Constrained Order Observer Design for Disturbance Decoupled Output Estimation

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Abstract—From industry there is an increasing interest in applying model based control techniques to large-scale systems. Control designs like $H_2$ and $H_{\infty}$ optimal control will typically contain a dynamic state observer in which the order will be equal to the model order. Consequently, real-time implementation of the controller may not be possible due to computational constraints. The problem of designing a constrained order observer for a large-scale system, with explicit guarantees on the output estimate is therefore a relevant problem in these applications.

This paper addresses the problem of constructing (if it exists) an observer with a constrained order that decouples the output estimation errors from the disturbances that are acting on the system. In addition, stability of the output estimate, a characterization of the orders for which the observer can achieve disturbance decoupled estimation and the explicit construction of the observer are discussed.

Index Terms—Model/Controller reduction, Estimation, Observers for Linear systems, Algebraic/geometric methods

I. INTRODUCTION

In various industrial applications, controllers are designed for systems that are described by partial differential equations [1][2]. Models of these systems are created by utilizing finite elements or finite volume methods, which lead to large-scale models that commonly contain well over 1,000 states. For model based control designs like $H_2$ and $H_{\infty}$ optimal control, the order of a dynamic output feedback controller is typically equal to the model order. For large-scale models, the synthesis of such a controller might therefore become numerically unreliable, or even infeasible. Furthermore, real-time implementation of the controller may not be possible due to computational constraints. The design of model based controllers with a constrained order is therefore a relevant problem in these applications.

Control designs like $H_2$ and $H_{\infty}$ optimal control will typically contain a dynamic state observer. Consequently, the order of such a controller is determined by the observer order. For the design of a constrained order observer $\hat{\Sigma}_O$ for a system $\Sigma$, typically 3 approaches are considered as depicted in Fig. 1:

1) First system $\Sigma$ is reduced in order, which leads to system $\hat{\Sigma}$. For $\hat{\Sigma}$ an observer $\hat{\Sigma}_O$ with the same order as $\hat{\Sigma}$ is created.
2) First an observer $\Sigma_O$ is created for system $\Sigma$. $\Sigma_O$ is then reduced in order, which leads to a low order observer $\hat{\Sigma}_O$.
3) The low order observer $\hat{\Sigma}_O$ is created directly for system $\Sigma$.

The design of a constrained order observer is typically performed by utilizing standard open-loop model order reduction techniques such as balanced truncation or moment matching.

Control relevant model order reduction has been investigated extensively, which has led to various techniques as described in [3][4][5][6][7]. However, these techniques consider standard state-space systems and do not provide explicit guarantees on the interconnection of the constrained order observer $\hat{\Sigma}_O$ and full order system $\Sigma$.

The design of controllers or observers with a constrained order that will provide explicit guarantees on performance has, to the knowledge of the authors, received little attention. The problem of designing a low order observer that is optimal for a full order system has been addressed shortly in [8] in an $H_2$ optimal control context. The problem has also been investigated for disturbance decoupling problems in [9][10][11].

However, the range of orders for which the problem can be solved is not investigated.

Disturbance decoupling problems are closely related to $H_2$ optimal control problems, which is observed in [8][12]. Therefore, it is decided to further investigate the design of constrained order observers in a disturbance decoupling context, with the intention to extend the results to $H_2$ optimal observer design.

This paper addresses the problem of constructing (if it exists) an observer with a constrained order that decouples the output estimation errors from the disturbances that are acting on the system. In addition, stability of the output estimate, a characterization of the orders for which the observer can achieve disturbance decoupled output estimation and the explicit construction of the observer are discussed.

The paper is organized as follows. In section II the main problem and additional subproblems will formally be defined. The mathematical preliminaries are discussed in section III. The standard disturbance decoupled estimation problem is discussed in section IV. In section V the main results to the problems as defined in section II are presented. The paper is finalized with an academic example in section VI, followed by conclusions and future works in section VII.

![Fig. 1. Constrained order observer design approaches.](image-url)
II. PROBLEM DEFINITION

Consider the generalized plant model of a system

\[
\Sigma = \begin{cases}
\dot{x}(t) = Ax(t) + Bu(t) + B_w w(t) \\
y(t) = C_y x(t) \\
z(t) = C_z x(t) + D_u u(t)
\end{cases}
\] (1)

where \(A: \mathcal{X} \rightarrow \mathcal{X}, B_u: \mathcal{U} \rightarrow \mathcal{X}, B_w: \mathcal{W} \rightarrow \mathcal{X}, C_y: \mathcal{X} \rightarrow \mathcal{Y}, C_z: \mathcal{X} \rightarrow \mathcal{Z}\) and \(D_u: \mathcal{U} \rightarrow \mathcal{Z}\) are linear mappings on finite dimensional vector spaces \(\mathcal{X}, \mathcal{U}, \mathcal{W}, \mathcal{Y}\) and \(\mathcal{Z}\). The vector signals \(x(t), u(t), w(t), y(t)\) and \(z(t)\) of dimension \(n_x, n_u, n_w, n_y\) and \(n_z\) represent the state, known input, unknown disturbance, measured output and the control output, respectively.

