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System identification for achieving robust performance

Tom Oomen, Okko Bosgra

Eindhoven University of Technology, Department of Mechanical Engineering, Control Systems Technology Group, Eindhoven, The Netherlands

Abstract

The performance of robust controllers hinges on the underlying model set. The aim of the present paper is to develop a system identification procedure that enables the design of a controller that achieves optimal robust performance. Hereeto, the complex interrelation between system identification and robust control is thoroughly analyzed and novel connections are established between (i) control-relevant and coprime factor identification and (ii) model uncertainty size and the control criterion. The key technical results include new robust-control-relevant and \( (W_u, W_y) \)-normalized coprime factorizations. The results enable the identification of multivariable model sets that achieve high robust performance in a subsequent robust control synthesis. Superiority of the proposed results compared to existing approaches is shown by means of an example.

1. Introduction

The purpose of any model should be accounted for when evaluating model quality. In Schrama (1992), Gevers (1993) and Albertos and Sala (2002), control-relevant system identification techniques are presented that match the identification criterion to the control criterion, aiming to deliver models that are especially suitable for subsequent control design. These approaches are typically iterative and alternate between closed-loop system identification and control design. These approaches have met with different outcomes due to the lack of a convergence proof. Indeed, model errors are not explicitly accounted for during controller synthesis, hence there are no stability and performance guarantees for a newly designed controller.

Robust control (Zhou, Doyle, & Glover, 1996) explicitly deals with model errors by designing a controller that stabilizes and achieves a certain guaranteed performance for a model set. Identification for robust control involves the problem of identifying the required model set. The robust control goal introduces two requirements on the identified model set:

(R1) the model set should encompass the true system behavior to guarantee robust stability, and

(R2) the model set should enable the synthesis of a controller that achieves high robust performance.

In general, these two requirements can be conflicting, since a straightforward approach to satisfy Requirement R1 is to select a large model set. However, if the model set contains candidate models that are difficult to control, then the guaranteed performance of the robust controller is poor, violating Requirement R2. The aim of this paper is to quantify and optimize the relation between these two requirements. In contrast, several approaches have already been developed that mainly address the robust stability Requirement R1 in system identification for robust control. These approaches are investigated next.

On the one hand, system identification techniques based on stochastic assumptions have been extended in, e.g., Hakvoort and Van den Hof (1997) and Ljung (1999), to deliver model sets for subsequent robust control. Although these methods have been further refined in Gevers, Bombois, Codrons, Scorletti, and Anderson (2003) and Gevers (2005) towards a certain notion of control-relevance, the adopted approach focusses on robust stability considerations and consequently does not guarantee that it is possible or straightforward to determine a high performance robust controller. Furthermore, although stochastic embedding techniques (Goodwin, Braslavsky, & Seron, 2002) have extended the traditional stochastic identification methodologies by considering the model uncertainty as a realization of a stochastic process, at present robust control techniques that can deal with such uncertainty descriptions are not available.

On the other hand, system identification techniques have been developed that consider deterministic assumptions on the involved signals instead of the traditional stochastic ones. Deterministic time domain approaches are reported, e.g., in Milanese and...
Vicino (1991), and generally lead to polytopic uncertain model descriptions. Due to a high computational demand, the application of these polytopic model structures is limited to small data sets. Robust identification techniques, see Helwicki, Jacobson, and Nett (1991) and Chen and Gu (2000), and references therein, have been developed that directly deliver a nominal model and a bound on the model uncertainty that are compatible with \( \mathcal{H}_\infty \)-optimization based robust control. However, these techniques lead to overly large model sets and consequently conservative control designs, as is also discussed in Vinnicombe (2001, Section 9.5.2). A further overview of approaches that address aspects of system identification for robust control can be found in, e.g., Ninness and Goodwin (1995), Hjalmarsson (2005) and Reinelt, Garulli, and Ljung (2002).

Besides the development of alternative system identification procedures, model uncertainty structures for robust control have been further refined and employed in system identification to extend control-relevant models with a description of model uncertainty. Specifically, Requirement R1 precludes the use of (inverse) additive and multiplicative uncertainty since these control-relevant models are generally identified in closed-loop, see Schrama (1992), Gevers (1993) and Albertos and Sala (2002), hence these models are generally uncertain with respect to both the open-loop unstable poles and zeros. To satisfy Requirement R1, perturbations on coprime factors of the system model can be considered to represent uncertainty with respect to both the open-loop unstable poles and zeros. Commonly, normalized coprime factorizations (McFarlane & Glover, 1990) are considered, since these have a close connection to robustness properties in the graph and \((\nu^{-1})\) gap metric; see Georgiou and Smith (1990), de Callafon, Van den Hof and Bongers (1996) and Vinnicombe (2001). Specifically, related results that connect control performance and model validation based on these normalized coprime factorizations are reported in Steele and Vinnicombe (2001) and Date and Cantoni (2005). The dual-Youla–Kučera structure (Anderson, 1998; de Callafon and Van den Hof, 1997; Douma & Van den Hof, 2005) further refines these coprime factorization-based model uncertainty structures by excluding candidate models that are not stabilized by the controller that is used during the identification experiment. In this respect, the dual-Youla–Kučera model uncertainty structure constitutes a necessary step to satisfy Requirement R2 by excluding falsified models based on the actual experimental conditions.

Although the exclusion of models that are not stabilized during the identification experiment is a necessary step to identify models that enable high performance control design, it is not sufficient to satisfy Requirement R2. Indeed, since the dual-Youla–Kučera parameterization represents all candidate systems that are stabilized by a certain controller, in general it may contain candidate models for which high performance cannot be achieved. This is further supported by the results in de Callafon and Van den Hof (2001), where the desire of achieving a certain level of robust performance using the dual-Youla–Kučera model uncertainty structure necessitates the use of highly structured model uncertainty blocks that essentially reduce the uncertainty to a large set of scalar blocks with a frequency-dependent scaling. However, such an approach leads to unnecessary conservatism and computational burden in certain uncertainty quantification procedures, see Toker and Chen (1998), and subsequent robust control synthesis (Doyle, 1982).

In this paper, a coprime-factorization solution to the system identification for the robust control problem is presented further generalizing and extending the existing theory of coprime factorizations. The proposed solution that satisfies both Requirement R1 and Requirement R2 constitutes the main contribution of the paper and enables the design of a controller that achieves the limit of robust performance. Two main steps are taken to solve the system identification for the robust control problem. In the first step, a new connection between control-relevant identification and the identification of coprime factorizations is established through a new technical result called a robust-control-relevant coprime factorization. Compared to the identification of normalized coprime factorizations, see Gu (1999), Date and Vinnicombe (2004), Van den Hof, Schrama, de Callafon and Bosgra (1995) and Zhou and Xing (2004), that are useful in certain robust control methodologies, including (McFarlane & Glover, 1990), the proposed robust-control-relevant coprime factorization has distinct advantages from a system identification perspective. Interestingly, the additional freedom associated with non-normalized coprime factorizations is also employed in the general distance measure framework in Lanzon and Papageorgiou (2009) and Lanzon, Engelken, Patra, and Papageorgiou (2012), however, in contrast to the present paper, the connection to system identification is not considered. Specifically, in this paper the following aspects are developed that extend existing results in this area.

(C1) Existing coprime factor identification techniques are mainly aimed at identifying normalized coprime factorizations. Here, the identification of coprime factorizations is directly connected to control-relevant identification, leading to a nominal model that is especially suitable for control.

(C2) The control-relevant system identification problem, which is generally a four-block problem, is recast as an equivalent two block problem, enabling a significant reduction of the computational burden.

(C3) The identification of normalized coprime factorizations typically requires an iterative procedure; see, e.g., Van den Hof et al. (1995). The approach taken in this paper enables the direct identification of a certain coprime factorization from data, enabling a significant reduction of the computational burden.

(C4) The robust-control-relevant coprime factorization can be efficiently identified through a frequency response-based algorithm.

(C5) The identified robust-control-relevant coprime factorization is an essential ingredient for constructing a novel model uncertainty structure, as is discussed in the second step, and state-space results are presented for the actual computational procedure.

In the second step, a new model uncertainty structure is established that extends earlier model uncertainty structures for robust control and enables the identification of multivariable model sets for achieving robust performance. The following specific aspects are developed in this paper that extend the existing results.

(C6) State-space results are presented to compute a new \((W_u, W_f)\)-normalized coprime factorization of the controller, which is used during the identification experiment, that in conjunction with the identified robust-control-relevant coprime factorization of the nominal model enables the direct construction of the new model uncertainty structure.

(C7) The proposed model uncertainty structure transparently connects the size of model uncertainty and the control criterion, which is a fundamental step forward in the nonconservative identification of model sets.

