

# A method of optimal system identification with applications in control

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Eindhoven University of Technology  
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A Method of Optimal System  
Identification with Applications in  
Control

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# A Method of Optimal System Identification with Applications in Control

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## Abstract

In this paper an optimal deterministic identification problem is solved in which a new measure for the misfit between data and system is minimized. It is shown that the misfit can be expressed as the Hankel norm of a specific operator. Optimal autonomous models are obtained by factorizing an optimal Hankel norm approximant of the Laplace transformed data matrix. An upperbound on the misfit between model and data is derived for a class of non-autonomous models of prescribed complexity. The identified autonomous systems are viewed as closed-loop behaviors of a feedback interconnection of two systems. Stability of these feedback interconnections is discussed.

## Key Words

optimal system identification, stabilization, linear systems, behaviors

## 1 Introduction

In the usual methods of system identification uncertainty of models is expressed as uncertainty in the parameters defining the model. In traditional axiomatic

frameworks this uncertainty is given a stochastic interpretation in the sense that deviations of nominal parameter values are modeled by prescribed probability distributions. The recent interest in deterministic techniques to quantify model uncertainty stems mainly from the present inability of robust control theory to cope with probabilistic assumptions on estimated model parameters.

A mathematical description of model uncertainty requires a quantification of a distance measure between models. In the context of deterministic system identification a distance measure needs to be specified between observed data and models belonging to an a priori specified set of candidate models. It is important that this misfit criterion is chosen independent of the parametrization of the model class and independent of the way individual models are represented. As such, parametrization and representation issues should be clearly separated from the model identification problem.

In the present paper we consider a deterministic identification problem using model sets of prescribed complexity. We restrict attention to the class of linear time-invariant systems and introduce a misfit criteria for the distance between data and elements in this model class. The proposed misfit function is independent of model representations and is characterized as the Hankel norm of an operator which is determined by the data and a specific (co-inner) kernel representation of the model. Optimal approximate models with prescribed complexity are characterized in this

way.

In the last section of this paper we will view these optimal models as the closed-loop behavior of a plant-controller feedback interconnection. Internal stability of these interconnections is characterized in an input-output independent context and it is shown how the class of all stabilizing controllers for a given plant (or the class of all plants stabilized by a given controller) can be parametrized.

## 2 Models and data

Consider a finite set of observed time series

$$\tilde{w}_i : \mathbb{Z}_+ \longrightarrow W, \quad i = 1, \dots, n \quad (2.1)$$

where  $W$  denotes the *signal space* which is assumed to be a  $q$  dimensional real vector space, i.e.,  $W = \mathbb{R}^q$ . We address the problem to identify linear time-invariant systems that model these time series.

Let  $l_2(\mathbb{Z}_+, \mathbb{R}^q)$  (or  $l_2^+$  for short) denote the set of time series  $w : \mathbb{Z}_+ \rightarrow \mathbb{R}^q$  for which  $\|w\|_2^2 := \sum_{t \in \mathbb{Z}_+} w^T(t)w(t) < \infty$ . It is assumed throughout that  $\tilde{w}_i \in l_2^+$  for all  $i = 1, \dots, n$ .

**Definition 2.1** An  $l_2$  system is a system  $\Sigma = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B})$  with time set  $\mathbb{Z}_+$ , signal space  $\mathbb{R}^q$  and behavior  $\mathcal{B} \subseteq l_2(\mathbb{Z}_+, \mathbb{R}^q)$ .

Denote by  $\mathcal{S}_2^q$  the class of all  $l_2$  systems  $\Sigma = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B})$  defined on the time set  $\mathbb{Z}_+$  whose behavior  $\mathcal{B} \subseteq l_2^+$  is a linear shift-invariant and closed subset of  $l_2(\mathbb{Z}_+, \mathbb{R}^q)$ . This class of linear time-invariant systems has been extensively studied in the work of Willems [8] and Heij [5] and corresponds to the class of systems whose behavior can be represented as the  $(l_2^+)$ -kernel of a finite number of polynomial difference equations in the system variables or, alternatively, as the  $(l_2^-)$  solution space of a linear time-invariant state space system with finite dimensional state space.