Assumption 2.1: It is assumed that any state of (1) can be reached using the pair \((u(t), w(t))\) and observed through the pair \((y(t), z(t))\).

An observer provides a causal estimate \(\hat{z}(t)\) of \(z(t)\) on the basis of \(u(t)\) and \(y(t)\) according to

\[
\Sigma_{Oh} = \begin{cases}
\dot{\hat{z}}(t) = M \hat{z}(t) + Nu(t) + Qy(t) \\
\hat{z}(t) = P \hat{z}(t) + Qu(t) + Ry(t)
\end{cases}
\] (2)

with linear mappings \(M: \mathcal{H} \rightarrow \mathcal{H}, N: \mathcal{U} \rightarrow \mathcal{H}, O: \mathcal{Y} \rightarrow \mathcal{H}, P: \mathcal{H} \rightarrow \mathcal{Z}, Q: \mathcal{U} \rightarrow \mathcal{Z}, R: \mathcal{Y} \rightarrow \mathcal{Z}\) and finite dimensional vector space \(\mathcal{H}\). The vector signals \(\hat{h}(t)\) and \(\hat{z}(t)\) of dimension \(n_h\) and \(n_z\) represent the state of the observer and the estimated control output, respectively. The order of the observer is given by \(\dim(\mathcal{H})\). Connecting \(\Sigma_{ch}\) to \(\Sigma\) leads to an error system \(\Sigma_{ch}\) with inputs \(u(t)\) and \(w(t)\) and output estimation error \(\epsilon_z(t) = z(t) - \hat{z}(t)\) as depicted in Fig. 2.

External signals \(u(t)\) and \(w(t)\) are both acting as inputs to the error system \(\Sigma_{ch}\). From an estimation perspective, both signals are viewed as disturbances and a distinction is made by assuming that the signal \(u(t)\) is known and \(w(t)\) unknown.

The main problem that will be addressed in this paper is the disturbance decoupled estimation problem with a constrained order (DDEP-CO). The DDEP-CO cannot be solved for all systems and all observer orders. Therefore, in addition to solving the DDEP-CO, it will be investigated under which conditions the DDEP-CO can be solved.

Definition 2.2: \(\Sigma_{Oh}\) (2) solves the DDEP-CO for \((\Sigma, n_o)\) if \(\dim(\mathcal{H}) = n_o\) and the output estimation error \(\epsilon_z(t) = z(t) - \hat{z}(t)\) is independent of input \(u(t)\) and disturbance \(w(t)\).

The DDEP-CO can be solved for \((\Sigma, n_o)\) if such an observer exists.

In addition, the following problems will be investigated:

- Adding stability to the estimation error in the DDEP-CO.
- The characterization of all integers \(n_o\) and a lower bound \(n_o^*\) for which the DDEP-CO can be solved.
- The explicit construction of an observer that will solve the DDEP-CO for a given value \(n_o\).

III. MATHEMATICAL PRELIMINARIES

A. Operators

For a matrix \(A\), its transpose, kernel, image, spectrum and pseudo inverse are denoted by \(A^T, \ker(A), \text{im}(A), \sigma(A)\) and \(A^+\), respectively.
the output estimation error $\epsilon_z(t) = z(t) - \hat{z}(t)$. This leads to the error system

$$
\Sigma_\epsilon = \begin{cases}
\dot{z}(t) &= \begin{pmatrix} A & 0 \\ 0 & A + LC_y \end{pmatrix} \begin{pmatrix} x(t) \\ \epsilon(t) \end{pmatrix} \\
&+ \begin{pmatrix} B_u \\ 0 \end{pmatrix} u(t) + \begin{pmatrix} B_u \\ B_w \end{pmatrix} w(t)
\end{cases}
$$

which has an extended state $x^e(t) = (x(t)^T \ \epsilon(t)^T)^T$ and extended system matrices $A^e, B_u^e, B_w^e, C_z^e$ and $D_{uz}^e$. The extended state-space is characterized by the vector space $X^e = X^x \oplus X^\epsilon$, which consists of subspaces $X^x = X$ for the state $x(t)$ and $X^\epsilon = \epsilon$ for the estimation error $\epsilon(t)$.

