(\rho)] = J(\rho) + \frac{1}{N} \sum_{t=1}^{N} \mathbb{E}\left[\left(K(\rho)(1-M)^2 \Delta G\delta(t) \right)^2 \right]$$

and its Parseval counterpart is

$$\mathbb{E}[J_{mb}(\rho)] = J(\rho) + \frac{1}{2\pi} \int_{-\pi}^{\pi} |1-M|^4 |K(\rho)|^2 \mathbb{E}\left[|\Delta G|^2\right] \Phi_\delta(\omega) d\omega. \quad (27)$$

In the literature [11], it is well-known that for high order models the following approximation holds

$$\mathbb{E}\left[|\Delta G|^2\right] \approx \frac{n}{N} |H|^2 \sigma^2 \Phi_u^{-1}(\omega)$$

Moreover, being δ an impulse, $\Phi_\delta(\omega) = 1$, $\forall \omega$ and therefore (26) holds, which completes the proof. ∎

Propositions 2 and 3 indicate that both the criteria $J_{N,l}$ and J_{mb} are biased and depending on l/n, the bias will be larger in one case or in the other.

A. Discussion

The results of the last subsection evaluate the average behavior of the model-based and data-driven controllers from a different view. In standard statistical analysis, the

performance of an estimator that is asymptotically consistent is evaluated by means of the asymptotic variance. The method that achieves the lowest asymptotic variance is usually considered to be the best estimator. If such an evaluation, combined with the invariance principle of maximum-likelihood estimation, is applied to the controller design methods discussed in this paper, the model-based design approach (that achieves optimal asymptotic variance) can be considered the best estimator. However, the results in Propositions 2 and 3 show that the expectation of the final control criterion is *lower* in the data-driven case, when the model is high-order and $n > 2l + 1$. The reason for this discrepancy is that the analysis based on asymptotic variance does not take into account the other factors affecting the final control criterion, *i.e.* l and n. These design parameters offer a trade-off between the minimizer of the real criterion to minimize, *i.e.* J, and the minimizer of a bias term that is null if $\rho = 0$. Notice that the case of $n > 2l + 1$ is all but unlikely in real-world applications. As a matter of fact, l should be close to the length of the impulse response of $M - KG(1 - M)$, which is unknown. However, standing on the assumption that it is possible to match most of M with K, the choice of l equal to the length of the impulse response of M is sufficient. For the condition $n > 2l + 1$ to be satisfied, it is then sufficient that the settling time of the FIR model $\hat{G}$ is larger than that of M or $\hat{G}$ is low-damped.

In standard practice of model-based design, when the system is complex and a low order model is not sufficient to accurately describe the I/O dynamics, one may think that increasing the order is the best way to find a good model. For what said above, one of the main conclusions of this paper is that *this is not generally true if the model has to be used for control design*. A data-driven method, that does not depend on a model of the system, might be a better solution.

Furthermore, it should also be considered that the "order" of a real system is a badly defined concept. Every model is only an approximation of the real world. It follows that the data-driven method might outperform the model-based method also when the model is low-order. In the following section, it will be shown that this might happen even when the model error is very small.

V. NUMERICAL EXAMPLE

A. The benchmark system

The flexible transmission system proposed as a benchmark in [10] was used in [1] and [9] to illustrate data-driven controller tuning approaches. The same example is used here. The plant and the controller structure are given by

$$G(q^{-1}) = \frac{0.28q^{-3} + 0.51q^{-4}}{1 - 1.42q^{-1} + 1.59q^{-2} - 1.32q^{-3} + 0.89q^{-4}}.$$

$$K(\rho) = \frac{\rho_1 + \rho_2 q^{-1} + \rho_3 q^{-2} + \rho_4 q^{-3} + \rho_5 q^{-4} + \rho_6 q^{-5}}{1 - q^{-1}}.$$

PRBS signals with unity amplitude are used as input to the system, $r(t)$. The output of the plant is disturbed by zero-mean white noise $v(t)$. Results are given for $N =$

1000, sampling time $T_s = 50ms$ and increasing length of the instrumental variable l. A Monte-Carlo simulation with $n_{MC} = 100$ experiments is performed, using a different noise realization for each experiment, for a signal-to-noise ratio (SNR) of 10 in terms of standard deviation. The noise realizations are the same for all methods. The reference model is defined as

$$M(q^{-1}) = \frac{K(\rho_o)G}{1 + K(\rho_o)G} \tag{28}$$

$\rho_o = [0.2045, -0.2715, 0.2931, -0.2396, 0.1643, 0.0084]^T$.

The optimal controller $K(\rho_o) \in \{K(\rho)\}$ and the objective can be achieved. Since the number of nonzero impulse response coefficient can be easily estimated to be (almost) 180 for G and (almost) 35 for M, an FIR model with $n = 180$ is used in the model-based approach whereas for CbT $l = 35$ is selected.

