ROBUST CONTROL DESIGN FOR A FLUID CATALYTIC CRACKING CONVERTER UNIT

Jose Maria Gálvez
Department of Mechanical Engineering, Federal University of Minas Gerais, Brazil.
Av. Antonio Carlos 6627, Pampulha, 31.270-901 Belo Horizonte, MG, Brazil.
Phone: +55 31 499-5236. Fax: +55 31 443-3783. E-mail: jmgm@dedalus.lcc.ufmg.br.

Sergio Ricardo de Souza
Department of Electrical Engineering, Fed. Center of Technological Education of Minas Gerais, Brazil.
Av. Amazonas 7675, Nova Gameleira, 30.510-000 Belo Horizonte, MG, Brazil.
Phone: +55 31 319-5210. Fax: +55 31 319-5212. E-mail: sergio@dppg.cefetmg.br.

Abstract— This work is concerned with the design of low-level multivariable control loops for Fluid Catalytic Cracking Units. The Fluid Catalytic Cracking (FCC) Unit control problem is a challenging task due to its model complexity, nonlinear dynamics, constrained variables and cross coupling interaction between inputs and outputs. Predictive control has been used to control FCC units and to optimize their production cycles. However, the complex interaction among the process variables and the constrains on the manipulated and controlled variables causes the computing cost to be high and time consuming. The proposed control strategy targets the simplification of the global control-optimization problem by including a low-level multi-input multi-output linear controller whose primary objective is to minimize the cross coupling between the plant inputs and outputs. Having achieved diagonal dominance at low frequency, a multi-input multi-output PI controller is then tuned to fulfill performance and robustness specifications. A dynamic model, based on Moro and Odloak's model (1998) for the Kellog-Orthoflow model F reactor/regenerator system, is used as the "plant" through the modeling and control design procedures. Multivariable techniques in the frequency domain are used to perform analysis, to obtain system decoupling and to design and validate the closed loop low-level multi-input multi-output linear controller. Simulation results are finally presented.

Keywords— Multivariable Control. FCC Control. Chemical Industry.

Nomenclature

u1 = Air Flow Rate to Regenerator Control Signal
u2 = Fresh Catalyst Valve Control Signal
u3 = Total Feed Flow Rate Control Signal
u4 = Feed Temp at Riser Entrance Control Signal
y1 = Regenerator 1st Stage Dense Phase Temp.
y2 = Regenerator 2nd Stage Dense Phase Temp.
y3 = Estimated Cracking Reaction Severity
y4 = Riser Cracking Mixture Temperature
[A,B,C,D] = State Space Realization
[An,Bn,Cn,Dn] = S. S. R. of the Nominal Plant
[Ar,Br,Cr,Dr] = S. S. R. of the Residual Plant
[Gn] = Controller Gain Matrix
[Kn] = Observer Gain Matrix
K = Scalar Static Gain
Gij(s) = Scalar Transfer Function
Nij(s) = Numerator of a Transfer Function
Dij(s) = Denominator of a Transfer Function
Kpij = Proportional Gain of a PID Controller
Kiij = Integral Gain of a PID Controller
[G(s)] = MIMO Plant Matrix Transfer Function
[K(s)] = MIMO Controller M. Transfer Function
[U(s)] = Plant Input Vector in Laplace Domain
[Y(s)] = Plant Output Vector in Laplace Domain
[R(s)] = Setpoint Vector in Laplace Domain
[E(s)] = Output Error Vector in Laplace Domain

1 Introduction

Most industrial processes are usually constituted of a large number of low-order nonlinear sub-systems. As a consequence of that, industrial processes are usually described by high-order nonlinear multivariable models. In the neighborhood of some operating point, the nonlinear models can be approximated by linear models of usually very-high order. These models, although linear ones, are not suitable for control design purposes due to their high dimension.

This work presents a heuristic modeling and control design procedure that requires model accuracy only at low frequency. It shows that parameter identification from process data, model linearization and output feedback control are feasible procedures for large scale multivariable industrial plants that usually present strong cross interaction between their inputs and outputs.

Section 2 presents a brief review on the general control problem of large scale systems (LSS) control problem. Section 3 reviews some basic ideas in multivariable control. Section 4 addresses the modeling problem of an FCC unit. Section 5 shows the controller design procedure. Finally, Section 6 presents simulation results of the proposed control strategy applied to a Fluid Catalytic Cracking (FCC) Converter.