The estimation error $\epsilon(t)$ of $\Sigma_\epsilon$ (4) can be influenced by the mapping $L$. Similar to lemma 3.2, there exists invariant subspaces related to the estimation error $\epsilon(t)$.

**Definition 3.4:** Given a subspace $K \subseteq X$, a conditioned invariant subspace $S(K)$ is a subspace $S(K) \subseteq X$ that contains $K$ and for which there exists a mapping $L : X \rightarrow \epsilon$ such that $(A + LC_y)S(K) \subseteq S(K)$. □

**Proposition 3.5:** Given a subspace $K \subseteq X$, there exists a unique smallest conditioned invariant subspace that contains $K$, which is denoted by $S^*(K)$. This subspace satisfies $S^*(K) \subseteq S(K)$, for any conditioned invariant subspace $S(K)$. □

**Proof:** The proof can be found in [12, Thm. 5.5.5, 5.7]. ■

IV. DISTURBANCE DECOUPLED ESTIMATION PROBLEM (DDEP)

A. Problem Definition

For the DDEP, the aim is to find mappings $L, P, Q$ and $R$ such that disturbance decoupling is achieved on $\Sigma_\epsilon$ (4). Similar to remark 3.3, the effects of $w(t)$ on the estimation error $\epsilon(t)$ of $\Sigma_\epsilon$ (4) should be restricted to some subspace. Therefore we will consider conditioned invariant subspaces that contain $im(B_u)$. For notational convenience we will define $S = S(\text{im}(B_u))$ and $S^* = S^*(\text{im}(B_u))$.

**Remark 4.1:** By using lemma 3.2 and by interpreting $u(t)$ as a disturbance, it follows that $\Sigma_\epsilon$ (4) is disturbance decoupled if and only if there exists a subspace $S_{A^e} \subseteq X^\epsilon$ such that

$im((B_u^e, B_w^e)) \subseteq S_{A^e} \subseteq ker(C_z^e)$ and $A^e S_{A^e} \subseteq S_{A^e}$, for $Q = D_{uz}$ and for some $L, P$ and $R$.

Using assumption 2.1, observe that $S_{A^e} = X^\epsilon \oplus S^*$ (with $S^* \subseteq X^\epsilon$) is the smallest subspace that will satisfy $im((B_u^e, B_w^e)) \subseteq S_{A^e}$ and $A^e S_{A^e} \subseteq S_{A^e}$, for some $L$. Finally, $\Sigma_\epsilon$ (4) can be disturbance decoupled when there exist mappings $P$ and $R$ such that $S_{A^e} \subseteq ker(C_z^e)$ is satisfied. □

The following lemma shows when this last inclusion can be satisfied for some $P$ and $R$.

**Lemma 4.2:** $\Sigma_\epsilon$ (4) can be disturbance decoupled if and only if $S^* \cap ker(C_y) \subseteq ker(C_z)$. □

**Proof:** The proof can be found in [12, Cor. 5.22] for an observer $\Sigma_{Oh}$ (2). In theorem 4.6 it will be shown that the use of a Luenberger observer is non-restrictive.

**Remark 4.3:** Lemma 4.2 can be interpreted as follows. Assumption 2.1 implies that $\epsilon_z(t)$ should be independent of $x(t)$. The subspace $S^*$ is the smallest subspace to which the effect of $w(t)$ on estimation error $\epsilon(t)$ can be restricted. Measurements $y(t)$ are not directly affected by $w(t)$, which implies that certain estimation errors $\epsilon(t)$ are directly visible on $y(t)$. $\Sigma_\epsilon$ (4) can therefore be disturbance decoupled if and only if $\epsilon_z(t)$ is independent of all estimation errors $\epsilon(t)$ that are affected by $w(t)$, but which cannot directly be compensated by $y(t)$. □

Whether the DDEP can be solved for $\Sigma_\epsilon$ (1) is strongly related to $S^*$, as shown in lemma 4.2. This is why in literature the subspace $S^*$ is considered [11][12]. However, it will be shown in section V that the values $n_o$ for which the DDEP- CO can be solved are related to the dimension of conditioned invariant subspaces. The DDEP will therefore be related to a set of conditioned invariant subspaces $S$ as defined in (5) below.