**Definition 2.2** A system  $\Sigma \in \mathcal{S}_2^q$  is said to be *autonomous* if there exists  $t \in \mathbb{Z}_+$  such that the mapping  $\pi : \mathcal{B} \rightarrow \mathcal{B}|_{[1,t]}$  defined by the restriction  $\pi_t(w) := w|_{[1,t]}$  is injective.

**Definition 2.3** A system  $\Sigma = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B})$  is *unfalsified* by the data (2.1) if  $\tilde{w}_i \in \mathcal{B}$  for  $i = 1, \dots, n$ . We call a system  $\Sigma_1 = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B}_1)$  *more powerful* than  $\Sigma_2 = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B}_2)$  if  $\mathcal{B}_1 \subseteq \mathcal{B}_2$ .

This defines a partial order  $\subseteq$  on systems in  $\mathcal{S}_2^q$  by defining  $\Sigma_1 \subseteq \Sigma_2$  if  $\Sigma_1$  is more powerful than  $\Sigma_2$ . Equivalently,  $\Sigma_1$  will be called a *subsystem* of  $\Sigma_2$  if  $\Sigma_1 \subseteq \Sigma_2$ . The *most powerful unfalsified system* (for the data (2.1)) is that system  $\Sigma_{\text{MPUM}} \in \mathcal{S}_2^q$  which is unfalsified by (2.1) and which is more powerful than any other  $\Sigma \in \mathcal{S}_2^q$  which is unfalsified by (2.1). In the following we use the fact that  $\Sigma_{\text{MPUM}} \in \mathcal{S}_2^q$  exists and is unique for any set of time series (2.1) which belong to  $l_2^+$ . See [5, 8, 9].

## 3 Models for data

In this section we address the question to characterize all systems  $\Sigma \in \mathcal{S}_2^q$  which are unfalsified by the data (2.1).

Define the Laplace transform of the data sequences  $\tilde{w}_i$  by putting

$$W(z) := \tilde{W}(1)z^{-1} + \tilde{W}(2)z^{-2} + \dots \quad (3.1)$$

where  $z \in \mathbb{C}$  and  $\tilde{W}(t) := [\tilde{w}_1(t) \dots \tilde{w}_n(t)]$ ,  $t \in \mathbb{Z}_+$  denotes the data matrix. We will assume the following.

**Assumption 3.1**  $W(z)$  is rational and analytic for all  $z \in \mathbb{C}$  with  $|z| < 1$ .

Specific examples of data sets that satisfy assumption 3.1 include finite sets of frequency response measurements, spectral data, or polynomial-exponential data series. See [6] for a methodology to approximate data sets by polynomial-exponential time series which satisfy assumption 3.1 using risk minimization techniques.

Let  $\Sigma_{\text{MPUM}} = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B}_{\text{MPUM}})$  denote the most powerful unfalsified model for this data and let  $\sigma$  denote the shift  $(\sigma w)(t) = w(t+1)$ .

**Proposition 3.2**  $\Sigma_{\text{MPUM}}$  is well defined and autonomous. Its behavior

$$\mathcal{B}_{\text{MPUM}} = \text{span} \{ \sigma^t(\tilde{w}_i); i = 1, \dots, n, t \in \mathbb{Z}_+ \}$$

is the smallest linear shift invariant finite dimensional and closed subspace of  $l_2^+$  that contains  $\tilde{w}_i$  for all  $i = 1, \dots, n$ .

**Proof.** See e.g. [2, 8]. ■

To represent  $\mathcal{B}_{MPUM}$  introduce the power series

$$\Theta(z) := \Theta_0 + \Theta_1 z + \dots + \Theta_k z^k + \dots$$

where  $z \in \mathbb{C}$  and  $\Theta_i$  are constant real matrices of dimension  $g \times q$ . Assume that  $\Theta \in H_\infty^-$  (all entries of  $\Theta(z)$  are analytic and bounded functions for  $z \in \mathbb{C}$  with  $|z| < 1$ ). Then  $\Theta$  represents a linear time-invariant system through the difference equations

$$\Theta(\sigma)w = 0. \quad (3.2)$$

Formally, (3.2) defines the  $l_2$  system  $\Sigma = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B}(\Theta)) \in \mathcal{S}_2^q$  with

$$\mathcal{B}(\Theta) := \{w \in l_2^+ \mid \Theta(\sigma)w = 0\}. \quad (3.3)$$

Let  $\hat{\mathcal{B}}$  denote the Laplace transform of  $\mathcal{B}$ . Then  $\Sigma$  is in the frequency domain equivalently described by

$$\hat{\mathcal{B}} = \{\hat{w} \in \mathcal{H}_2^+ \mid (\Pi_+ \Theta \hat{w})(z) = 0, z \in \mathbb{C}\}.$$

Here,  $\mathcal{H}_2^+$  denotes the image of  $l_2^+$  under the Laplace transform and  $\Pi_+$  denotes the canonical projection  $\Pi_+ : \mathcal{L}_2 \rightarrow \mathcal{H}_2^+$ .