2 The LSS Control Problem -- A Brief Review

The term "large scale systems" (LSS) is usually applied to processes whose high-order mathematical model requires some kind of model reduction for control design purposes, such is the case of flexible large space structures, petrochemical processes and paper mill plants.

The fast development of the space industry has produced new control techniques for large-scale systems, which have not been fully tested, particularly outside the space research environment. New modeling and control techniques for large-scale systems have to be tried and compared with the classical and well-accepted control algorithms. This is the case of the worldwide well-consolidated petrochemical industry.

To face the control problem of FCC units, several alternatives can be found in the technical literature. For the sake of the argument and considering the structure of the control algorithm as the classifying element, the wide spread set of control techniques for MIMO systems might be loosely grouped in four fundamental strategies.

2.1. ROM Based State Feedback Control

The control problem of large scale systems has been a main issue among the control community due to its challenging characteristics.

The difficulty in obtaining an accurate plant model has led to the development of several design techniques based on some reduced-order-model (ROM) of the plant.

In this case, the plant is partitioned as shown in Equation 1. The nominal plant [A_n B_n C_n D_n] corresponds to the plant reduced order model which is believed to be accurate. The unknown residual plant [A_r B_r C_r D_r] represents model uncertainties and unmodeled dynamics. Thus, the plant partition becomes:

$$\begin{bmatrix} \dot{\boldsymbol{x}}_n \\ \dot{\boldsymbol{x}}_r \end{bmatrix} = \begin{bmatrix} \boldsymbol{A}_n & 0 \\ 0 & \boldsymbol{A}_r \end{bmatrix} \begin{bmatrix} \boldsymbol{B}_n \\ \boldsymbol{B}_r \end{bmatrix} [\boldsymbol{u}_n] \qquad (1a)$$

$$\boldsymbol{y} = \boldsymbol{y}_n + \boldsymbol{y}_r = [\boldsymbol{C}_n \quad \boldsymbol{C}_r] \begin{bmatrix} \boldsymbol{x}_n \\ \boldsymbol{x}_r \end{bmatrix} \qquad (1b)$$

The control law is designed based on the plant reduced order model.

$$\boldsymbol{u}_n = \boldsymbol{r} + \boldsymbol{G}_n \hat{\boldsymbol{x}}_n \qquad (2)$$

In this case, the observer equation is given by

$$\dot{\hat{\boldsymbol{x}}}_n = \boldsymbol{A}_n \hat{\boldsymbol{x}}_n + \boldsymbol{B}_n \boldsymbol{u}_n + \boldsymbol{K}_n (\boldsymbol{y} - \hat{\boldsymbol{y}}_n) \qquad (3)$$

Defining $e_x = x_n - \hat{x}_n$, the closed loop state space equation will be given by

$$\begin{bmatrix} \dot{\boldsymbol{x}}_n \\ \dot{\boldsymbol{e}}_x \\ \dot{\boldsymbol{x}}_r \end{bmatrix} = \begin{bmatrix} & & \\ & \boldsymbol{Ac} & \\ & & \end{bmatrix} \begin{bmatrix} \boldsymbol{x}_n \\ \boldsymbol{e}_x \\ \boldsymbol{x}_r \end{bmatrix} + \begin{bmatrix} \boldsymbol{B}_n \\ 0 \\ \boldsymbol{B}_r \end{bmatrix} [\boldsymbol{r}] \qquad (4)$$

where

$$\boldsymbol{Ac} = \begin{bmatrix} (\boldsymbol{A}_n + \boldsymbol{B}_n \boldsymbol{G}_n) & -\boldsymbol{B}_n \boldsymbol{G}_n & 0 \\ 0 & (\boldsymbol{A}_n - \boldsymbol{K}_n \boldsymbol{C}_n) & -\boldsymbol{K}_n \boldsymbol{C}_r \\ \boldsymbol{B}_r \boldsymbol{G}_n & -\boldsymbol{B}_r \boldsymbol{G}_n & \boldsymbol{A}_r \end{bmatrix} \qquad (5)$$

The main drawback of this approach is that there are no formal means to assess closed loop stability. The terms [B_r G_n] and [K_n C_r] are known as control spillover and observation spillover, respectively and because of them there is no guaranty that the closed loop system will remain stable.

This is especially important in the case of LSS in which the dimension of [A_r B_r C_r D_r] is usually larger than the one of [A_n B_n C_n D_n]. Further discussion can be found in Balas (1982).

