# Massachusetts Institute of Technology <br> Department of Electrical Engineering and Computer Science <br> 6.242, Fall 2004: MODEL REDUCTION * 

## Reduction of systems with real parameters ${ }^{1}$

In this lecture, model reduction of LTI systems depending on real parameters is discussed. While it appears that there is no single approach offering a satisfactory solution to the problem, a number of techniques studied in the previous lectures can be extended to the case of parameterized models.

To streamline the presentation, we will only consider the case of a single constant a-priori bounded parameter, when the original model is defined by

$$
\begin{equation*}
\dot{x}(t)=(A+F \delta L) x(t)+B f(t), y(t)=C x(t) \tag{12.1}
\end{equation*}
$$

where $\delta \in[-1,1]$ is the parameter, $A, B, C, F, L$ are given matrices of dimensions $n$-by- $n$, $n$-by- $m$, $k$-by- $n, n$-by- $d$, and $d$-by- $n$ respectively. It is assumed that $A+F \delta L$ is a Hurwitz matrix for all $\delta \in[-1,1]$. The objective is to derive a reduced model in the form

$$
\begin{equation*}
\dot{x}_{r}(t)=A_{r}(\delta) x_{r}(\delta)+B_{r}(\delta) f(t), \quad y_{r}(t)=C_{r}(\delta) x_{r}(t), \tag{12.2}
\end{equation*}
$$

where $A_{r}(\delta), B_{r}(\delta), C_{r}(\delta)$ are easy to calculate for a given $\delta \in[-1,1]$. The reduced model in (12.2) is acceptable when, for every $\delta \in[-1,1], A_{r}(\delta)$ is a Hurwitz matrix and the H-Infinity norm of the model reduction error system is small.

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### 12.1 Treating parameter dependence as model uncertainty

System (12.1) can be viewed as an uncertain system

$$
\begin{equation*}
\dot{x}=A x+F w+B f, y=C x, v=L x, w(\cdot)=\Delta(v(\cdot)), \tag{12.3}
\end{equation*}
$$

where $\Delta$ is the operator of multiplication by constant $\delta \in[-1,1]$.
As $\Delta$ is linear, and can be described by a set of integral quadratic constraints (IQC) the balanced truncation approach can be applied to produce reduced models with guaranteed stability and error bounds.

### 12.1.1 Static IQC for real parameter uncertainty

Static IQC describe the dependence of $w$ on $v$ in terms of integral relations

$$
\begin{equation*}
\int_{0}^{\infty} \sigma(x(t), w(t), f(t)) d t \geq 0 \tag{12.4}
\end{equation*}
$$

where $\sigma$ are quadratic forms, which has to be satisfied whenever $x, v, w, f$ are square integrable signals satisfying conditions (12.3). Once a set $\tilde{\sigma}$ of such $\sigma$ is available, the (weak) controllability and observability Gramians can be defined as symmetric matrix solutions $W_{o}, W_{c}>0$ of the quadratic form inequalities

$$
\begin{gather*}
2 x^{\prime} W_{o}(A x+F w)+|C x|^{2}+\sigma_{o}(x, w, 0) \leq 0 \quad \forall x, w,  \tag{12.5}\\
2 x^{\prime} W_{c}^{-1}(A x+B f+F w)-|f|^{2}+\sigma_{c}(x, w, f) \leq 0 \quad \forall x, w, f, \tag{12.6}
\end{gather*}
$$

where $\sigma_{o}, \sigma_{c} \in \tilde{\sigma}$, and the standard balanced truncation algorithm utilizing $W_{o}, W_{c}$ can be applied to get a reduced projected model with guaranteed stability and the usual error bounds.

A set of IQC for $\Delta(v)=\delta v$, where $\delta \in[-1,1]$ is an uncertain constant is given by

$$
\begin{equation*}
\sigma(x, w, f)=\sigma_{R}^{0}(x, w, f)=(L x)^{\prime} R(L x)-w^{\prime} R w, \quad R=R^{\prime} \geq 0 \tag{12.7}
\end{equation*}
$$

where $R=R^{\prime} \geq 0$ is an arbitrary positive semidefinite matrix. Indeed, since $w(t)=\delta v(t)$, where $\delta \in[-1,1]$ is a scalar, we have

$$
v^{\prime} R v-w^{\prime} R w=\left(1-\delta^{2}\right) v^{\prime} R v \geq 0 .
$$