The use of existing uncertainty structures for multivariable systems necessitates the use of structured and frequency dependent uncertainty models, as in Van de Wal, van Baars, Sperling, and Bosgra (2002) and de Callafon and Van den Hof (2001). The result C7 essentially provides an appropriate scaling for the uncertainty channels, thereby enabling the use of unstructured uncertainty models that have important advantages from a computational perspective.

To facilitate the exposition, an explicit distinction is made between the identification of a nominal model and the quantification
of model uncertainty. Such a distinction is also made in, e.g., de Callafon and Van den Hof (1997), and is commonly done in applications, including (de Callafon and Van den Hof, 2001; Van de Wal et al., 2002). This distinction in the present paper is made for two reasons. First, this explicit separation sheds light on prior results in control-relevant system identification. Second, it results in a general framework that can straightforwardly be used in conjunction with a wide variety of model uncertainty quantification techniques. This separation is nonrestrictive and several approaches can be pursued to intertwine these steps, e.g., as in Hindi, Seong, and Boyd (2002). Systematic modeling errors are emphasized during the nominal model identification. The underlying assumption for the pursued frequency response-based approach is that the available measured data is sufficiently large, in which case the considered identification criterion is independent of the noise that contaminates the data.

This paper is organized as follows. In Section 2, the robust-control-relevant system identification problem is defined. As a first step, a novel connection between control-relevant system identification and the identification of coprime factorizations is presented in Section 3. The key technical result is a new robust-control-relevant coprime factorization and, in addition to Contribution C1–C5, several properties of this coprime factorization are established. As a second step, a new model uncertainty structure is presented in Section 4 that enables the identification of a model set in view of achieving robust performance, constituting Contributions C6–C7. In Section 5, the results of this paper are illustrated set in view of achieving robust performance, constituting Contributions C1–C5, several properties of this coprime factorization are established. As a second step, a new model uncertainty structure is presented in Section 4 that enables the identification of a model set in view of achieving robust performance, constituting Contributions C6–C7. Finally, conclusions are drawn in Section 6. Proofs and auxiliary are provided in the Appendix.

2. Problem formulation

2.1. Control goal definition

Throughout, the feedback interconnection in Fig. 1 is considered, where \( P \) denotes the system and \( C \) denotes the controller. It is emphasized that for all results in the present paper, both \( P \) and \( C \) can be multivariable with appropriate dimensions. The control goal is to minimize a control criterion, denoted by \( J(P, C) \), for the true system \( P_o \), i.e.,

\[
C^{\text{opt}} = \arg \min_C J(P_o, C)
\]  

A norm-based criterion is considered, i.e.,

\[
J(P, C) = \| W(T(P, C) V_1) \|_{\infty},
\]

where

\[
T(P, C) : \begin{bmatrix} r_2 \\ r_1 \end{bmatrix} \mapsto \begin{bmatrix} y \\ u \end{bmatrix} = \begin{bmatrix} P \\ I \end{bmatrix} \left( I + CP \right)^{-1} \left[ C I \right]
\]

is the closed-loop transfer function matrix corresponding to Fig. 1 and \( W = \text{diag} \left( W_1, W_2 \right) \), \( V = \text{diag} \left( V_2, V_1 \right) \) are weighting filters that satisfy \( W \cdot W^{-1} \), \( V \cdot V^{-1} \in \mathbb{RH}_\infty \). The requirement \( W \cdot W^{-1} \), \( V \cdot V^{-1} \in \mathbb{RH}_\infty \) is imposed to simplify the notation and is nonrestrictive, since it can be relaxed by absorbing \( W \) and \( V \) in the feedback control loop. The criterion (2)–(3) encompasses many performance goals that are based on the \( \mathbb{RH}_\infty \)-norm, since essentially all closed-loop transfer function matrices are weighted in (2). The motivation for using the \( \mathbb{RH}_\infty \)-norm in (2) is threefold: (i) it satisfies the multiplicativity property that facilitates the incorporation of model uncertainty; (ii) in conjunction with the four-block criterion in (2) and (3), it guarantees well-posedness and internal stability; and (iii) it facilitates the selection of \( W \) and \( V \) based on loop-shaping design techniques; see, e.g., McFarlane and Glover (1990).

2.2. Robust control

Since the true system \( P_o \) is unknown, a model-based control design approach is pursued to perform the actual optimization in (2). In general, uncertainty with respect to the dynamical behavior is always present when modeling physical systems. Thereto, a model set \( \mathcal{P} \) of candidate models is considered that presumably encompasses the true system behavior, i.e.,

\[
P_o \in \mathcal{P}.
\]

Associated with \( \mathcal{P} \) is the worst-case criterion

\[
J_{\text{wc}}(\mathcal{P}, C) = \sup_{P \in \mathcal{P}} J(P, C)
\]

that in conjunction with (4) immediately reveals that

\[
J(P_o, C) \leq J_{\text{wc}}(\mathcal{P}, C).
\]

Hence, if the controller satisfies a certain worst-case performance bound, then the controller is guaranteed to yield at least the same level of performance when it is implemented on the true system \( P_o \). This motivates the robust control design

\[
C^\text{opt} = \arg \min_C J_{\text{wc}}(\mathcal{P}, C).
\]

2.3. Robust-control-relevant system identification

In system identification for robust control, the model set \( \mathcal{P} \) is determined from measured data. As discussed in Section 1, the model set should enable a high performance control design. In terms of the criterion (2), this implies that the right hand side of (5) should be small when evaluated for \( C^\text{opt} \) in (6). In general,
the achievable worst-case performance in (6) is a complicated function of \( P \), both in terms of its shape and size. To ensure that the identified model set indeed delivers a high performance robust controller in (6), the identification criterion is connected to the control criterion. Conceptually, the dual problem to (6) is considered during system identification by using \( \min_{\mathcal{P}} J_{\text{WC}}(\mathcal{P}, C) \), as identification criterion. A crucial aspect here is that the latter criterion is a function of the variable \( C \). In the ideal case, \( C \) should be selected as in (6), i.e., \( C^{\text{R}}(\mathcal{P}) \). However, the mapping from \( \mathcal{P} \) to \( C^{\text{R}} \) in general is complicated and no analytic results exist, thereby excluding \( C^{\text{R}}(\mathcal{P}) \) as a candidate controller for use in the identification criterion. The alternative \( C^{\exp} \), see (1), is unknown and cannot be used for system identification purposes. To formulate a solvable identification criterion, a stabilizing non-optimal controller \( C^{\exp} \) is employed and implemented during the identification experiment.

The choice of the controller \( C^{\exp} \) that is used during the identification experiment crucially affects the robust-control-relevant identification criterion; see Definition 1. In fact, this is a well-known aspect in control-relevant system identification. Specifically, in relation to the proposed procedure in this paper, several aspects are important. (i) If the distance between \( C^{\exp} \) and the designed \( C^{\text{R}}(\mathcal{P}) \) or \( C^{\exp} \) is too large, then \( \min_{\mathcal{P}} J_{\text{WC}}(\mathcal{P}, C) \) and (6) may be solved iteratively. In contrast to iterative identification and control design schemes that are solely based on a nominal model, see Gevers (1993); Schrama (1992), and Albertos and Sala (2002), an iterative system identification and control design approach based on model sets, as is considered in this paper, leads to a monotonous performance improvement; see de Callafon and Van den Hof (1997), and Garatti, Campi, and Bittanti (2010).

As a result, the achievable performance after several iterations is invariant under the choice of the initial controller \( C^{\exp} \). (ii) The approximation that is introduced by replacing \( C^{\text{R}}(\mathcal{P}) \) with \( C^{\exp} \) can be mitigated using dynamic weighting filters. (iii) If \( P_\circ \) is stable, then \( C^{\exp} = 0 \) is a stabilizing controller, hence the procedure also applies to open-loop stable systems. (iv) In the case of systems that are not strongly stabilizable, the controller \( C^{\exp} \) has to be unstable to stabilize \( P_\circ \) in closed-loop. Such a choice is also admissible for the proposed procedure in this paper. Prior to formally defining robust-control-relevant system identification, the model set \( \mathcal{P} \) has to be defined more precisely. To ensure a direct connection with \( \mathcal{H}_\infty \)-optimization based robust control, a \( \mathcal{H}_\infty \)-norm-bounded perturbation is connected to the nominal model through an \( \mathcal{L}_\infty \)-based interconnection structure, i.e.,

\[
\mathcal{P} = \{ P | P = F_0(\hat{H}, \Delta_u), \Delta_u \in \Delta_u \},
\]

(7)

where \( \Delta_u \subseteq \mathcal{H}_\infty \) is a norm-bounded set that is possibly subject to additional structural constraints. In addition, \( \hat{H} \) contains \( \hat{P} \), the uncertainty structure, and possibly weighting filters to shape the uncertainty over frequency.

The involved robust-control-relevant model set system identification problem is formalized next.