**Definition 4.4:** $\Sigma_{O\epsilon}$ (3) solves the DDEP for $(\Sigma_\epsilon, S)$ if the output estimation error $\epsilon_z(t)$ of $\Sigma_\epsilon$ (4) is independent of input $u(t)$ and disturbance $w(t)$. Furthermore, for $\Sigma_\epsilon$ (4) it holds that $\epsilon(t) \in S$ for all $t \geq t_0$ and for any $w(t)$, provided that $\epsilon(t_0) = e_0 \in S$. □

B. Design of a Full Order Luenberger Observer

Consider a set of conditioned invariant subspaces $S = \{S : S = S(\text{im}(B_u)), S \cap ker(C_y) \subseteq ker(C_z)\}$. (5)

Note that $S^*(\text{im}(B_u)) \subseteq S$, whenever $S \neq \emptyset$. 

**Theorem 4.5:** $\Sigma_{O\epsilon}$ (3) can solve the DDEP for $(\Sigma_\epsilon, S)$ if and only if $S \subseteq S$. □

**Proof:** ($\Rightarrow$) If $S \subseteq S$, the subspace $S_{A^e} = X^\epsilon \oplus S$ must be used in remark 4.1. Then $S_{A^e} \subseteq ker(C_z^e)$ can be satisfied for some $P$ and $R$ if, according to lemma 4.2, $S \cap ker(C_y) \subseteq ker(C_z)$ is satisfied. This is true for any $S \in S$. ($\Rightarrow S$ must be a conditioned invariant subspace in order to satisfy the requirement that $\epsilon(t) \in S$ for all $t \geq t_0$ and for any $w(t)$, provided that $\epsilon(t_0) = e_0 \in S$. Again consider the subspace $S_{A^e} = X^\epsilon \oplus S$ in remark 4.1 and observe that $S_{A^e} \subseteq ker(C_z^e)$ requires that $S \cap ker(C_y) \subseteq ker(C_z)$, which implies that $S \subseteq S$. ■

**Theorem 4.6:** Let $S \subseteq S$. Then the following statements are equivalent:

(i) $\Sigma_{O\epsilon}$ (3) solves the DDEP for $(\Sigma_\epsilon, S)$.
(ii) For $\Sigma_\epsilon$ (4) it holds that $\epsilon(t) \in S$ for all $t \geq t_0$ and for any $w(t)$, provided that $\epsilon(t_0) = e_0 \in S$. $\epsilon_z(t)$ is independent of $u(t)$. In addition, $\epsilon_z(t_0) = 0$ for any $x(t_0), e(t_0) \in S$.
(iii) $(A + LC_y)S \subseteq S, \quad Q = D_{uz}, \quad C_z - RC_y - P = 0, \quad PS = 0$. □

**Proof:** (i) $\Rightarrow$ (ii): By definition, the first 2 requirements in (ii) are satisfied. Then observe that “$\epsilon_z(t)$ is independent of $u(t)$ and $w(t)$”, will imply that $\epsilon_z(t)$ is independent of $x(t)$ (by assumption 2.1) and estimation errors $\epsilon(t)$ that are affected by $w(t)$, which are $\epsilon(t) \in S$. This implies that $\epsilon_z(t_0) = 0$ for any $x(t_0), e(t_0) \in S$.

(ii) $\Rightarrow$ (iii): $\epsilon(t) \in S$ for all $t \geq t_0$ and for any $w(t)$, provided that $\epsilon(t_0) = e_0 \in S$ implies that $(A + LC_y)S \subseteq S$. ■
\[ \varepsilon_z(t_0) = 0 \] for any \( x(t_0), e(t_0) \in S \), implies that \( C_z - RC_y - P = 0, PS = 0 \), \( \varepsilon_z(t) \) is independent of \( u(t) \) by additionally imposing \( Q = D_{az} \).

(iii) \( \Rightarrow \) (i): \((A + LC_y)S \subseteq S \) implies that \( e(t) \in S \) for all \( t \geq t_0 \) and for any \( w(t) \), provided that \( e(t_0) = 0 \in S \). Then, by adding \( C_z - RC_y - P = 0, PS = 0 \) it can be concluded that \( \varepsilon_z(t) \) is independent of \( w(t) \). Finally, by imposing \( Q = D_{az} \) it can be concluded that \( \varepsilon_z(t) \) is independent of \( u(t) \).

\[ (A + LC_y)S \subseteq S \text{ holds if and only if } \Pi(S_m, S)A|S + \Pi(S_m, S)LC_y|S = 0. \] Observe that \( L_m = \Pi(S_m, S)L \), to conclude that \( \Sigma_O \) (6) solves the DDEP-CO for \( \Sigma(1), n_o \).