In this case, (12.5) is equivalent to the LMI with respect to $W_{o}, R_{0} \geq 0$ :

$$
\left[\begin{array}{cc}
W_{o} A+A^{\prime} W_{o}+C^{\prime} C+L^{\prime} R_{o} L & W_{o} F \\
F^{\prime} W_{o} & -R_{o}
\end{array}\right] \leq 0
$$

which, for $R_{o}>0$, can be transformed into

$$
W_{o} A+A^{\prime} W_{o}+C^{\prime} C+L^{\prime} R_{o} L+W_{o} F R_{o}^{-1} F^{\prime} W_{o} \leq 0
$$

As one can see, the usual Lyapunov inequality (linear with respect to $W_{o}$ ) is transformed into a Riccati inequality (convex quadratic with respect to $W_{o}$ ), parameterized by $R_{o}=$ $R_{o}^{\prime}>0$.

Similarly, (12.6) is equivalent to the LMI with respect to $W_{c}^{-1}, R_{0}>0$ :

$$
\left[\begin{array}{ccc}
W_{c}^{-1} A+A^{\prime} W_{c}^{-1}+L^{\prime} R_{c} L & W_{c}^{-1} B & W_{c}^{-1} F \\
B_{c}^{\prime} W_{c}^{-1} & -I_{m} & 0 \\
F^{\prime} W_{c}^{-1} & 0 & -R_{c}
\end{array}\right] \leq 0
$$

which can be transformed into the Riccati inequality

$$
A W_{c}+W_{c} A^{\prime}+W_{c} L^{\prime} R_{c} L W_{c}+B B^{\prime}+F R_{c}^{-1} F^{\prime} \leq 0
$$

quadratic convex with respect to $W_{c}$ and parameterized by $R_{c}=R_{c}^{\prime}>0$.
It is important to understand that IQC (12.4) defined by (12.7) are satisfied for a very large class of systems $\Delta$. For example, multiplication by a time-varying scalar $\delta=\delta(t)$ satisfies the same IQC. Moreover, it van be shown that the IQC are also valid when $\delta=\delta(s)$ is an arbitrary stable SISO LTI system with H-Infinity norm not exceeding 1. Informally, it would be fair to say that IQC (12.4) defined by (12.7) does not utilize time-invariance and memorylessness properties of system $\Delta$ defined as multiplication by a constant scalar.

Additional IQC can be obtained by noticing that

$$
\int_{0}^{\infty} 2 \delta v(t)^{\prime} H \dot{v}(t) d t=\left.\delta v(t)^{\prime} H v(t)\right|_{0} ^{\infty}=0
$$

when $H=H^{\prime}$ is a symmetric matrix, $x, w, f$ are square integrable and $x(0)=0$. In other terms, quadratic forms

$$
\begin{equation*}
\sigma(x, w, f)=\sigma_{H}^{1}(x, w, f)=2(L x)^{\prime} H L(A x+F w+B f), \quad H=H^{\prime} \tag{12.8}
\end{equation*}
$$

define valid static IQC for $\Delta$. Note that quadratic forms $\sigma_{H}^{1}$ do not define, in general, IQC valid when $\Delta$ is time-varying or has memory.

If $L F=0$ and $L B=0$, one can use the equality

$$
\int_{0}^{\infty} \delta v(t)^{\prime} R \ddot{v}(t) d t=-\delta \int_{0}^{\infty} \dot{v}(t)^{\prime} R \dot{v}(t) d t
$$

to derive additional IQC (12.4) with

$$
\begin{equation*}
\sigma(x, w, f)=\sigma_{R}^{+}(x, w, f)=2 w^{\prime} R L A(A x+F w+B f)+(L A x)^{\prime} R(L A x), \quad R=R^{\prime} \geq 0 \tag{12.9}
\end{equation*}
$$

and

$$
\begin{equation*}
\sigma(x, w, f)=\sigma_{R}^{-}(x, w, f)=-2 w^{\prime} R L A(A x+F w+B f)+(L A x)^{\prime} R(L A x), \quad R=R^{\prime} \geq 0 \tag{12.10}
\end{equation*}
$$

Indeed, these tricks with differentiation can be continued further when $L A B=0$ and $L A F=0$.


[^0]:    *(C)A. Megretski, 2004
    ${ }^{1}$ Version of December 1, 2004