**Definition 1.** The robust-control-relevant model set identification with respect to an existing controller \( C^{\exp} \) is the result of the optimization problem

\[
\mathcal{P}^{\text{RCR}} = \arg \min_{\mathcal{P}} J_{\text{WC}}(\mathcal{P}, C^{\exp}),
\]

subject to the constraint in (4), where \( \mathcal{P} \) is defined in (7).

To perform the actual optimization in Definition 1, the model set \( \mathcal{P} \) has to be the result of data. Clearly, it is desired that \( \hat{P} = P_\circ \) and \( \Delta_u = 0 \). However, the nominal model \( \hat{P} \) is necessarily an approximation for any physical system. Hence, the use of a model set \( \mathcal{P} \) is crucial.

2.4. Identification setup and approach

The identification setup in Fig. 2 is considered, where \( r_1, r_2 \) are manipulated signals and \( u, y \) are measured signals. In addition, \( C^{\exp} \) is a known, stabilizing controller. The superscript \( \exp \) is occasionally omitted to simplify the notation. In addition, \( \epsilon \) is an additive signal that represents measurement disturbances and is defined precisely in Section 3.4.

As is motivated in Section 1, the model set \( \mathcal{P} \) is identified by subsequently (i) identifying a nominal model, followed by (ii) quantifying model uncertainty. As a result, both the nominal model (step i) and model uncertainty (step ii) should be aimed at identifying robust-control-relevant model sets in the sense of Definition 1. In the next section, a new connection between control-relevant identification of a nominal model and coprime factor identification is presented, leading to a new coprime factor realization of the model. Then, in Section 4, it is shown that when the identified robust-control-relevant coprime factorization is used to construct a new model uncertainty structure, then the nominal model identification and the model uncertainty jointly aim at identifying a robust-control-relevant model set in the sense of Definition 1.

3. Robust-control-relevant coprime factor identification

3.1. Control-relevant identification of a nominal model

The quality of approximate models depends on the goal. When restricting attention to a nominal model \( \hat{P} \), then the performance of any candidate system \( P \) can be bounded through application of the triangle inequality (Schrama, 1992), i.e.,

\[
\| P(C, \hat{P}, C) \| \leq \| P(C, \hat{P}) \| + \| \hat{P} - \hat{P} \| \| P(C, \hat{P}) \|, \quad (9)
\]

where \( \| \hat{P} \| \) is defined in (2). Evaluating (9) for \( P_\circ \) reveals that if the metric

\[
\| P(C, \hat{P}) \| \quad \| \hat{P} - \hat{P} \| \| P(C, \hat{P}) \|, \quad (10)
\]

is small, then \( \| \hat{P} - \hat{P} \| \approx \| P_\circ - \hat{P} \| \) and the distance between \( P_\circ \) and \( \hat{P} \) is small from a closed-loop perspective for an arbitrary controller \( C \). When evaluating (10) for the controller \( C^{\exp} \), Section 2.4, the following control-relevant identification criterion is obtained.

**Definition 2.** The control-relevant identification of a nominal model \( P \) with respect to an existing controller \( C^{\exp} \) is the result of the optimization problem

\[
\min_{\hat{P}} \| P(T(P_\circ, C^{\exp}) - T(\hat{P}, C^{\exp})) \|_{\infty}. \quad (11)
\]

Criterion (2) guarantees internal stability of the feedback loops corresponding to \( T(P_\circ, C^{\exp}) \) and \( T(\hat{P}, C^{\exp}) \), respectively. Indeed, since \( T(P_\circ, C^{\exp}) \in \mathcal{H}_\infty \) by assumption, potential unstable modes in \( T(\hat{P}, C^{\exp}) \) cannot cancel out in the difference in (11).

The criterion (11) is at the heart of common iterative identification and control approaches, including (Albertos & Sala, 2002; Gevers, 1993; Schrama, 1992). These approaches are solely based on nominal models and alternate between minimizing the two terms on the right hand side of (9). A severe criticism of these
approaches is that these are not guaranteed to converge. Indeed, due to the iterative procedure, the controller $C$ is updated, whereas the bound in (9) holds for a single $C$. In contrast, in this paper it is shown that the nominal model resulting from the criterion (11) can effectively be used to construct a robust-control-relevant model set, which can possibly be used in an iterative scheme with guaranteed convergence.

3.2. Towards coprime factor identification

To anticipate on robust control design, the constraint (4) needs to be satisfied when extending the control-relevant nominal model $\hat{P}$, see (11), with model uncertainty $\Delta_u \in \Delta_u$. This imposes severe constraints on the model uncertainty structure, see $\hat{H}$ in (7), since analysis of (11) reveals that boundedness of the norm implies $\hat{P}$ and $C$ are stable. However, no statements can be made with respect to open-loop stability or the minimum phase character of both $P_o$ and $\hat{P}$. As a result, standard (inverse) additive or multiplicative model uncertainty structures cannot be used to guarantee (4), as is exemplified next.

Example 1. Let $P_o$ and $\hat{P}$ be simultaneously stabilized by $C$ and (i) $P_o \not\in \mathcal{RH}_\infty$ and $\hat{P} \in \mathcal{RH}_\infty$. Then, an additive uncertainty model $\Delta_u = \{P|P = \hat{P} + \Delta_u, \|\Delta_u\|_\infty \leq \gamma\}$, leads to $P_o \not\in \mathcal{P}_\gamma, \forall \gamma \in \mathbb{R}_+$. To guarantee that the constraint (4) holds for a certain $\Delta_u$-norm-bounded perturbation in the case of both uncertain open-loop unstable poles and unbounded zeros, a coprime factorization-based model uncertainty structure is considered. In this case, let

$$\Delta_u = [\Delta_u^N \Delta_u^D]^T, \quad (12)$$

let $[\hat{N}, \hat{D}]$ be an RCF of $\hat{P}$, and consider the model set

$$\{P|P = (\hat{N} + \Delta_N)(\hat{D} + \Delta_D)^{-1}, \|\Delta_u\|_\infty \leq \gamma\}. \quad (13)$$

In this case, it is straightforward to verify that (4) holds for a certain $\gamma \in \mathbb{R}_+$. The preceding discussion reveals that the internal structure of $\hat{P}$ based on coprime factorizations is essential to guarantee that the constraint (4) holds for a certain norm-bound. Although this fact has been observed in the system identification for control literature, as is evidenced by the results in Gu (1999), Date and Vinnicombe (2004), Van den Hof et al. (1995) and Zhou and Xing (2004), this is not taken into account in the control-relevant criterion (11) that only involves the input–output behavior of the model. To show this, let $[\hat{N}, \hat{D}]$ be an RCF of $\hat{P}$. Then, the set of all RCFs of $\hat{P}$ is generated by

$$\{[\hat{NQ}, \hat{DQ}]|Q, Q^{-1} \in \mathcal{RH}_\infty\}. \quad (14)$$

hence there is freedom in the choice of coprime factorization of $\hat{P}$. In fact, (14) reveals that infinitely many RCFs of $\hat{P}$ exist. Next, observe that the control-relevant identification criterion (11) for a coprime factorization in the set (14) is given by

$$\|W(T(P_o, C) - T(Q \hat{DQ})^{-1}, C)\|_\infty. \quad (15)$$

The result (15) directly reveals that the criterion (11) is invariant under a change of coprime factorization. In the next section, a novel connection between control-relevant identification and coprime factor identification is presented. The key technical result is a new robust-control-relevant coprime factorization that leads to a new model uncertainty structure in Section 4.

3.3. Robust-control-relevant coprime factor identification

In Section 3.1, a motivation for identification of control-relevant nominal models is given, whereas the use of coprime factorization-based model uncertainty structures is advocated in Section 3.2. However, (15) revealed that criterion (11) is invariant under a change of coprime factorization. Hence, from a control-relevant perspective of a nominal model, see Definition 2, there is no preference for a specific realization. In, e.g., Van den Hof et al. (1995), an approach is presented that exploits the nonuniqueness of coprime factorizations to identify normalized coprime factors. Such normalized coprime factorizations can directly be used in the robust control procedure in McFarlane and Glover (1990). In addition, these normalized coprime factorizations have a McMillan degree that is upper bounded by the McMillan degree of the underlying model $\hat{P}$. In contrast to the identification of normalized coprime factors, the aim of this paper is to exploit the freedom in coprime factorizations to establish a further connection with system identification for robust control. The following definition is essential in the subsequent derivations.

Definition 3. The pair $[\hat{N}, \hat{D}]$ is called an LCF of $[CV_2 V_1]$ with co-inner numerator if it is an LCF of $[CV_2 V_1]$ and, in addition, $\hat{N}\hat{N}^* = I$. An LCF with co-inner numerator of $[CV_2 V_1]$ exists if and only if $[CV_2 V_1]$ has no zeros on $\mathbb{B}$, see, e.g., Chu (1988), which is satisfied under the assumptions that are posed in this paper; see Remark 2. The following theorem, in conjunction with Theorem 2, is the main result of this section. This result provides a novel connection between control-relevant identification of a nominal model, see Definition 2, and coprime factor identification through the introduction of a new coprime factorization.