**B. Stability**

In the previous sections, the output estimation error \( \varepsilon_z(t) \) is made independent of \( w(t) \) and \( u(t) \). An additional requirement is that \( \varepsilon_z(t) \rightarrow 0 \) as \( t \rightarrow \infty \) for any initial estimation error \( e(t) \). This is related to stability of \( e(t) \).

**Definition 5.3:** A subset \( \mathbb{C}_g \subseteq \mathbb{C} \) is a stability domain, if \( \mathbb{C}_g \cap \mathbb{R} \) is nonempty and \( \mathbb{C}_g \) is symmetric with respect to the real axis.

In the absence of disturbances and inputs, the estimation error satisfies \( \dot{e}(t) = (A + LC_y)e(t) \). The requirement that \((A + LC_y)S \subseteq S \), in combination with the fact that \( \Sigma_O \) (6) does not estimate the states in \( S \), implies that \( \sigma(A + LC_y) = \sigma((A + LC_y)(X' \text{ mod } S)) \). This can be seen by partitioning the error dynamics as \( \dot{e}(t) = (e_1(t)^T e_2(t)^T) \), where \( e_1(t) \) describes the estimation error in \( S \) and \( e_2(t) \) the estimation error in \( X' \text{ mod } S \). This leads to

\[ A + LC_y = \left( \begin{array}{cc} A_{LS} & 0 \\ A + LC_y & \text{(X mod )} \end{array} \right)^* \]

For this reason, the observer gain \( L \) only determines \( \sigma((A + LC_y)(X \text{ mod } S)) \). This gives rise to a result that is similar to definition 3.4 and proposition 3.5.

**Definition 5.4:** Given a subspace \( K \subseteq X \) and a stability domain \( \mathbb{C}_g \), a detectability subspace \( S_g(K) \) is a subspace \( S_g(K) \subseteq X \) that contains \( K \) and for which there exists a mapping \( L : Y \rightarrow X \) such that \((A + LC_y)S_g(K) \subseteq S_g(K) \) and \( \sigma((A + LC_y)(X' \text{ mod } S_g(K))) \subseteq \mathbb{C}_g \).

**Proposition 5.5:** Given a subspace \( \mathbb{K} \subseteq X \) and a stability domain \( \mathbb{C}_g \), there exists a unique smallest detectability subspace that contains \( \mathbb{K} \), which is denoted by \( S_g^*(K) \). This subspace satisfies \( S_g^*(K) \subseteq S_g(K) \), for any detectability subspace \( S_g(K) \).

**Proof:** The proof can be found in [12, Thm. 5.11, 5.14].

Stability is added to \( \varepsilon_z(t) \) by utilizing the set \( S_g = \{ S_g : S_g = S_g(\text{im}(B_w)) \} \), \( S_g \cap \ker(C_z) \subseteq \ker(C_z) \) in the observer design according to theorem 5.2, with \( L_m \) satisfying \( \Pi(S_m, S_g)A|S_m + L_mC_y|S_g = 0 \) and \( \sigma(\Pi(S_m, S_g)A|S_m + L_mC_y|S_m) \subseteq \mathbb{C}_g \) for some stability domain \( \mathbb{C}_g \).

Finally, observe that \( S_g \subseteq S_g \), whenever \( \mathbb{C}_g \subseteq \mathbb{C}_g \). This implies that \( S_g \subseteq S \), and \( \mathbb{C}_g \subseteq \mathbb{C} \).

**C. Conditions on the Observer Order**

Given any stability domain \( \mathbb{C}_g \), the values \( n_o \) for which the DDEP-CO can be solved are determined by the dimension of elements in \( S_g \). This leads to the following main result.

**Theorem 5.6:** Let \( S_m \) be such that \( S_g(\subseteq S_m) = X \). Then \( \Sigma_O \) (6) can solve the DDEP-CO for \( \Sigma(1), n_o \), with \( \sigma(\Pi(S_m, S_g)A|S_m + L_mC_y|S_m) \subseteq \mathbb{C}_g \) if and only if there exists an \( S_g \subseteq S \) with \( \text{dim}(S_g) = \text{dim}(X) - n_o \).

\[ (A + LC_y)S \subseteq S \text{ holds if and only if } \Pi(S_m, S)A|S + \Pi(S_m, S)LC_y|S = 0. \] Observe that \( L_m = \Pi(S_m, S)L \), to conclude that \( \Sigma_O \) solves the DDEP-CO for \( \Sigma(1), n_o \).
Proof: This follows directly from theorem 5.2.