The most powerful unfalsified system  $\Sigma_{MPUM}$  admits an  $\mathcal{H}_\infty^-$  kernel representation which is obtained as follows

**Theorem 3.3** *Let  $W = \Theta_{mpum}^{-1} \Psi$  be a left co-prime factorization over  $H_\infty^-$  of  $W$ . Then  $\Sigma_{MPUM} = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B}_{MPUM})$  where  $\mathcal{B}_{MPUM} = \mathcal{B}(\Theta_{mpum})$  or, equivalently,  $\hat{\mathcal{B}}_{MPUM} = \ker \Pi_+ \Theta_{MPUM}$ .*

Once  $\Sigma_{MPUM}$  is known, a system  $\Sigma$  is unfalsified by the data (2.1) if and only if  $\Sigma_{MPUM} \subseteq \Sigma$ .

**Theorem 3.4** *Let  $\Sigma_{MPUM}$  be represented by  $\Theta_{MPUM}$  and let  $\Sigma = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B}(\Theta))$ . Then the following statements are equivalent.*

1.  $\Sigma_{MPUM} \subseteq \Sigma$
2.  $\Theta = \Lambda \Theta_{MPUM}$  for some rational  $\Lambda \in H_\infty^-$ .

All unfalsified models  $\Sigma \in \mathcal{S}_2^q$  are therefore generated by  $\Sigma_{MPUM}$  by premultiplying  $\Theta_{MPUM}$  with rational elements in  $H_\infty^-$ . We will use this result in section 4 below.

## 4 Optimal approximate models

### 4.1 Model complexity

In this section  $\Sigma = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B})$  belongs to  $\mathcal{S}_2^q$  and it is supposed that  $\mathcal{B} = \mathcal{B}(\Theta)$  with  $\Theta$  a rational element in  $H_\infty^-$ .

**Definition 4.1** The *complexity*  $c(\Sigma)$  of  $\Sigma$  is a pair  $c(\Sigma) = (m(\Sigma), n(\Sigma))$  where  $m(\Sigma) = q - \text{rank}(\Theta)$  and  $n(\Sigma)$  is the McMillan degree of  $\Theta$ .

In this definition  $m(\Sigma) + n(\Sigma)$  is to be interpreted as the total degree of freedom to uniquely determine a trajectory in  $\Sigma$ . This consists of the dimension  $m(\Sigma)$  of the input space in a (and hence any) input-output representation of  $\Sigma$  and the dimension  $n(\Sigma)$  of the space of initial conditions (or the state space dimension in any minimal state space representation of  $\Sigma$ ). Introduce a lexicographic ordering on system complexities as follows. Define  $c(\Sigma_1) \leq c(\Sigma_2)$  if

$$\begin{cases} m(\Sigma_1) = m(\Sigma_2), n(\Sigma_1) = n(\Sigma_2) & \text{or} \\ m(\Sigma_1) < m(\Sigma_2), n(\Sigma_1) = n(\Sigma_2) & \text{or} \\ m(\Sigma_1) = m(\Sigma_2), n(\Sigma_1) < n(\Sigma_2) \end{cases}$$

Since autonomous systems  $\Sigma \in \mathcal{S}_2^q$  have finite dimensional behavior, it follows that their corresponding kernel representations have full rank or, equivalently,  $m(\Sigma) = 0$ . Therefore, the least complex systems are the autonomous ones.