Theorem 1. Let $[\hat{N}_e, \hat{D}_e]$ be an LCF of $[CV_2 V_1]$ with co-inner numerator, where $\hat{N}_e = [\hat{N}_{e2} \hat{N}_{e1}]$ is partitioned accordingly. Then, (11) is equivalent to

$$\min_{\hat{N}, \hat{D}} \|W\left([\hat{N}_o \hat{D}_o] - [\hat{N} \hat{D}]\right)\|_\infty, \quad (16)$$

where

$$\hat{N}_o \hat{D}_o = \begin{pmatrix} p & \hat{N}_e CV_2 V_1^{-1} - I \end{pmatrix} \begin{pmatrix} \hat{D}_e + \hat{N}_{e2} V_2^{-1} \hat{P}_o \end{pmatrix}^{-1} \quad (17)$$

Proof. Let $[\hat{N}_e, \hat{D}_e]$ be any LCF of $[CV_2 V_1]$. Then,

$$\begin{align*}
WT(P, C) V &= W\begin{pmatrix} p & \hat{N}_e CV_2 V_1^{-1} - I \end{pmatrix} \begin{pmatrix} \hat{D}_e + \hat{N}_{e2} V_2^{-1} \hat{P}_o \end{pmatrix}^{-1} \quad (18)
\end{align*}$$

Substitution of (19) into (11), using $CV_2 = \hat{D}_e^{-1} \hat{N}_e$ and rearranging yields: $\min_{\hat{N}, \hat{D}} \|W\left([\hat{N}_o \hat{D}_o] - [\hat{N} \hat{D}]\right)\|_\infty$. Next, $\|XY\|_\infty = \|X\|_\infty \|Y\|_\infty$ when $Y$ is co-inner. By considering an LCF with co-inner numerator $[\hat{N}_e, \hat{D}_e]$ of $[CV_2 V_1]$ immediately yields the desired result in (16).

Theorem 2. Let $T(P, C) \in \mathcal{RH}_\infty$ and let $[\hat{N}_e, \hat{D}_e]$ be an LCF of $[CV_2 V_1]$, with $\hat{N}_e = [\hat{N}_{e2} \hat{N}_{e1}]$. Then,
The coprime factorizations \( g \)-gated. First, uniqueness is investigated. Section 4. Relevant system identification and the identification of coprime factorizations is limited to the class of constant unitary matrices. This has important consequences when comparing the coprime factorizations in Theorem 3. Indeed, let \( \hat{N}, \hat{D} \) be as defined in Theorem 1, then \( \hat{N}^{*} \hat{N} + \hat{D}^{*} \hat{D} = Z \), and assume that \( (\hat{N}, \hat{D}) \) are not normalized, i.e., \( Z \neq 1 \). Since \( \hat{N}, \hat{D} \) is a constant unitary matrix, it is clearly not a stable and minimum phase spectral factor of \( Z \). As a result, the freedom in \( Q \) cannot be exploited to normalize \( (\hat{N}, \hat{D}) \).

Remark 1. A similar dimension reduction as in Theorem 1 can be achieved for different coprime factorizations, including NRCFs. Hereto, observe that if the pair \( (\hat{N}, \hat{D}) \) is a robust-control-relevant coprime factorization of \( \hat{P} \), then \( \exists Q, \hat{Q}^{-1} \in \mathcal{RH}_{\infty} \) such that \( (\hat{N}, \hat{D}) \hat{Q} = (\hat{N}, \hat{D}) \hat{Q} \) is a NRCF of \( \hat{P} \), where \( \hat{Q} \) is unique modulo a constant unitary matrix. Then, (16) is equivalent to \( \min_{\hat{Q} \in \mathcal{RH}_{\infty}} \| W \left( \begin{bmatrix} N_o \\ D_o \end{bmatrix} \right) \hat{Q} - \left( \begin{bmatrix} N_i \\ D_i \end{bmatrix} \right) \hat{Q} \|_{\infty} \). Where \( \hat{Q} \) is the role of weighting filter. Although the complexity also reduces, it is emphasized that NRCFs lack the advantages of robust-control-relevant coprime factorizations in Contribution C3 and C5.

3.4. Towards a frequency response-based algorithm

The control-relevant identification criterion (11) and consequently also (16) are not straightforward to solve due to the presence of the \( \mathcal{H}_{\infty} \)-norm. The pursued strategy to obtain a tractable identification problem is to exploit the frequency domain interpretation of the \( \mathcal{H}_{\infty} \)-norm, i.e., the maximum modulus theorem states that if \( G(\xi) \in \mathcal{RH}_{\infty} \), then

\[
\| G(\xi) \|_{\infty} = \sup_{\omega \in [0, \pi]} | G(\omega) |.
\]

(21)

The result (21) motivates the intermediate step of nonparametric frequency response function identification. In this case, the frequency response function of the true system is generally obtained on a discrete frequency grid \( \Omega \subseteq \mathbb{R} \), which is an immediate consequence of the use of finite time data sets. In contrast, the \( \mathcal{H}_{\infty} \)-norm in (21) is defined on a continuous frequency grid. Although identification methods, e.g., Chen and Gu (2000), are available that can deal with a discrete frequency grid by imposing certain assumptions regarding the true system, these methods typically lead to conservative results as is discussed in Vinnicombe (2001, Section 9.5.2).

In this section, an alternative procedure is pursued that is based on the following lemma.

Lemma 1. The optimization problem

\[
\min_{N, D} \sup_{\omega i \in \Omega} | W \left( \begin{bmatrix} N_o \\ D_o \end{bmatrix} \right) \hat{Q} - \left( \begin{bmatrix} N_i \\ D_i \end{bmatrix} \right) \hat{Q} \|_{\infty}.
\]

(22)

subject to \( T(\hat{P}, C) \in \mathcal{RH}_{\infty} \).

(23)

minimizes a lower bound of the \( \mathcal{H}_{\infty} \)-norm in (16).

The proof of Lemma 1 follows directly from (16) and (21). It is emphasized that the discrete frequency grid \( \Omega \) should be chosen sufficiently dense to guarantee that the lower bound (22) of (16) is tight.

To solve the optimization problem (22)–(23), the frequency response of the coprime factorization \( [N_o, D_o] \) for \( \omega i \in \Omega \) is required. This frequency response function can be identified through the following procedure.

Procedure 1. Perform the following sequence of steps:

(1) Identify \( T(P_o, C^{exp}) \) for \( \omega i \in \Omega \).

(2) Append \( T(P_o, C^{exp}) \) with weighting filters \( V \), as a result \( T(P_o, C^{exp})V \) is obtained for \( \omega i \in \Omega \).

(3) Right multiply \( T(P_o, C^{exp})V \) by \( \left[ \begin{bmatrix} N_o \\\ D_o \end{bmatrix} \right] \), yielding \( \left[ \begin{bmatrix} N_i \\\ D_i \end{bmatrix} \right] \) \( \hat{Q} \) for \( \omega i \in \Omega \).

To reduce the effects of finite time noisy observations, a suitable identification experiment should be designed to obtain a good estimate in Step 1. For many systems, a realistic assumption on \( v \) is given by \( v = He \), where \( H, H^{-1} \in \mathcal{RH}_{\infty} \), and \( e \) is a sequence of independent identically distributed random vectors. Consequently, the error in estimating \( T(P_o, C^{exp}) \) is circular complex normally distributed and the estimation error can be quantified solely through its variance; see Pintelon and Schoukens (2001, Theorem 14.25). One the one hand, the resulting variance error may be made negligibly small through an appropriate experiment design using periodic input signals \( r_2 \) and \( r_1 \) and collecting sufficiently large data sets. On the other hand, in the case where variance error is significant, then these can be taken into account, e.g., as in Pintelon and Schoukens (2001, Chapter 8).

A remaining aspect in the optimization problem (22)–(23) is the parameterization of \( [\hat{N}, \hat{D}] \) that is investigated in detail in the next section.