2.2. Model Based Predictive Control

Model-based predictive control (MBPC) is a large family of control algorithms developed around certain common ideas. The basic approach behind the predictive control family is to use a simulation model to predict the future behavior of the plant and to use this information to implement some optimal control law. MBPC can be used to control a great variety of processes, from plants with relatively simple dynamics to those with more complex ones.

Several predictive control algorithms have been proposed by the control community. Some relevant contributions were produced by Campos and Morari (1987), Muske and Rawlings (1993), Zheng and Morari (1995). Mile stone surveys were given by from Richalet et al (1978), Garcia et al (1989), Qin and Badgwell (1997) and Mayne et al (2000).

One of the most popular MBPC strategies, in both, industry and academia, is the Generalized Predictive Control (GPC) method proposed by Clarke et al (1987, 1989). It is argued that the GPC technique can deal with unstable and non minimum phase plants and the control law has an explicit solution for the case of linear plants (with no constrained variables). Considering the GPC original idea, a diversity of control schemes have been proposed by the scientific community and they might be considered as subsets or limiting cases of the GPC approach.

Predictive control has been used as a suitable approach to solve the control problem of complex large scale systems. Furthermore, since the basic concepts are very intuitive, predictive control has become a particularly attractive control strategy.

However, the computational efficiency of the control algorithms is frequently poor and time consuming, especially in the case of complex nonlinear plants. Besides that, predictive control schemes require accurate plant models to reach good performance. The practice has shown that the controller performance is strongly dependent on model accuracy that makes the model identification and parameter estimation strenuous tasks, particularly in an industrial environment.

2.3. Artificial Intelligence and LSS Control

Intelligent Control is a broad term for control strategies that basically include three aspects of the artificial intelligence area: Neural Network Based Control, Fuzzy Control and Knowledge-Based Control.

Although important results can be found in the technical literature there still are no answers to fundamental questions that come from the control area. Disturbance compensation and measurement noise reduction are basic objectives in the controller design that are not easily evaluated in the artificial intelligence framework.

2.4. MIMO Output Feedback Control

Output feedback has been the industrial standard for control purposes not only to shape the plant response, fulfilling performance specifications, but also to deal with output disturbances and model uncertainties. Traditionally, the industrial control community has relied on the intrinsic robustness of output feedback controllers to face the control design problem for SISO plants. A diversity of controller tuning algorithms has been successfully developed and applied to SISO industrial plants. Behind this success there has always been a property that exists for all physical system, the dominance of the low-frequency poles in the system time response. This fact has been the background of nearly all robust control design techniques. Considering this concept in the controller design, there is no need for solving the modeling problem as rigorously as it could be required without the pole dominance property.

Several attempts have been made to extend the SISO design techniques to the MIMO case. With some exceptions, the success of MIMO control design also depends on the pole dominance property. In this context, the size (order) of large scale systems becomes less important when compared with the usually strong input-output cross-coupling existent in MIMO systems. In recent years, the research has been focused in new uncoupling techniques. It is worthwhile to mention the pioneer contributions from Bristol (1966), Kouvaritakis (1979), Mees (1981), McAvoy, (1983) and Grosdidier and Morari (1986). Some characteristics of these techniques are:

a) The design procedure is usually carried out in the frequency domain.
b) Model uncertainties are easily represented in the frequency domain (particularly, non structural uncertainties).
c) In general, low frequency models are accurate enough for control design in this environment.
d) The standard PI controllers (that responds for more de 90% of the industrial controllers) are designed to perform in the low frequency.
e) Output disturbances are usually low frequency signals.

3 Multivariable Control

This section presents a brief review of the basic concepts on multivariable control systems. The following is based on the books from Maciejowski (1989) and Skogestad et al (1996).

The system output, *y(s)*, is given by a matrix function of the form

$$\boldsymbol{y}(s) = \boldsymbol{T}(s)\boldsymbol{P}(s)\boldsymbol{r}(s) + \boldsymbol{S}(s)\boldsymbol{d}(s) - \boldsymbol{T}(s)\boldsymbol{m}(s) \quad (6)$$

where *r(s)* is the reference input, *d(s)* represents the disturbances and *m(s)* is the measurement noise.