Let $n_{o}^{*}$ be the smallest value for which the DDEP-CO can be solved, which is interesting from a computational perspective.

**Theorem 5.7:** Let, without loss of generality, $C_{g}$ and $C_{z}$ be of full row rank. Then $n_{o}^{*} \geq \dim(Z) - \dim(Y)$. □

**Proof:** Observe that $S_{y} \subseteq S$, for any $C_{g}$. For this reason we will consider elements $S$ from the largest set $S$. Theorem 5.6 indicates that the DDEP-CO can be solved if there exists a subspace $S$ for which it must hold that $\dim(S) - \dim(Y) \leq \dim(S \cap \ker(C_{g})) \leq \dim(\ker(C_{z})) = \dim(X) - \dim(Z)$. This imposes an upper bound on $\dim(S) \leq \dim(X) - \dim(Z) + \dim(Y)$, which combined with $n_{o} = \dim(X) - \dim(S)$ implies that $n_{o}^{*} \geq \dim(Z) - \dim(Y)$. ■

**D. Construction of the Constrained Order Observer**

There exist various numerical algorithms to construct a basis for $S^*$. Subspace operations, in combination with an iterative procedure to construct a basis for $S^*$ are implemented in [16]. The so-called special coordinate basis of a system, as introduced in [8] and which is numerically implemented in [17], can be used to determine a basis for both $S^*$ and $S'$. These algorithms can be used to numerically create an observer that will solve the DDEP-CO. An observer of small order is created by finding elements $S_{g} \in S_{g}$ of large dimension. However, a characterization of elements $S_{g} \in S_{g}$ and a numerical algorithm to find largest dimensional elements remains, to the knowledge of the authors, an open problem. For this reason, it is assumed that a basis for $S_{g} \in S_{g}$ is found.

Observe that a state transformation, given by a nonsingular mapping $T$ such that $\tilde{x}(t) = Tx(t)$, will not change the input to output behavior of a system. Therefore an observer can be designed for $\Sigma (1)$, using any equivalent system that is created by applying a state transformation.

For $S_{g} \in S_{g}$, let $S_{m}$ be such that $S_{g} \subseteq S_{m}$ = $X$. Furthermore introduce $S_{1} = S_{g} \cap \ker(C_{g})$ and let $S_{2}$ be such that $S_{1} \oplus S_{2} = S_{g}$. For example, one could choose $S_{m} = S_{g}$ and $S_{2} = \ker(C_{g})$. Define

$$T_{S} = (\Pi(S_{1}, S_{2} \oplus S_{m})^{\top} \Pi(S_{2}, S_{1} \oplus S_{m})^{\top} \Pi(S_{m}, S_{g})^{\top})^{\top}$$

and observe that $T_{S} : X \to X$ is nonsingular.

**Proposition 5.8:** Let the columns of $K_{1} \in \mathbb{R}^{n_{x} \times k_{1}}$ and $K_{2} \in \mathbb{R}^{n_{x} \times k_{2}}$ be orthonormal bases for subspaces $K_{1} \subseteq X$ and $K_{2} \subseteq X$ of dimension $k_{1}$ and $k_{2}$, respectively. Let these subspaces satisfy $K_{1} \oplus K_{2} = X$, which implies that $n_{x} = k_{1} + k_{2}$. Furthermore, let $K_{2p} \in \mathbb{R}^{n_{x} \times k_{x}}$ be an orthonormal basis for $K_{2}$. Then the projection onto $K_{1}$ and along $K_{2}$ is numerically given by $\Pi(K_{1}, K_{2}) = K_{1}^{T}K_{1}(K_{2p}K_{2})^{-1}K_{2p}$ as discussed in [15, Sec. 1.12].

State transformation $T_{S}$ applied to $\Sigma (1)$ creates the system

$$\Sigma^{T} = \begin{bmatrix}
    \dot{x}_{1}(t) \\
    \dot{x}_{2}(t) \\
    \dot{x}_{3}(t) \\
    y(t) \\
    z(t)
\end{bmatrix} = \begin{bmatrix}
    A_{11} & A_{12} & A_{13} \\
    A_{21} & A_{22} & A_{23} \\
    0 & 0 & A_{32}
\end{bmatrix}
\begin{bmatrix}
    x_{1}(t) \\
    x_{2}(t) \\
    x_{3}(t)
\end{bmatrix}
+ \begin{bmatrix}
    B_{u1} \\
    B_{u2} \\
    B_{u3}
\end{bmatrix} u(t) + \begin{bmatrix}
    B_{w1} \\
    B_{w2} \\
    B_{w3}
\end{bmatrix} w(t)
$$

(1)

where the state-space of $\Sigma (1)$ is partitioned in such a way that $X_{1} = T_{S}S_{1}$, $X_{2} = T_{S}S_{2}$ and $X_{3} = T_{S}S_{m}$. Therefore $X_{1} \oplus X_{2}$ is a detectability subspace for $\Sigma^{T}$.