3.5. Parametric coprime factor identification

The coprime factorization \( [\hat{N}, \hat{D}] \) needs to be appropriately parameterized to perform the actual optimization in (22)–(23). During the optimization, two constraints should be satisfied: (i) \( [\hat{N}, \hat{D}] \in \mathcal{RH}_{\infty} \) for the pair \( [\hat{N}, \hat{D}] \) to be an RCF over \( \mathcal{RH}_{\infty} \), and (ii) \( T(\hat{P}, C) \in \mathcal{RH}_{\infty} \); see (23). The main contribution of this section is a novel parameterization that connects the two stability constraints. Hereto, let

\[
\hat{P}(\theta) = B(\theta) A(\theta)^{-1},
\]

(24)

where \( A(\theta) \in \mathbb{R}[\xi]_{n_o \times n_0}, B(\theta) \in \mathbb{R}[\xi]_{m_o \times n_0}, \) and \( \theta \) is a real-valued parameter vector. If \( A(\theta) \) and \( B(\theta) \) are coprime polynomial matrices, then the McMillan degree of \( \hat{P} \) equals \( \text{deg det } A \). An example of a suitable parameterization is the full polynomial matrix fraction description that can directly be used to represent strictly proper
systems and enables the straightforward formulation of polynomial matrices that are linear in its coefficients.

Next, the coprime factorization \( \{\hat{N}, \hat{D}\} \) is parameterized by substituting (24) into (18), leading to

\[
\begin{bmatrix} \hat{N}(	heta) \\ \hat{D}(	heta) \end{bmatrix} = \begin{bmatrix} B(\theta) \\ A(\theta) \end{bmatrix} (D_A(\theta) + \hat{N}_c V^{-1} B(\theta))^{-1}.
\]  
(25)

The main advantage of explicitly introducing the knowledge of the weighting filters \( V_1, V_2 \) and the controller \( C_{\text{esp}} \), which is defined in Section 2.4, in the parameterization in (25) is that it enables a connection between the two stability conditions, above, as is formalized next.

**Theorem 4.** Consider parameterization (25). Then, \( T(\hat{P}(\theta), C) \in \mathcal{R} \mathcal{H}_\infty \) if and only if \( \hat{N}(\theta), \hat{D}(\theta) \in \mathcal{R} \mathcal{H}_\infty \).

Theorem 4 facilitates the design of an identification algorithm, see, e.g., Oomen and Bosgra (2008) for a closed-loop generalization of Lawson, Sanathanan–Koerner, and Gauss–Newton iterations. Summarizing, the nonparametric and parametric identification results in Sections 3.4 and 3.5, respectively, jointly constitute Contribution C4.

### 3.6. State-space results

In this section, essential results are presented that enable the analysis of the McMillan degree of the robust-control-relevant coprime factorization and the construction of a model uncertainty structure in Section 4. These state-space results constitute Contribution C5. The following theorem is the main result of this section.

**Theorem 5.** Given minimal state-space realizations \( (A, B, C, D) \) of \( C \), \( (A_2, B_2, C_2, D_2) \) of \( V_2 \), \( (A_1, B_1, C_1, D_1) \) of \( V_1 \) let \( L_e \) denote the output injection and \( M_2 \) output transformation matrix corresponding to the LCF with co-inner numerator of \( [C V_2 V_1] \), and let \( (A_p, B_p, C_p, D_p) \) be a state-space realization of \( \hat{P} \). Then, a state-space realization of \( \{\hat{N}^T \hat{D}^T\}^T \) is given by \( (A_{WD}, B_{WD}, C_{WD}, D_{WD}) \), where

\[
A_{WD} = \begin{bmatrix} A_1 + B_1 (l - D_1 D_1)^{-1} D_2 C_p & B_1 (l - D_1 D_1)^{-1} C_c \\ B_2 (l - D_1 D_1)^{-1} D_2 C_c & A_1 + B_1 (l - D_1 D_1)^{-1} D_2 C_c \end{bmatrix},
\]

\[
B_{WD} = \begin{bmatrix} B_1 (l - D_1 D_1)^{-1} D_1 & A_1 + B_1 (l - D_1 D_1)^{-1} D_2 C_c \\ C_1 & l - D_1 D_1 \end{bmatrix},
\]

\[
C_{WD} = \begin{bmatrix} C_1 & l - D_1 D_1 \end{bmatrix},
\]

\[
D_{WD} = \begin{bmatrix} D_1 & l - D_1 D_1 \end{bmatrix}.
\]

and

\[
\begin{bmatrix} A_z & B_z C_2 \\ D_z & D_z \end{bmatrix} = \begin{bmatrix} A_c & B_c C_2 & 0 \\ 0 & A_2 & 0 \\ 0 & 0 & A_1 \\ C_2 & D_z & C_1 \end{bmatrix} \left[ \begin{array}{c} -L_{M_z}^{-1} - B_z \\ 0 \\ 0 \end{array} \right],
\]

\[
M_z^{-1} = \begin{bmatrix} D_z & & & \\ & -D_z & & \\ & & -D_z & \\ & & & \end{bmatrix}.
\]

and \( M_z \) and \( L_z \) are defined as in Lemma 4 in Appendix C.

**Remark 2.** The output injection matrix and output transformation matrix corresponding to the LCF \( \{\hat{N}_e, \hat{D}_e\} \) of \( [C V_2 V_1] \), see also Lemma 4 in Appendix C, can be computed by solving an algebraic Riccati equation and can be determined by considering the dual problem to the results in Chu (1988) and references therein. The assumption \( V_1, V_1^{-1} \in \mathcal{R} \mathcal{H}_\infty \) guarantees the existence of an LCF \( \{\hat{N}_e, \hat{D}_e\} \) with \( \hat{N}_e N_e^c = I \).

**Theorem 5** reveals that the McMillan degree of \( \{\hat{N}^T \hat{D}^T\}^T \) is bounded by the sum of the McMillan degrees of \( \hat{P}, C, V_2, \) and \( V_1 \). Although coprime factorizations exist that have a McMillan degree that is bounded by the McMillan degree of \( \hat{P} \), see Vinnicombe (2001), the incorporation of the dynamics in \( C, V_2, \) and \( V_1 \) leads to a specific internal structure of the model that enables the construction of a new model uncertainty structure that has distinct advantages in view of Definition 1, as is shown in the next section. It is emphasized that due to the specific parameterization that is employed in (25), the additional dynamics that are introduced by \( C, V_2, \) and \( V_1 \) cancel out exactly when computing \( \hat{P} = N \hat{D}^{-1} \). Consequently, the internal structure of the model does not affect the input–output behavior of \( \hat{P} \).

### 4. Robust-control-relevant model uncertainty structure

In the previous section, the first step towards solving the system identification for the robust control problem was established by connecting control-relevant system identification and the identification of coprime factorizations through a new robust-control-relevant coprime factorization. In this section, the second and final step towards solving the system identification for the robust control problem is taken by constructing a new model uncertainty structure. A key technical result to enable this is first established in Section 4.1. Then, limitations of existing model uncertainty structures are presented in Section 4.2. The new model uncertainty structure that, in conjunction with the control-relevant nominal model, solves the system identification for the robust control problem is presented in Section 4.3.

#### 4.1. \( (W_u, W_y) \)-normalized coprime factorizations

In this section, a new coprime factorization is introduced that, in conjunction with the coprime factorization in Section 3.3, is used to construct a model uncertainty structure that directly connects to the control criterion. This factorization is referred to as a \( (W_u, W_y) \)-normalized coprime factorization and state-space results are presented for the actual computation, thereby constituting Contribution C6 of this paper.

**Definition 4.** The pair \( \{N_e, D_e\} \) is a \( (W_u, W_y) \)-normalized RCF of \( C \) if it is an RCF of \( C \) and, in addition,

\[
\begin{bmatrix} W_u N_e \\ W_y D_e \end{bmatrix} = \begin{bmatrix} W_u N_c \\ W_y D_c \end{bmatrix} = I.
\]

The following result addresses uniqueness of \( (W_u, W_y) \)-normalized RCFs.

**Theorem 6.** A \( (W_u, W_y) \)-normalized RCF of \( C \) is unique modulo a right multiplication by a constant unitary matrix \( Q \).

The following results enable the computation of such a \( (W_u, W_y) \)-normalized coprime factorization.