In this case, $S(s)$ is known as the output sensitivity function and is defined as

$$\boldsymbol{S}(s) = [\boldsymbol{I} + \boldsymbol{G}(s)\boldsymbol{K}(s)]^{-1} \quad (7)$$

the system closed loop transfer function (or complementary sensitivity), *T(s)*, is then given by

$$\boldsymbol{T}(s) = \boldsymbol{S}(s)\boldsymbol{G}(s)\boldsymbol{K}(s) \quad (8)$$

The input sensitivity function is defined as

$$\boldsymbol{S_i}(s) = [\boldsymbol{I} + \boldsymbol{K}(s)\boldsymbol{G}(s)]^{-1} \quad (9)$$

and its corresponding complementary function as

$$\boldsymbol{T_i}(s) = \boldsymbol{K}(s)\boldsymbol{G}(s)\boldsymbol{S_i}(s) \quad (10)$$

A multiplicative model for the plant uncertainty can be written as

$$\boldsymbol{G}(s) = \boldsymbol{G}_0(s)[\boldsymbol{I} + \boldsymbol{W_i}(s)] \quad (11)$$

Hence, the following criteria to assess the system performance and stability can be established:

- The criterion for nominal performance is defined by

$$\left\| \boldsymbol{S}(s)\boldsymbol{W_p}(s) \right\|_\infty < 1 \quad (12)$$

where $W_p(s)$ is a performance weighting matrix and has the form

$$\boldsymbol{W_p}(s) = \boldsymbol{w_p}(s)[\boldsymbol{I}] \quad (13)$$

in this work, the nominal performance criterion was specified as

$$\bar{\sigma}[\boldsymbol{S}(s)] < \frac{1}{\boldsymbol{w_p}(s)} = \frac{1000\ s}{150\ s + 1} \quad (14)$$

where $\bar{\sigma}[.]$ is the greatest singular value of [.]

- The criterion for robust performance (non structured uncertainty) is given by

$$\gamma\bar{\sigma}\left(\boldsymbol{w_p}(s)\boldsymbol{S_i}(s)\right) + \bar{\sigma}\left(\boldsymbol{w_i}(s)\boldsymbol{T_i}(s)\right) \le 1 \quad (15)$$

where γ = min(plant condition number, controller condition number).

- The criterion for robust stability (non structured uncertainty) is defined by

$$\left\| \boldsymbol{T}(s)\boldsymbol{W_i}(s) \right\|_\infty < 1 \quad (16)$$

where $W_i(s)$ is an uncertainty weighting matrix and has the form

$$\boldsymbol{W_i}(s) = \boldsymbol{w_i}(s)[\boldsymbol{I}] \quad (17)$$

in this case, the criterion for robust stability was chosen as

$$\bar{\sigma}[\boldsymbol{T}(s)] < \frac{1}{\boldsymbol{w_i}(s)} = \frac{10}{s + 1} \quad (18)$$

- The robust performance condition for structured uncertainty (Doyle et al, 1981) is

$$\mu(\boldsymbol{Q}(s)) < 1 \qquad \forall\omega \quad (19)$$

where, the matrix $Q(s)$ is defined as

$$\boldsymbol{Q}(s) = \begin{bmatrix} \boldsymbol{Q}_{11}(s) & \boldsymbol{Q}_{12}(s) \\ \boldsymbol{Q}_{21}(s) & \boldsymbol{Q}_{22}(s) \end{bmatrix}$$

with

$$\boldsymbol{Q}_{11}(s) = \boldsymbol{w_p}(s)\ \ \boldsymbol{S}_0(s)$$

$$\boldsymbol{Q}_{12}(s) = \boldsymbol{w_p}(s)\ \ \boldsymbol{S}_0(s)\ \ \boldsymbol{G}_0(s)$$

$$\boldsymbol{Q}_{21}(s) = -\boldsymbol{w_i}(s)\ \ \boldsymbol{K}(s)\ \ \boldsymbol{S}_0(s)$$

$$\boldsymbol{Q}_{22}(s) = -\boldsymbol{w_i}(s)\ \ \boldsymbol{K}(s)\ \ \boldsymbol{S}_0(s)\ \ \boldsymbol{G}_0(s)$$

and

$$\boldsymbol{S}_0(s) = \left(\boldsymbol{I} + \boldsymbol{G}_0(s)\boldsymbol{K}(s)\right)^{-1}$$

- The robust stability condition for structured uncertainty (Doyle et al 1981) is given by

$$\mu\big(\boldsymbol{Q}_{22}(\boldsymbol{s})\big) < 1 \qquad \forall\omega \qquad (20)$$

Equations from (12) to (20) are used in Section 6 to validate the controller design.