Observe that $\dim(B_{u}) \subseteq S_{y}$ is satisfied for $\Sigma (1)$, which implies for $\Sigma^{T}$ that $B_{u3} = 0$. $S_{1} \subseteq \ker(C_{y})$ for $\Sigma (1)$ implies that $C_{g1} = 0$ for $\Sigma^{T}$. Finally, there exists a mapping $L$ such that $(A + L_{C_{y}})S_{y} \subseteq S_{y}$ for $\Sigma (1)$, which implies for $\Sigma^{T}$ that there exists a mapping $L_{3}$ such that $(A_{31} A_{32} + L_{3}C_{y2}) = 0$ and therefore $A_{31} = 0$.

An implementation of $\Sigma_{O}$ (6) is created by using $X_{3}$ of $\Sigma^{T}$, which is related to $S_{m}$ of $\Sigma (1)$, to the construct the observer

$$\begin{align*}
\hat{x}_{3}(t) &= (A_{33} + L_{3}C_{y3})\hat{x}_{3}(t) + B_{w3}u(t) - L_{3}y(t) \\
\hat{z}(t) &= (C_{13} - C_{23}C_{y3})\hat{x}_{3}(t) + D_{u2}u(t) + (C_{23}C_{y3})y(t)
\end{align*}
$$

(8)

Applying $\hat{x}_{3}(t) = x_{3}(t)$ to $\Sigma^{T}$ (7) will result in the error system $\hat{x}_{3}(t)$ (9) by observing that $e_{1}(t) = x_{1}(t)$ and $e_{2}(t) = x_{2}(t)$. For stability domain $C_{g}$ and $S_{g} \in S_{g}$ there exists, by definition, a mapping $L_{3}$ such that $A_{32} + L_{3}C_{y2} = 0$ and $\sigma(A_{33} + L_{3}C_{y3}) \subseteq C_{g}$. $\Sigma^{T}$ (9) can therefore be disturbance decoupled when $C_{21} = 0$. This requires that $S_{g} \cap \ker(C_{y}) \subseteq \ker(C_{z})$ holds $\Sigma (1)$, which is satisfied for any $S_{g} \in S_{g}$.

**VI. EXAMPLE**

As addressed in section V-D, numerical algorithms to characterize large dimensional elements $S \in S$ and $S_{g} \in S_{g}$ do not exist yet. At this moment it is therefore unclear what orders of $\Sigma_{O}$ (6) can be achieved for large-scale systems. An example is therefore presented in order to illustrate the construction of constrained order observers. Consider a system in a form similar to $\Sigma^{T}$ (7), as described by

$$\begin{align*}
\Sigma_{1} &= \begin{bmatrix}
    \dot{x}_{1}(t) \\
    \dot{x}_{2}(t) \\
    \dot{x}_{3}(t) \\
    y(t)
\end{bmatrix} = \begin{bmatrix}
    -1 & 0 & 0 & 1 \\
    0.1 & -2 & 0 & 0 \\
    0 & -0.5 & -0.4 & 0 \\
    0 & 0.2 & 0.2 & -2
\end{bmatrix}
\begin{bmatrix}
    x_{1}(t) \\
    x_{2}(t) \\
    x_{3}(t) \\
    x_{4}(t)
\end{bmatrix}
+ \begin{bmatrix}
    1 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0 \\
    0 & 0 & 0 & 0
\end{bmatrix} w(t)
\end{align*}
$$

(10)

where $S^{*} = X_{1} \oplus X_{2}$ and $S^{* \perp} = X_{3} \oplus X_{4}$. Furthermore, observe that for stability domain $C_{g} \subseteq C_{-}$ it holds that $S_{g}^{*} = X_{1} \oplus X_{2} \oplus X_{3}$ and $S_{g}^{* \perp} = X_{4}$.

There exists an observer $\Sigma_{O1}$ that solves the DDEP-CO for $\Sigma_{1}$ (10), with $n_{o} = 2$. The inclusion $S^{*} \subseteq S^{*}$ leads to the conclusion that $S^{*} \notin S_{g}$, which by theorem 5.6 implies that the observer will be unstable. This can also be seen from the fact that $L_{3} = 0.5$ must hold in order to decouple state 3 from state 2, which will render the dynamics for $x_{3}$ unstable.