### 4.2 Misfits

The discrepancy between model and data is formalized by the definition of a misfit function between the data (2.1) and models in  $\mathcal{S}_2^q$ . We assume that the data is represented by the matrix  $W$  defined in (3.1). The misfit is defined as follows

**Definition 4.2** The *misfit* between  $\mathcal{B}$  and  $W$  is defined as

$$d(\mathcal{B}, W) := \sup \left\{ \frac{\langle Wx, v \rangle}{\|v\| \|x\|} \mid v \in \hat{\mathcal{B}}^\perp, x \in \mathcal{H}_2^- \right\}$$

Here,

$$\hat{\mathcal{B}}^\perp = \{v \in \mathcal{H}_2^+ \mid \langle v, w \rangle = 0 \text{ for all } w \in \mathcal{B}\}$$

is the orthogonal complement of  $\hat{\mathcal{B}}$  in  $\mathcal{H}_2^+$  and  $W$  is viewed as a multiplicative operator  $W : \mathcal{H}_2^- \rightarrow \mathcal{L}_2$ ,  $W : x \mapsto Wx$ .

Clearly  $d(\mathcal{B}, W) \geq 0$  and  $d(\mathcal{B}, W) = 0$  if, and only if  $\Sigma$  is unfalsified by the data. Note that the misfit is independent of representations of  $\Sigma \in \mathcal{S}_2^q$ . In other words,  $d(\mathcal{B}, W)$  is a non-parametric criterion.

The following theorem relates the misfit to the Hankel norm of a specific operator. See also [7] for other characterizations of the misfit  $d(\mathcal{B}, W)$ .

**Theorem 4.3** *Let  $\Sigma \in \mathcal{S}_2^q$  and let its behavior  $\mathcal{B} = \mathcal{B}(\Theta)$  where  $\Theta$  is co-inner, i.e.  $\Theta\Theta^* = I$ . Then*

$$d(\mathcal{B}, W) = \|\Pi_+\Theta W\|_H$$

where  $\|\cdot\|_H$  denotes the induced operator (or Hankel) norm of the composite function  $\Pi_+\Theta W$  viewed as a mapping from  $\mathcal{H}_2^-$  to  $\mathcal{H}_2^+$ .

Co-inner kernel representations of systems in  $\mathcal{S}_2^q$  indeed exist.

**Proposition 4.4** *The behavior  $\mathcal{B}$  of every system  $\Sigma \in \mathcal{S}_2^q$  admits a representation  $\mathcal{B} = \mathcal{B}(\Theta)$  with  $\Theta$  co-inner.*

### 4.3 Optimal identification

The approximate modeling problem consists of finding low complexity models which minimize the misfit between model and data. Precisely, given the data (2.1) together with prescribed complexity  $(m, n)$ , find systems  $\Sigma \in \mathcal{S}_2^q$  with  $c(\Sigma) \preceq (m, n)$  such that the misfit  $d(\mathcal{B}, W)$  is minimal. A complete solution for the case where  $m = 0$  is given in the following result.

**Theorem 4.5** *Let  $W$  be given by (3.1) and let  $\Sigma_{MPUM}$  be the most powerful unfalsified model for  $W$ . Suppose that  $c(\Sigma_{MPUM}) = (0, N)$  and let*

$$\sigma_1 \geq \sigma_2 \dots \geq \sigma_N > 0$$

denote the singular values of  $W$ . Denote by  $W_n \in H_\infty$  an optimal Hankel norm approximant of  $W$  of McMillan degree  $\leq n$ . Let  $\Sigma_n = (\mathbb{Z}_+, W, \mathcal{B}_n)$  be the most powerful unfalsified model associated with  $W_n$ . Then

1.  $\Sigma_n$  is autonomous.
2.  $d(\mathcal{B}_n, W) = \sigma_{n+1}$ .
3.  $d(\mathcal{B}'_n, W) \geq d(\mathcal{B}_n, W)$  for all  $\Sigma'_n \in \mathcal{S}_2^q$  with  $c(\Sigma'_n) \preceq c(\Sigma_n)$ .

4. if  $\Sigma_n \subseteq \Sigma'_n$  then  $d(\mathcal{B}'_n, W) \leq \sigma_{n+1}$ .

**Proof.** See [7]. ■

Note that  $c(\Sigma_n) = (0, n^*)$  with  $n^* \leq n$  the McMillan degree of  $W_n$ . Conclude from Theorem 4.5 that

$$\Sigma_n = \arg \min\{d(\mathcal{B}, W) \mid \Sigma \in \mathcal{S}_2^q, c(\Sigma) \preceq (0, n)\}$$

For given data (2.1), Theorem 4.5 leads to the following constructive method for the computation of a kernel representation of  $\Sigma_n$ .