4 The FCC Linear Model

The results presented in this section show that it is always feasible to determine an accurate linear model for large scale plants, particularly, for FCC units.

The modeling of Fluid Catalytic Cracking Converters is one of the most challenging problems in the petrochemical industry. To be able to test and compare new control algorithms a test bench was established, in this case a numerical model for simulation. In the context of this work, an FCC nonlinear dynamic model was chosen as a benchmark by the Chemical Processes Control Group, created under the RECOPE Program, sponsored by the FINEP Brazilian Agency.

The benchmark model is basically the same one as presented by Moro and Odloak (1998) for the FCC Kellog Orthoflow F Reactor/Regenerator Unit. It is used here to illustrate the whole control design procedure: from modeling and parameter identification through out controller design and closed loop simulation.

Experimental data (for the modeling and parameter identification procedures) was generated using the benchmark nonlinear model. Although, the original FCC nonlinear model is a medium scale one. The resulting linear model is excessively large for full-order linear control design purposes, as it will be shown in the next sections.

The model identification was performed using the Eigenvalue Realization Algorithm (ERA) introduced by Juang and Pappa (1985). The ERA procedure starts with a Hankel matrix built from the plant impulse response. Then, a minimal order realization can be found from the Hankel matrix through a matrix factorization based on its singular value decomposition (SVD). The singular values of the impulse response matrix produce a quantitative measure to determine the model order.

In this case, the benchmark "plant" was a 4x4 MIMO nonlinear system. It was observed in simulation and verified through analysis that $y_1(t)$ and $y_2(t)$ are strongly correlated as well as $y_3(t)$ and $y_4(t)$, as shown in Figure 1. Thus, only two inputs and two outputs were considered for design.

Applying the ERA procedure to the full "plant" a 2x2 MIMO linear model was obtained corresponding to a Matrix Transfer Function (MTF) of the form:

$$\begin{bmatrix}\boldsymbol{Y}_2(\boldsymbol{s})\\ \boldsymbol{Y}_4(\boldsymbol{s})\end{bmatrix} = \begin{bmatrix}\boldsymbol{G}_{22}(\boldsymbol{s}) & \boldsymbol{G}_{24}(\boldsymbol{s})\\ \boldsymbol{G}_{42}(\boldsymbol{s}) & \boldsymbol{G}_{44}(\boldsymbol{s})\end{bmatrix}\begin{bmatrix}\boldsymbol{U}_2(\boldsymbol{s})\\ \boldsymbol{U}_4(\boldsymbol{s})\end{bmatrix} \qquad (21)$$

5 The MIMO Controller Design

Recently, research has been focused in solving the FCC control problem and the production optimization in one single step. A fine predictive control algorithm would include both problems and solve them in one package (Moro and Odloak, 1998). A drawback of this approach is that the transitory performance is not usually considered in the control design.

Here, an alternate approach is suggested. It is shown that the global controller structure may include an inner loop designed to solve a linear control problem and an outer loop (the predictive control and optimization algorithm) placed to fulfill economics and operational specifications.

The main objective of this work is to introduce a design procedure for the inner loop, which corresponds to the control of a MIMO unconstrained linear plant. The inner loop is designed to fulfill performance specifications, to reduce plant disturbances and to compensate for model uncertainties.

The proposed strategy is basically a frequency-domain procedure. In this case, the MIMO controller design is carried out in two steps. First a MIMO pre-compensator, $K_1(s)$, is designed to scale the system and reach diagonal dominance at low frequency and then a MIMO controller, $K_2(s)$, is designed to meet performance specifications.

Then, the control law has the form:

$$[\boldsymbol{U}(\boldsymbol{s})] = [\boldsymbol{K}_1(\boldsymbol{s})]\,[\boldsymbol{K}_2(\boldsymbol{s})]\,[\boldsymbol{R}(\boldsymbol{s}) - \boldsymbol{Y}(\boldsymbol{s})] \qquad (22a)$$

or

$$[\boldsymbol{U}(\boldsymbol{s})] = [\boldsymbol{K}(\boldsymbol{s})]\,[\boldsymbol{E}(\boldsymbol{s})] \qquad (22b)$$

with

$$\boldsymbol{K}(\boldsymbol{s}) = \begin{bmatrix}\dfrac{\boldsymbol{N}_{11}(\boldsymbol{s})}{\boldsymbol{D}_{11}(\boldsymbol{s})} & \dfrac{\boldsymbol{N}_{12}(\boldsymbol{s})}{\boldsymbol{D}_{12}(\boldsymbol{s})}\\[2ex] \dfrac{\boldsymbol{N}_{21}(\boldsymbol{s})}{\boldsymbol{D}_{21}(\boldsymbol{s})} & \dfrac{\boldsymbol{N}_{22}(\boldsymbol{s})}{\boldsymbol{D}_{22}(\boldsymbol{s})}\end{bmatrix} \qquad (23)$$