**Theorem 7.** Given the discrete time systems \( W_u, W_y, \) and \( C \), where \( W_u, W_y, W_y^{-1} \in \mathcal{R} \mathcal{H}_\infty \) and minimal state-space realizations \( (A_u, B_u, C_u, D_u) \) of \( W_u, (A_y, B_y, C_y, D_y) \) of \( W_y^{-1}, \) and \( (A_c, B_c, C_c, D_c) \) of \( C, \) then a \( (W_u, W_y) \)-normalized RCF \( \{N_e, D_e\} \) of \( C \) is given by the state-space realization

\[
\begin{bmatrix} D_e \\ N_e \end{bmatrix} = \begin{bmatrix} A + BF \\ C + DF \end{bmatrix} \begin{bmatrix} BG \end{bmatrix},
\]

where
\[ G = Z^{-1}, \quad F = -Z^{-1}(B^*XA + D^*C), \]
\[ Z = R + B^*XB. \]

\( X \) is the unique, positive semi-definite solution to the algebraic Riccati equation
\[ \tilde{A}^*X\tilde{A} - X - \tilde{A}^*XB(B^*XB + R)^{-1}B^*X\tilde{A} + Q = 0, \]
and
\[ \tilde{A} = A - B^*R^{-1}D^*C, \quad Q = C^*R^{-1}C. \]

**Theorem 8.** Let \( \hat{P} \) be internally stabilized by \( C^{\exp} \) and let \( (\hat{N}, \hat{D}) \) and \( \{N_\ell, D_\ell\} \) be an RCF of \( \hat{P} \) and \( C^{\exp} \), respectively. Then, the class of all systems \( P \) that are internally stabilized by \( C^{\exp} \) is given by
\[ \mathcal{P}^{\text{DV}} = \{P | P = (\hat{N} + D_\ell \Delta_\ell)(\hat{D} - N_\ell \Delta_\ell)^{-1}, \Delta_\ell \in \mathcal{H}_\infty \}. \]

The proof of Theorem 8 is dual to the proof of the Youla–Kučera-\( \mathcal{H}_\infty \)-parameterization of all controllers that stabilize a certain system by interchanging \( P \) and \( C^{\exp} \). When comparing (13) and (32), the refinement involves a connection between the perturbations \( \Delta_\ell \) and \( \Delta_0 \) through a coprime factorization of the stabilizing controller \( C = N_\ell D_\ell^{-1} \). Typically, the model uncertainty structure (32) is used in conjunction with a certain norm-bound \( \gamma \) to satisfy (4), i.e.,
\[ \Delta_\ell = \{\Delta_\ell \mid \Delta_\ell \| \leq \gamma \}. \]

When evaluating the worst-case performance for the model set defined by (32) and (33), this leads to
\[ \mathcal{J}_{\text{WC}}(\mathcal{P}, C^{\exp}) = \sup_{\Delta_\ell \in \mathcal{A}_\ell} \| \hat{M}_{22} + \hat{M}_{21} \Delta_\ell \hat{M}_{12} \|. \]

The affine dependence of \( \mathcal{J}_{\text{WC}} \) on \( \Delta_\ell \) guarantees that the LFT is well-posed for all \( \Delta_\ell \in \mathcal{A}_\ell \), and consequently \( \mathcal{J}_{\text{WC}} \) remains bounded. This advantage from a robust stability perspective is well-established. However, the analysis from a performance perspective is less obvious, since in general \( \hat{M}_{21} \) and \( \hat{M}_{12} \) are multivariable and frequency dependent. This is resolved in Section 4.3 by introducing a new uncertainty structure that connects the size of model uncertainty and the control criterion.

### 4.3. Enabling system identification for robust control through a new model uncertainty structure

In this section, the second and final step towards solving the system identification for the robust control problem is taken by establishing a new model uncertainty structure that transparently connects to the control criterion. The key idea is to employ the robust-control-relevant coprime factorization of \( \hat{P} \) in (18) in conjunction with the \( \{W_\ell, W_\ell^{-1}\} \)-normalized coprime factorization of \( C^{\exp} \) in (28). The following theorem constitutes Contribution C7 of the paper and reveals that the procedure presented in this paper provides a solution to the system identification for the robust control problem.

**Theorem 9.** Consider the model set in (32) and (33), where \( (\hat{N}, \hat{D}) \) satisfies (18), and \( \{N_\ell, D_\ell\} \) satisfies (28). Then, the worst-case performance is bounded by
\[ \mathcal{J}_{\text{WC}}(\mathcal{P}, C^{\exp}) \leq \mathcal{J}(\hat{P}, C^{\exp}) + \gamma. \]
\[ \hat{M} = \begin{bmatrix} \hat{M}_{11} & \hat{M}_{12} \\ \hat{M}_{21} & \hat{M}_{22} \end{bmatrix} \\
= \begin{bmatrix} W \hat{D}_c & -W \hat{N}_c \\ 0 & \hat{N}_{e2} \hat{N}_{e1} \end{bmatrix} \left( I + \hat{P} \right) \left( I + C \hat{P} \right)^{-1} [C \hat{I} V] \tag{35} \]

With respect to \( \hat{M}_{12} \), (18) leads to

\[ \hat{M}_{12} = (\hat{D} + C \hat{N})^{-1} [C \hat{I} V] = \hat{N}_{e2} \hat{N}_{e1} \]

Next, substitution of (35) into the LFT (31) and application of the triangle inequality yields

\[ \| \mathcal{F}_2(\hat{M}, \Delta_u) \|_\infty \leq \| \hat{M}_{22} \|_\infty + \| \hat{M}_{21} \Delta_u \hat{M}_{12} \|_\infty. \tag{36} \]

Observing that \( \hat{M}_{21} \) and \( \hat{M}_{12} \) are inner and co-inner, respectively, implies that \( \exists \hat{M}_{21}, \hat{M}_{12} \) such that \( [\hat{M}_{21}, \hat{M}_{12}] \in \mathcal{RH}_\infty \) are all-pass transfer function matrices. Next, observing that (36) equals

\[ \| \hat{M}_{22} \|_\infty + \| \hat{M}_{21} \hat{M}_{12} \|_\infty \]

and employing the norm-preserving property of all-pass matrices and noting that \( \| \Delta_u \|_\infty \leq \gamma \) for all \( \Delta_u \in \Delta_u \) immediately reveals the desired result in (34).

The result of Theorem 9 provides a transparent connection between the size of model uncertainty \( \gamma \) on the one hand and the worst-case performance criterion \( \mathcal{J}_{\text{MC}}(P, C^{\text{exp}}) \) on the other hand. Intuitively, this result reveals that the control-relevant nominal model \( \hat{P} \), see Theorem 1, and the model uncertainty structure in Theorem 9 jointly aim at identifying a robust-control-relevant model set in view of Definition 1.

An important aspect in Theorem 9 is that the considered model uncertainty \( \Delta_u \), see (33), is an unstructured set. Hence, the proposed approach enables the use of unstructured model uncertainty, see Contribution C7. This is an important extension of dual-Youla–Kučera-based model uncertainty, since prior applications, including (de Callafon and Van den Hof, 2001), resorted to a structured model uncertainty formulation in attempts to reduce conservatism. The use of unstructured uncertainty has significant advantages for the complexity and conservativeness of certain uncertainty quantification procedures, see Toker and Chen (1998), and robust control; see Doyle (1982). In this respect, the result of Theorem 9 can be interpreted as a scaling of the model uncertainty channels with respect to the control criterion.

5. Example

Consider the true system \( P_o \) with McMillan degree 6 in Fig. 3. Closed-loop frequency response functions \( T(P_o, C^{\text{exp}}) \) are identified with a stabilizing \( C^{\text{exp}} \) implemented on the system; see Fig. 4. In addition, \( W \) and \( V \) in (2) according to the procedure in McFarlane and Glover (1990).

In view of Procedure 1, \( T(P_o, C^{\text{exp}}) \) is appended with the weighting filters \( W \) and \( V \) and \( \left( \hat{N}_c, D_o \right) \) is computed for \( \hat{\gamma} \in \hat{\Omega} \); see Fig. 5. Next, a parametric coprime factorization \( [\hat{N}, \hat{D}] \) is determined that is control-relevant in view of Theorem 1 and Lemma 1; see Fig. 5. The parametric model \( \hat{P} = \hat{N} \hat{D}^{-1} \) is restricted to have a McMillan degree equal to 4, leading to undermodeling; see also Fig. 3. The resulting performance when the experimental controller \( C^{\text{exp}} \) is evaluated on the model \( \hat{P} \) equals \( \mathcal{J}(\hat{P}, C^{\text{exp}}) = 19.9 \).