1. Compute an optimal Hankel norm approximant  $W_n \in H_\infty$  of  $W$  with McMillan degree  $n$  [4].
2. Let  $W_n = \Theta_{MPUM, n}^{-1} \Psi_n$  be a left coprime factorization over  $H_\infty^-$  of  $W_n$ .
3. Put  $\mathcal{B}_n = \mathcal{B}(\Theta) := \ker \Theta_{MPUM, n}(\sigma)$ .

The optimal approximate model is then given by  $\Sigma_n = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B}_n)$  whereas all models which have  $\Sigma_n$  as subsystem have misfit  $\leq \sigma_{n+1}$ .

## 5 Stabilization of systems

In this section kernel representations of autonomous systems are used as descriptions of closed-loop behaviors. A "closed-loop<sup>1</sup>" behavior consists of the interconnection of two  $l_2$  systems  $\Sigma_p$  and  $\Sigma_c$  which will be referred to as the *plant* and the *controller*, respectively.

**Definition 5.1** Let  $\Sigma_p$  and  $\Sigma_c$  be elements of  $\mathcal{S}_2^q$ . Their *interconnection* is defined as the system  $\Sigma_{\text{int}} := \Sigma_p \wedge \Sigma_c = (\mathbb{Z}_+, \mathbb{R}^q, \mathcal{B}_{\text{int}})$  where  $\mathcal{B}_{\text{int}} = \mathcal{B}_p \cap \mathcal{B}_c$ .

Hence, interconnection and intersection are synonymous. It is easily seen that  $\Sigma_{\text{int}}$  again belongs to  $\mathcal{S}_2^q$ .

**Definition 5.2** The interconnection  $\Sigma_{\text{int}} = \Sigma_p \wedge \Sigma_c$  is called a *feedback interconnection* if  $\Sigma_{\text{int}}$  is autonomous.

<sup>1</sup>in this input-output independent context the traditional looping configuration of input and output signals is not implied.



The Laplace transform  $\hat{B}_p$  of  $B_p$  is given by

$$\begin{aligned}\hat{B}_p &= \{\hat{w} \in \mathcal{H}_2^+ \mid \Pi_+ \Lambda_p \Theta \hat{w} = 0\} \\ &= \{\hat{w} \in \mathcal{H}_2^+ \mid \langle \Lambda_p \Theta \hat{w}, \hat{v} \rangle = 0 \forall \hat{v} \in \mathcal{H}_2^+\} \\ &= \{\hat{w} \in \mathcal{H}_2^+ \mid \langle \hat{w}, \Theta^* \Lambda_p^* \hat{v} \rangle = 0 \forall \hat{v} \in \mathcal{H}_2^+\} \\ &= \{\hat{w} \in \mathcal{H}_2^+ \mid \hat{w} \in [\Theta^* \Lambda_p^* \mathcal{H}_2^+]^\perp\} \\ &= [\text{im } \Theta^* \Lambda_p^*]^\perp\end{aligned}$$

where  $\Theta^* \in H_\infty$  denotes the dual of  $\Theta \in H_\infty^-$ . Therefore, the behavior of  $\Sigma_p$  can equivalently be represented as the orthogonal complement (in  $\mathcal{H}_2^+$ ) of the  $\mathcal{H}_2^+$  image of  $\Theta^* \Lambda_p^*$ .

The following result provides a characterization of stabilizing systems for  $\Sigma_p$ .

**Theorem 5.7** *The following are equivalent*

1.  $\Sigma_c$  stabilizes  $\Sigma_p$ .
2.  $\hat{B}_p^\perp + \hat{B}_c^\perp = \mathcal{H}_2^+$
3.  $B_c = B(\Lambda_c \Theta)$  where  $\Lambda := \begin{pmatrix} \Lambda_c \\ \Lambda_p \end{pmatrix}$  is a nonsingular  $q \times q$  matrix and  $(\Lambda \Theta)^{-1} \in \mathcal{H}_\infty$ .

The above Theorem 5.7 provides a characterization of all stabilizing controllers of the linear time-invariant system  $\Sigma_p$ . Note that input/output representations of  $\Sigma_p$  and/or  $\Sigma_c$  are not necessary to provide such a characterization.

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