In the case of a 2x2 MIMO PI controller, Equation 23 becomes:

$$\boldsymbol{K}(\boldsymbol{s}) = \begin{bmatrix}\boldsymbol{Kp}_{11} + \dfrac{\boldsymbol{Ki}_{11}}{\boldsymbol{s}} & \boldsymbol{Kp}_{12} + \dfrac{\boldsymbol{Ki}_{12}}{\boldsymbol{s}}\\ \boldsymbol{Kp}_{21} + \dfrac{\boldsymbol{Ki}_{21}}{\boldsymbol{s}} & \boldsymbol{Kp}_{22} + \dfrac{\boldsymbol{Ki}_{22}}{\boldsymbol{s}}\end{bmatrix} \qquad (24)$$

Several techniques for multivariable loop shaping can be found in the literature (Maciejowski, 1989, Skogestad, 1996, Ho & Xu, 1998). Following a simple trail and error procedure, an acceptable performance was achieved using:

$$\boldsymbol{K}(\boldsymbol{s}) = \begin{bmatrix}-\dfrac{615\ \boldsymbol{s}+3}{\boldsymbol{s}} & \dfrac{566\ \boldsymbol{s}+3}{\boldsymbol{s}}\\ -\dfrac{1710\ \boldsymbol{s}+9}{\boldsymbol{s}} & -\dfrac{526\ \boldsymbol{s}+3}{\boldsymbol{s}}\end{bmatrix} \qquad (25)$$

6 Simulation Results

Simulation results are presented here to illustrate the proposed design procedure that includes: modeling, model validation, controller design and finally control system analysis and validation.

Figure 1 shows the simulation results for the 4x4 MIMO FCC plant. It can be seen the strong correlation between outputs y1(t) and y2(t) and between y3(t) and y4(t). Figure 2 shows the results for the 2x2 MIMO model validation. In this case, the ERA procedure led to a 90th order model. It can be seen that the model time response fits the plant response almost perfectly. Figure 3 presents the open loop plant frequency responses. It can be observed the high values of the cross-coupling gains. Figure 4 displays the open loop plant step responses. Figure 5 presents the simulation results for the closed loop system. A unit step signal was applied to the plant inputs, u2(t) and u4(t), one at a time. In this case, the control tuning led to a fast time response. Figure 6 shows the weighting functions, the controller frequency response, the open loop principal gains and also the nominal performance for the plant + controller open loop system. Finally, Figure 7 presents the system robustness characteristics for non structured and structured uncertainties based on the criteria given by Equations 14 and 18.

7 Final Comments and Conclusions

This work presented a frequency domain procedure for modeling and control design of large scale systems. The procedure was applied to the model of a Kellog-Orthoflow Reactor/Regenerator Unit that was adopted as the “plant” to illustrate the performance of the chosen strategy.

The proposed scheme can be seen as a pre-conditioning multivariable linear controller that shapes the plant dynamics in order to simplify the subsequent steps of the FCC global control-optimization problem.

It was shown through a challenging example that the control problem of high order MIMO systems has a solution by using multivariable output feedback control. It was also seen that control design in the frequency domain is a proper technique to deal with the modeling and control problem of nonlinear large scale systems. It has been verified that only the low frequency part of the linearized model requires to be accurate to satisfy steady state specification.

Finally, the results obtained in simulation are good enough to validate the proposed technique and to point out toward a feasible strategy for the solution of the FCC global control problem. However, in the scope of this paper, no attempt was made to solve the control problem under variable constrains, therefore, the results are not fully conclusive yet and further research has to be done.

8 References

Balas, M.J., "Trends in Large Space Structure Control: Fondest Hopes, Wildest Dreams," IEEE Transactions on Automatic Control, Vol. AC-27, No. 3, pp. 522-535, 1982.