The results of the 100 Monte Carlo runs for the model-based design using an FIR model with $n = 180$, for CbT with $l = 35$ and for CbT with $l = 130$ are summarized in Table I and II. Two estimates of $\mathbb{E}[J(\rho)]$ and $\mathbb{E}[J_{mr}(\rho)]$ are calculated, respectively, as

$$V_c = \frac{1}{n_{MC}} \sum_{i=1}^{n_{MC}} J(\hat{\rho}^{(i)}) \tag{29}$$

$$V_{mr} = \frac{1}{n_{MC}} \sum_{i=1}^{n_{MC}} J_{mr}(\hat{\rho}^{(i)}) \tag{30}$$

where $\hat{\rho}^{(i)}$ is the controller parameter vector at the ith Montecarlo run, and the average trace of the variance

$$V_t = \frac{1}{n_{MC}} \sum_{i=1}^{n_{MC}} tr \left\{ var[\hat{\rho}^{(i)}] \right\} \tag{31}$$

is also given. For comparison, the performance achieved using low order models estimated using the OE approach is finally presented in Table I.

As predicted by the theory of Propositions 2 and 3, the average of the cost criterion is lower in the data-driven case when $n > 2l + 1$, even if the parameter variance is larger. When l is overestimated, *e.g.* when $l = 130$ and $n < 2l + 1$, the variance of the model-based design remains smaller, but now the average of the control cost is also lower than that for the data-driven design.

If both the model structure (OE) and the model order are known, the low order model-based solution outperforms the data-driven approach (note that in this case, since the order of the real system $n = 4$ is low, the result of Proposition 3 no longer holds). However, this does not mean that the model-based approach is more suitable in practice. In the real-world, a "full-order model" does not exist and any description is by definition an approximation. The results presented in Table I show that even a small under-modeling error may jeopardize the control performance. The case where an OE model with the right number of poles and the right relative degree but without zeros introduces a modeling error that is very likely in practice. As a matter of fact, note that the physics usually

	MB			
	OE(2,4,3)	OE(2,4,4)	OE(1,4,3)	FIR: $n = 180$
V_t ($\times 10^{-3}$)	0.3676	0.3896	0.0144	0.7378
V_c	0.0064	0.0688	0.1332	0.0573
V_{mr}	0.0064	0.0759	0.1424	0.0575

TABLE II

ACHIEVED PERFORMANCE (29), (30) AND (31) OVER 100 RUNS FOR
DATA-DRIVEN (CbT) DESIGN.

	CbT	
	$l = 35$	$l = 130$
V_t ($\times 10^{-3}$)	3.0578	0.9646
V_c	0.0375	0.0586
V_{mr}	0.0376	0.0587

suggest the order of the model but not the exact number of zeros, especially in discrete time. The identified model is very similar to the real system, as illustrated in Figure 2 and the user may believe that this is an accurate description of the system, but the resulting controller does not yield good control performance. The same observations can be made for the case where the relative degree is 4 instead of 3 (only one more than the "real" system).

The average of the achieved original model-reference criterion J_{mr} is reported to show that the approximate criterion J is a good approximation and that therefore the conclusions hold for the original model reference criterion, even if the analysis has been carried out with respect to the convexified one. The results show that J_{mr} and J are very similar for the FIR and CbT approaches as well as the low-order model approach when no under-modeling is present. In the case of under-modeling in the model-based approach, the approximation is less good since (18) depends on the model (and not on system) dynamics. As a result, the model reference control cost (1) is larger than (6), which further encourages the use of a data-driven technique.
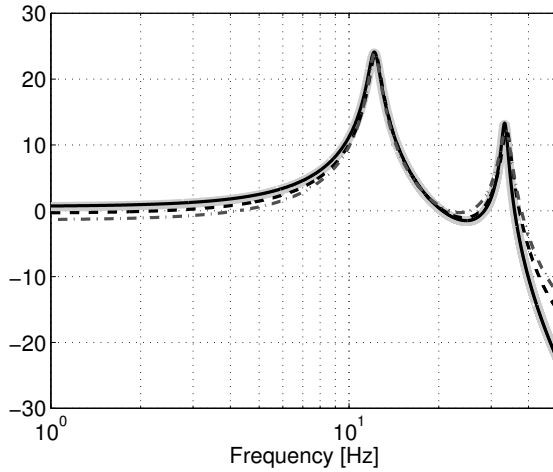

Fig. 2. Output error modeling of G: magnitude of the frequency response of the real plant (thick grey line), of the OE(2,4,3) model (solid black line), of the OE(1,4,3) model (dashed black line) and of the OE(2,4,4) model (dash-dotted grey line).

VI. CONCLUSIONS

In this work, the statistical performance of model-based and data-driven controller tuning are compared by looking at the final control objective to be minimized. The main conclusions of this paper are the following:

- if the model structure is perfectly known and the model order is low, the model-based approach is theoretically always the best in terms of statistical performance [6];
- if the model structure is not completely known and/or a high-order model is identified using a ML estimator, the data-driven approach can statistically outperform the model-based solution in terms of the control cost, even if the variance of the parameters remains larger.
- Since in the real world the model structure is never *perfectly* known and under-modeling cannot be avoided with a low-order model, the data-driven approach may give better results in real applications.

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