Next, a model set \( \mathcal{P}^{\text{RCR}} \) is constructed using the results in Section 4. Hereto, a \( \{W_o, W_p\} \)-normalized coprime factorization of

\[ \text{Fig. 3. Model } \hat{P} \text{ (solid), true system } P_o \text{ (dashed), bounds on candidate model set } \mathcal{P}^{\text{RCR}} \text{ (dash–dotted), bounds on candidate model set } \mathcal{P} \text{ (dotted).} \]

\[ \text{Fig. 4. Identified } T(P_o, C^{\text{exp}}) \text{ (x), true closed-loop system } T(P_o, C^{\text{exp}}) \text{ (dashed).} \]

\[ \text{C}^{\text{exp}} \text{ is computed. This leads to the model uncertainty structure in Section 4. Hence, it remains to estimate the size of } \Delta_u \text{ to guarantee that (4) holds. For the sake of exposition, the dual-Youla–Kučera parameter corresponding to the true system, i.e., the } \Delta_u, \text{ that induces } P^\text{opt}_o \text{ in (32) is computed, leading to the bound } \gamma^{\text{RCR}} = \| \Delta_u, \|_\infty = 0.2. \text{ Next, a skewed structured singular value analysis reveals that } \mathcal{J}_{\text{MC}}(\mathcal{P}^{\text{RCR}}, C^{\text{exp}}) = 20.1. \text{ Clearly, the obtained values for } \mathcal{J}(\mathcal{P}, C^{\text{exp}}), \gamma^{\text{RCR}}, \text{ and } \mathcal{J}_{\text{MC}}(\mathcal{P}^{\text{RCR}}, C^{\text{exp}}) \text{ reveal that the bound in (34) holds and is tight. Hence, the model uncertainty indeed is estimated in a robust-control-relevant structure and consequently also a robust-control-relevant model set } \mathcal{P}^{\text{RCR}} \text{ is obtained.} \]

To confirm that \( \mathcal{P}^{\text{RCR}} \) enables the design of a high performance robust controller, (6) is computed, leading to \( \mathcal{J}_{\text{MC}}(\mathcal{P}^{\text{RCR}}, C^{\text{exp}}) = 2.7 \). Since the worst-case performance has been reduced by an order of magnitude. The question is whether \( C^{\text{exp}} \) was sufficiently close to \( C^{\text{opt}}(\mathcal{P}^{\text{RCR}}) \). Hereto, the true optimal performance is given by (1) and given by \( \mathcal{J}(P_o, C^{\text{exp}}) = 2.5 \). Since \( \mathcal{J}(P_o, C^{\text{exp}}) \approx \mathcal{J}_{\text{MC}}(\mathcal{P}^{\text{RCR}}, C^{\text{exp}}) \), the definition of robust-control-relevance in Definition 1 indeed is useful. Finally, a comparison is made with commonly used NRCFs (McFarlane & Glover, 1990; Vidyasagar, 1985; Vinnicombe, 2001). Hereto, \( \{N, D\} = \{NQ^{-1}, DQ^{-1}\} \) and \( \{\hat{N}_c, D_o\} = \{N_Q, D_Q\} \) of \( \hat{P} \) and \( C^{\text{exp}} \) are computed, with \( Q, Q^{-1} \in \mathcal{RH}_\infty \); see Fig. 5. This leads to a dual-Youla–Kučera model uncertainty structure based on normalized coprime factorizations; see (32). The norm bound on the dual-Youla–Kučera parameter to guarantee that (4) holds is given by \( \hat{\gamma} = 0.9 \). The resulting model set \( \mathcal{P} \) achieves a worst-case performance \( \mathcal{J}_{\text{MC}}(\mathcal{P}, C^{\text{exp}}) = 38.6 \), for which the bound (34) clearly does not hold. To corroborate the fact that \( \mathcal{P} \) is not robust-control-relevant in view of Definition 1, the model sets \( \mathcal{P}^{\text{RCR}} \) and
themodelset aregenerated;see Fig. 3 fortheresults.Clearly, theboundsfor $P$ arevisualized. Hereto, boundsontheBodemagnitudediagram discussionsregardinganearlydraftofthepaper.

$\tilde{P}$ arevisualized. Hereto, boundsonthe Bode magnitude diagram are generated; see Fig. 3 for the results. Clearly, the bounds for the model set $P^{RBC}$ are tight in the region that corresponds to the cross-over region of both the experimental controller $C^{Exp}$ of 10 [Hz] and the desired cross-over region of 25 [Hz]. These regions are known to be of high importance for control. In contrast, the model set $\tilde{P}$ is only accurate at the high frequent parasitic dynamics that are not relevant for control.

6. Conclusions

This paper addresses the system identification for the robust control problem. Existing results have employed coprime factorization-based uncertainty descriptions. However, these can unintentionally lead to conservative results that have not been well understood.

To avoid the conservatism and solve the system identification for the robust control problem, two main steps are taken in this paper. First, a new connection between control-relevant identification and the identification of coprime factorizations is developed, see Theorem 1, leading to a new robust-control-relevant coprime factorization that can be identified directly from data, see Procedure 1, and that is control-relevant in the sense of Definition 2. Second, a new coprime factor-based model uncertainty structure is presented that is based on the robust-control-relevant coprime factorization of Theorem 1 in conjunction with a new $(W_u,W_p)$-normalized coprime factorization, see Definition 4 and Theorem 7, leading to a transparent connection in Theorem 9 between the size of model uncertainty $\gamma$ and the control criterion $J(P,C)$. Thus, Theorem 9 reveals that the use of the proposed coprime factorizations avoids the introduction of conservatism and provides a solution to the considered system identification for the robust control problem. The improvements of the presented results compared to existing approaches are confirmed in a simulation example.

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Appendix A. Proofs of Section 3.3

The following auxiliary result is required to show that both $[N_u, D_u]$ and $[\hat{N}, \hat{D}]$ are in fact right coprime factorizations of $P_o$ and $\hat{P}$, respectively; see Theorem 2.

Lemma 3. Let $[CV_2 V_1]$ have full row rank and let $[\hat{N}_\gamma, \hat{D}_\gamma]$ be an LCF of $[CV_2 V_1]$, where $N_\gamma = [N_{\gamma,2} N_{\gamma,1}]$. Then, $N_{\gamma,2}$ and $N_{\gamma,1}$ are left coprime if and only if $[CV_2 V_1]$ has no transmission zeros in $\mathbb{C}$.

Proof. Suppose that $z_0 \in \mathbb{C}$ is a transmission zero of $[CV_2 V_1]$. Then, by virtue of Zhou et al. (1996, Lemma 3.28), $3u_0 \neq 0$ such that

$$u_0^*([CV_2 V_1](z_0) = 0.$$  

(A.1)

Since $[\hat{N}_\gamma, \hat{D}_\gamma]$ is an LCF of $[CV_2 V_1]$, $\hat{D}_\gamma, \hat{D}_\gamma \in \mathbb{S}_\infty$, hence (A.1) is equivalent to $u_0^*N_\gamma(z_0) = 0$. To show that $N_{\gamma,2}$ and $N_{\gamma,1}$ are not left coprime, recall that left coprimeness implies that $\exists Y_i$, $X_i \in \mathbb{S}_\infty$ such that

$$\hat{N}_{\gamma,2}Y_i + \hat{N}_{\gamma,1}X_i = 1.$$  

(A.2)

However, $Y_i$, $X_i \in \mathbb{S}_\infty$ implies that $Y_i(z_0)$ and $X_i(z_0)$ are finite. As a result,

$$u_0^*([\hat{N}_{\gamma,2} Y_i](z_0) + u_0^*([\hat{N}_{\gamma,1} X_i](z_0) = 0.$$  

Since no $Y_i$, $X_i \in \mathbb{S}_\infty$ exist that satisfy the Bézout identity (A.2), $N_{\gamma,2}$ and $N_{\gamma,1}$ are not left coprime if $[CV_2 V_1]$ has a transmission zero in $\mathbb{C}$. 

To show the converse, suppose that $[CV_2 V_1]$ does not have any transmission zeros in $\mathbb{C}$. Then, by left coprimeness of $[N_{\gamma,2}, N_{\gamma,1}]$, $N_\gamma$ does not have any transmission zeros in $\mathbb{C}$, i.e., there does not exist a $z_0 \in \mathbb{C}$ and a vector $u_0 \neq 0$ such that $u_0^*([N_{\gamma,2} N_{\gamma,1}](z_0) = 0$. Since such $z_0$ and $u_0$ do not exist, $\exists Y_i$, $X_i \in \mathbb{S}_\infty$ such that (A.2) holds, see, e.g., Vidyasagar (1985), hence $N_{\gamma,2}$ and $N_{\gamma,1}$ are left coprime.

Proof of Theorem 2. Suppose that $T(P, C) \in \mathbb{S}_\infty$, $V, V^{-1} \in \mathbb{S}_\infty$. Then, $V^{-1} \in \mathbb{S}_\infty$ implies that $V$ is invertible and thus $[CV_2 V_1]$ has full row rank. In addition, $V^{-1} \in \mathbb{S}_\infty$ implies that $V_1$ does not have any transmission zeros in $\mathbb{C}$, hence by virtue of Lemma 3, $N_{\gamma,2}$ and $N_{\gamma,1}$ are left coprime, i.e., $\exists Y_i$, $X_i \in \mathbb{S}_\infty$ such that

$$\hat{N}_{\gamma,2}Y_i + \hat{N}_{\gamma,1}X_i = 1.$$  

Hence, $T(P, C) \in \mathbb{S}_\infty$ implies $T(P, C) \in \mathbb{S}_\infty$.

Proof of Theorem 3. Let $[N_o, D_o]$ be defined as in Theorem 1. Then, all coprime factorizations are generated by $[N_o, D_o]$ for $Q, Q^{-1} \in \mathbb{S}_\infty$. Substituting of the coprime factorization $[N_o, D_o]$ into $WT(P, C)V$ yields $[N_o, D_o]Q^{-1}D_o$. Clearly, the latter expression can only be reduced from a four-block problem into a two-block problem if $Q^{-1}D_o$ is co-inner. If $D_o$ is co-inner, this implies that $Q^{-1}D_o(Q^{-1}D_o)^* = Q^{-1}(Q^{-1})^* = I$, hence $Q$ is a constant unitary matrix. A proof for $[N_o, D_o]$ follows along similar lines.