Bristol, E.H., “On a New Measure of Interaction for Multivariable Process Control”, IEEE Transactions on Automatic Control, Vol. 11, pp.133-134, 1966.

Campos, P.J., and Morari, M., “Predictive Control”, Proceedings of the American Control Conference, pp. 1021-1026, 1987.

Clarke, D.W. and Mohtadi, C., “A Generalized Predictive Control”, Automatica, Vol 25, Nº 6, pp. 859-875, 1989.

Clarke, D.W., Mohtadi, C. and Tuffs, P.S., “A Generalized Predictive Control - Part I: The Basic Algorithm”, Automatica, Vol 23, Nº 2, pp. 137-148, 1987.

Clarke, D.W., Mohtadi, C. and Tuffs, P.S., “A Generalized Predictive Control - Part II: Extensions and Interpretations”, Automatica, Vol 23, Nº 2, pp. 149-160, 1987.

García, E.C., Prett, D.M., and Morari, M., “Model Predictive Control: Theory and Practice” Automatica, 25, pp. 335–348, 1989.

Grosdidier, P. and Morari, M., “Interactions Measurements for Systems under Decentralized Control”, Automatica, vol. 22, pp. 309-319, 1986.

Ho, W.K. and Xu, W., “Multivariable PID Controller Design Based on the Direct Nyquist Array Method”, Proceedings of the American Control Conference, Philadelphia, Pennsylvania, pp. 3524-3528, 1998.

Juang, J.N. and Pappa, R.S., “Eigen-System Realization Algorithm”, Journal of Guidance and Control, Vol. 8, No 3, September-October, 1985.

Kouvaritakis, B., "Theory and Practice of the Characteristic-Locus Design Method", IEE Proceedings, Vol. 126, pp. 542-548, 1979.

Maciejowski, J.M., “Multivariable Feedback Design”, Addison-Wesley Publishing Company, 1989.

Mayne and H. Michalska, “Receding Horizon Control of Nonlinear Systems”, IEEE Transactions on Automatic Control, 35, pp. 814–824, 1990.

Mayne, D.Q., Rawlings, J.B., Rao, C.V., and Scokaert, P.O.M., “Constrained Model Predictive Control: Stability and Optimality, Survey Paper”, Automatica 36, pp. 789-814, 2000.

McAvoy, T. J., “Interaction Analysis - Principles and Applications”, ISA, 1983.

Mees, A.I., "Achieving Diagonal Dominance", Systems and Control Letters, Vol. 1, pp. 155-158, 1981.

Michalska and Mayne, D.Q., “Robust Receding Horizon Control of Constrained Nonlinear

Systems”, IEEE Transactions on Automatic Control, 38, pp. 1623–1633, 1993.

Moro, L.F.J., Spandri, R. and Odloak, D., "Constrained Multivariable Control of Fluid Catalytic Cracking Converters, A Practical Application", AIChE, Spring National Meeting, paper 84b, Houston, 1998.

Moro, L.F.L. and Odloak, D., "Constrained Multivariable Control of Fluid Catalytic Cracking Converters", Journal of Process Control, 5, 1, 29-39, 1998.

Muske and Rawlings, J.B., “Model Predictive Control with Linear Models”, AIChE Journal, 39, pp. 262–287, 1993.

Qin, S.J. and Badgwell, T.A., “An Overview of Industrial Model Predictive Control Technology”, Fifth International Conference on Chemical Process Control, CACHE, AIChE, PP. 232-256, 1997.

Rawlings and Muske, K.R., “Stability of Constrained Receding Horizon Control”, IEEE Transactions on Automatic Control, 38, pp. 1512–1516, 1993.

Richalet, J., Rault, A., Testud, J.L. and Papon, J., “Model Predictive Heuristic Control: Applications to Industrial Process”, Automatica, vol. 14, no 5, pp. 413-428, 1978.

Skogestad, S. and Postlethwaite, I., “Multivariable Feedback Control - Analysis and Design”, John Wiley & Sons, 1996.

Zheng, A.Q., Morari, M., “Stability of Constrained Model Predictive Control”, Proceedings of the American Control Conference, pp. 379-382, 1995.