The observer that solves the DDEP-CO for $\Sigma_{1}$ (10), with $n_{o} = 1$ and for stability domain $C_{g} \subseteq C_{-}$, will guarantee that $e_{2}(t)$ is independent of $w(t)$ and that $e_{2}(t) \to 0$ as $t \to \infty$ for any initial estimation error. This observer is given by

$$\begin{align*}
\hat{x}_{4}(t) &= -2\hat{x}_{4}(t) + 0.2y(t) \\
\dot{\hat{z}}(t) &= 2\hat{x}_{4}(t) + 1y(t)
\end{align*}
$$

(11)

Let disturbances be of the form $w(t) = c_{10} + c_{11} \sin(\omega t) + c_{22}n(t)$, where $n(t)$ is unitary white noise. Assume that the disturbances are characterized by $c_{10} = -c_{20} = 10$, $c_{11} = \cdot$
\[
\dot{\Sigma}_e^T = \begin{cases}
\dot{x}_1(t) \\
\dot{x}_2(t) \\
\dot{x}_3(t) \\
\epsilon_z(t)
\end{cases} = \begin{bmatrix}
A_{11} & A_{12} & A_{13} \\
A_{21} & A_{22} & A_{23} \\
0 & 0 & 0 \\
A_{31} + A_{32}C_{1/2} & 0 & 0
\end{bmatrix} \begin{bmatrix}
x_1(t) \\
x_2(t) \\
x_3(t) \\
\epsilon_z(t)
\end{bmatrix} + \begin{bmatrix}
B_{u1} \\
B_{u2} \\
B_{w1} \\
B_{w2}
\end{bmatrix} u(t) + \begin{bmatrix}
0 \\
0 \\
0 \\
0
\end{bmatrix} w(t)
\]

(9)

c_{21} = 20, \, \omega_1 = 1, \, \omega_2 = 3 \text{ and } c_{12} = c_{22} = 100. \text{ Then Fig. 3 shows } \Sigma_{CO2} (11) \text{ applied to } \Sigma_1 (10) \text{ in a simulation, with initial states } x(0) = (10 \ 10 \ 10 \ 10) \text{ and } \dot{x}_4(0) = -30. \text{ The simulation shows that } \epsilon_z(t) \text{ is not affected by } w(t) \text{ and it will converge to 0 as time progresses.}

VII. CONCLUSIONS & FUTURE WORKS

This paper addresses the characterization and synthesis of an observer for a linear and time-invariant generalized plant model of a system. The observer renders the output estimation error \( \epsilon_z(t) \) of \( \Sigma_e \) (4) independent of input \( u(t) \) and disturbance \( w(t) \), while in addition imposing a constraint on the state dimension of the observer. The constrained order observer is designed directly for the full order system, which is corresponding to approach 3 in Fig. 1.

A novel insight into the direct relation between the state dimension of the constrained order observer and the dimension of conditioned invariant subspaces \( S_g \in S_g \) is presented. An observer of small order is created by finding elements \( S_g \in S_g \) with a large dimension.

There exist algorithms that can construct a basis for \( S^* \) [16] and \( S^*_g \) [17]. A numerical procedure to construct bases for elements \( S_g \in S_g \) of larger dimension, does to the knowledge of the authors, not exist. A lower bound on the observer order is constructed. However, the actual smallest order of the observer has analytically not been characterized yet. Consequently, both of these problems must be investigated further in order to make the presented approach applicable in practice.

The absence of a direct feed-through term from \( w(t) \) to \( y(t) \) has been assumed. If this term is present, the design of an observer will be similar when the definition of conditioned invariant subspaces is extended as described in [11, Sec. 4.5][18, Def. 2.1]. The design of observer gain \( L \) will remain unchanged, while matrices \( P \) and \( R \) must be adjusted. However, these adjustments are not required when the observer is used in a dynamic output feedback controller, for which these matrices are chosen with a different objective.

The design of a dynamic output feedback controller with a constrained order that achieves disturbance decoupling will be considered next. In order to design such a controller, the geometric control concepts of controlled invariant subspaces \( V \) and \( (S, V) \)-pairs are used.

Disturbance decoupling problems play an important role in \( H_2 \) optimal control problems. It has been shown in [8][12] that a proper transformation of a generalized plant establishes that a controller (or observer) is \( H_2 \) optimal if and only if it achieves disturbance decoupling for the transformed (error) system. The results of this paper are therefore relevant for constrained order \( H_2 \) optimal observers as well.

REFERENCES