Appendix B. Proofs of Section 3.5

Proof of Theorem 4. Let $[\hat{N}_\gamma, \hat{D}_\gamma]$ be an LCF of $[CV_2 V_1]$, where $N_\gamma = [N_{\gamma,2} N_{\gamma,1}]$. Then, $N_{\gamma,2}$ and $N_{\gamma,1}$ are left coprime by virtue of Theorem 2. Hence, $\exists Y_i$, $X_i \in \mathbb{S}_\infty$ such that $N_{\gamma,2}Y_i + N_{\gamma,1}X_i = 1$. To show the if part, suppose that $T(\hat{P}(\theta), C) \in \mathbb{S}_\infty$. Substituting (24), this is equivalent to

$$\hat{B}(\theta) \hat{A}(\theta) + (\hat{A}(\theta)^* + CB(\theta))^{-1}[CV_2 V_1] \in \mathbb{S}_\infty.$$  

Fig. 5. Coprime factors: $N_u, D_u$ (×), $\hat{N}, \hat{D}$ (dashed), $\bar{N}, \bar{D}$ (dash-dotted).
with corresponding state vector \( x = [x_1^T \ x_2^T \ x_3^T]^T \), where \( x_c, x_2, \) and \( x_1 \) are the corresponding state vectors of \( C, V_2, \) and \( V_1 \), respectively.

Next, consider an output injection, resulting in \( \dot{x} = A_s x + B_s u + L_e (e + y) \) and define the transformed output \( \tilde{e} = M_e (e + y) \). Observe that by an appropriate selection of \( L_e \) and \( M_e \),

\[ \tilde{D}_e \tilde{N}_e,2 V_2^{-1} : [y^T \ u_i^T \ u_i^T] \mapsto \tilde{e} \]  

(D.1)

corresponds to an LCF with co-inner numerator of \([CV_2 \ V_1]\). See Remark 2. A state-space realization for (D.1) is given by

\[ \begin{bmatrix} A_e + L_c C_e & L_e & B_e + L_d D_e \\ \frac{M_e}{c} & I & M_d D_e \end{bmatrix}. \]

(D.2)

Considering Fig. D.1 again in conjunction with (D.1) and (D.2) reveals that \( \tilde{D}_e \tilde{N}_e,2 V_2^{-1} \) corresponds to the system \([y^T \ u_i^T \ u_i^T] \mapsto \tilde{e} \), see Fig. D.1, hence the desired state-space realization in (C.1) follows immediately. \( \square \)

Proof of Lemma 5.  

Observe from Lemma 4 that a state-space realization of \([I \ - \tilde{N}_e,2 V_2^{-1}]\) is given by

\[ \begin{bmatrix} A_e + L_c C_e & L_e & B_e - L_d D_e \\ \frac{M_e}{c} & I & -M_d D_e \end{bmatrix}. \]

By observing that a state-space realization of \( H^{-1} \) is given by \( H^{-1} = (A - BD^{-1}C, -BD^{-1}, D^{-1}C, D^{-1}) \), with \( D \) square and full rank, which can easily be verified since \( H^{-1}H = HH^{-1} = I \), a state-space realization of \( \tilde{D}_e^{-1} \) is given by

\[ \begin{bmatrix} A_e - L_e M_e^{-1} \\ C_e & M_e^{-1} \end{bmatrix} \]

Next, a state-space realization of the series connection of \([I \ - \tilde{N}_e,2 V_2^{-1}]\) and \( \tilde{D}_e^{-1} \) is given by

\[ \begin{bmatrix} A_e + L_c C_e & 0 & 0 & 0 \\ -L_e D_e - B_e \\ L_e M_e^{-1} M_c C_e & A_e - L_e M_e^{-1} D_e & L_e M_e^{-1} M_d D_e \\ M_e^{-1} M_c C_e & \frac{C_e}{M_e} & -M_e^{-1} M_d D_e \end{bmatrix} \]

(D.3)

Next, applying a state transformation \([I \ 0 \ 0 \ 0]^{-1}\) to the state-space realization in (D.3) and subsequently removing the unobservable states leads to the desired result in (C.2). \( \square \)

Appendix E. Proofs of Section 4.1

Proof of Theorem 6. Suppose that \([N_c, D_c] \) is a \((W_n, W_r)\)-normalized RCF of \( C \). Then, all coprime factorizations of \( C \) are generated by \([N_Q, D_Q], Q, Q^{-1} \in \mathcal{RH}_\infty \). In view of (28), these coprime factorizations are \((W_n, W_r)\)-normalized RCF iff \( Q^T Q = I \). \( \square \)

Proof of Theorem 7. First, consider the interconnected system in Fig. E.1, where a state-space realization of the system \( u_{ii} \mapsto e \) is given by

\[ \begin{bmatrix} A & B \\ \frac{M}{c} & D \end{bmatrix}, \]

with state vector \( x = [x_i^T \ x_c^T \ x_{yi}^T]^T \), where \( x_{a}, x_c, \) and \( x_{yi} \) are the state vectors corresponding to \( W_n, C, \) and
where $F$ and $G$ are matrices of appropriate dimensions. Then, a state-space realization of the system $\begin{bmatrix} D/A & C \\ D & D \end{bmatrix}$ is given by $\begin{bmatrix} A + BF \\ F \\ D \end{bmatrix}$. Clearly, by the specific choice of $F$ in (29), $A + BF$ is stable by construction, hence $N_r, D_r \in \mathcal{RH}_\infty$ and $C = N_rD_r^{-1}$. It remains to be shown that the pair $[N_r, D_r]$ indeed constitutes a $(W_0, W_r)$-normalized RCF of $C$. Here, consider the system $u_0 \mapsto y_0$ as defined in Fig. E.1, which has a state-space realization $\begin{bmatrix} A \\ F \\ C \end{bmatrix} = \begin{bmatrix} D & D \end{bmatrix}$. Using (E.1), $\begin{bmatrix} N_r \\ y_0 \\ y_0 \end{bmatrix}$ is given by $\begin{bmatrix} A + BF \\ F \\ G \end{bmatrix}$. It can directly be verified that the pair $[N_r, D_r]$ constitutes a normalized RCF of $W_0CW_r^{-1}$. Indeed, observe that (30) can be written as $\tilde{A}^*X(I + \tilde{B}^*X)^{-1}\tilde{A} - X = 0$, which corresponds to the algebraic Riccati equation in Zhou et al. (1996, Theorem 21.25) to compute a normalized coprime factorization. In addition, this also reveals that a unique, positive semi-definite solution to (E.2) exists. Next, to show that $[N_r, D_r]$ is an RCF, observe that coprimeness of $N_r, D_r$ implies $\exists X_r, Y_r, Y_0 \in \mathcal{RH}_\infty$ satisfying $X_r \nu_0 = Y_r u + Y_0 w = I$. Next, let $X_r = X_r w_0$ and $Y_r e = Y_r w_0$, hence $X_r, Y_r \in \mathcal{RH}_\infty$. Observing that $N_r = W_0^{-1}N_0$ and $D_r = W_0^{-1}D_0$, and using (E.3) reveals that $X_r \nu_0 + Y_r e = I$, hence the pair $[N_r, D_r]$ indeed is an RCF. To show that $[N_r, D_r]$ is a $(W_0, W_r)$-normalized RCF of $C$, note that $[W_0N_r, W_0D_r] = [N_r, D_r]$. Hence (28) is satisfied and $[N_r, D_r]$ is a $(W_0, W_r)$-normalized RCF of $C$.

References


Tom Oomen received the M.Sc. degree (cum laude) and the Ph.D. degree from the Eindhoven University of Technology, Eindhoven, The Netherlands, in 2005 and 2010, respectively. He was awarded the Corus Young Talent Graduation Award in 2005. Presently, he is with the Department of Mechanical Engineering at the Eindhoven University of Technology. He held visiting positions at the KTH, Stockholm, Sweden and at The University of Newcastle, Newcastle, Australia. His research interests are in the field of identification and robust control, with applications in high-precision mechanical servo systems.

Okko Bosgra obtained his M.S. degree with research diploma from Delft University of Technology, The Netherlands. From 1980 to 1985 he was the professor of systems and control at Wageningen University, and since 1986 he has chaired the Mechanical Engineering Systems and Control Group at Delft University of Technology. Since 2003 he has held a joint appointment at Eindhoven University of Technology, The Netherlands. His research interests are in applications of robust control and system identification to the areas of process control and motion control.