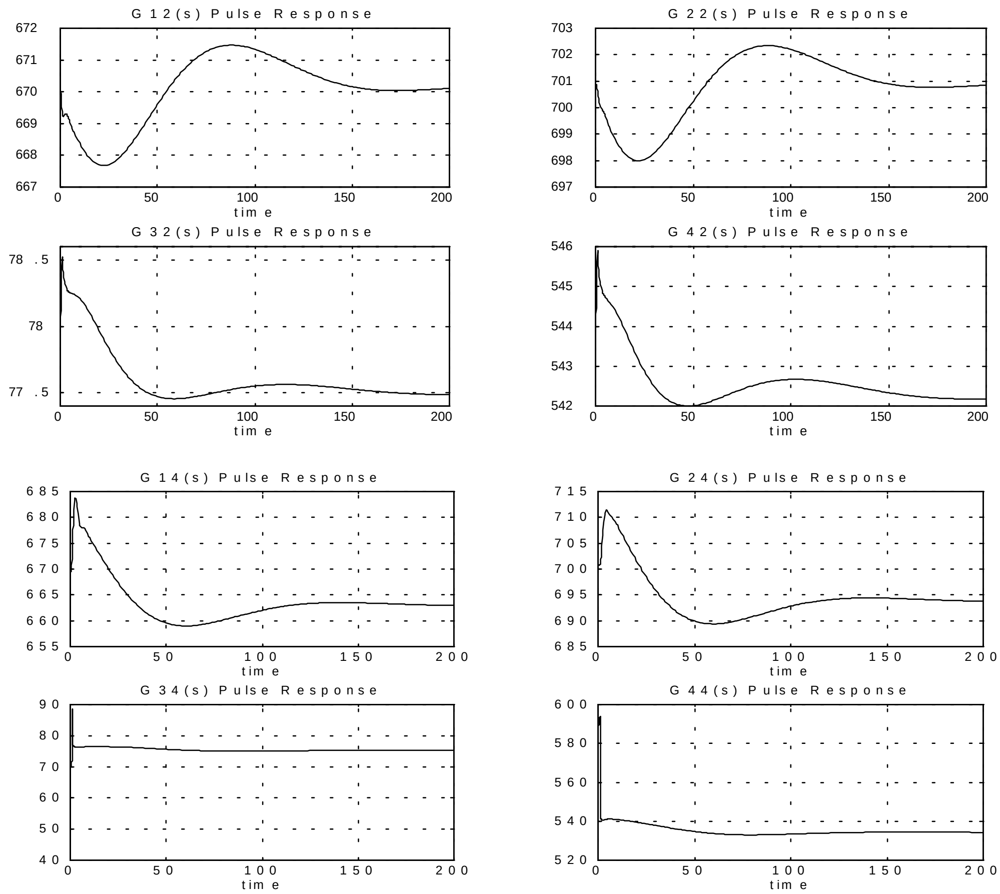

Figure 1. The 4x4 MIMO Plant Pulse Responses

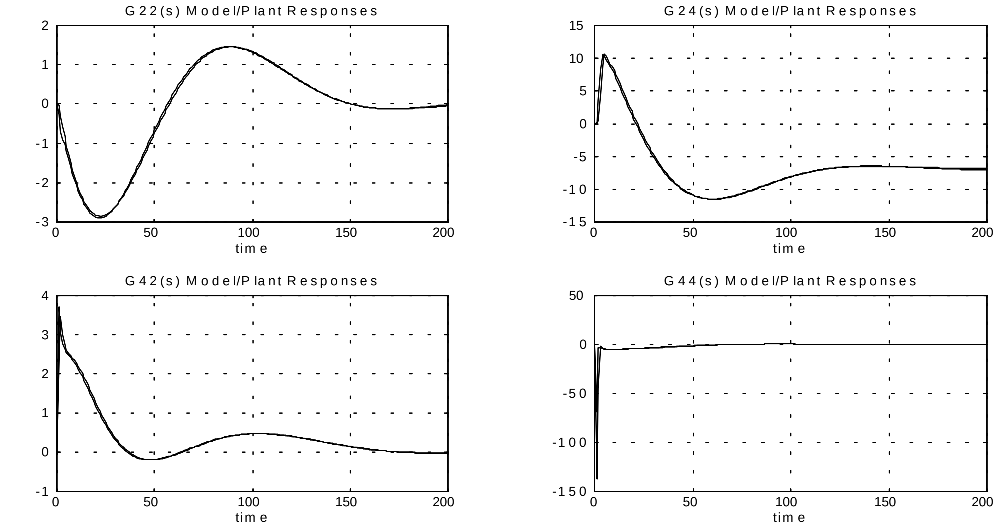

Figure 2. The Model Validation Tests.

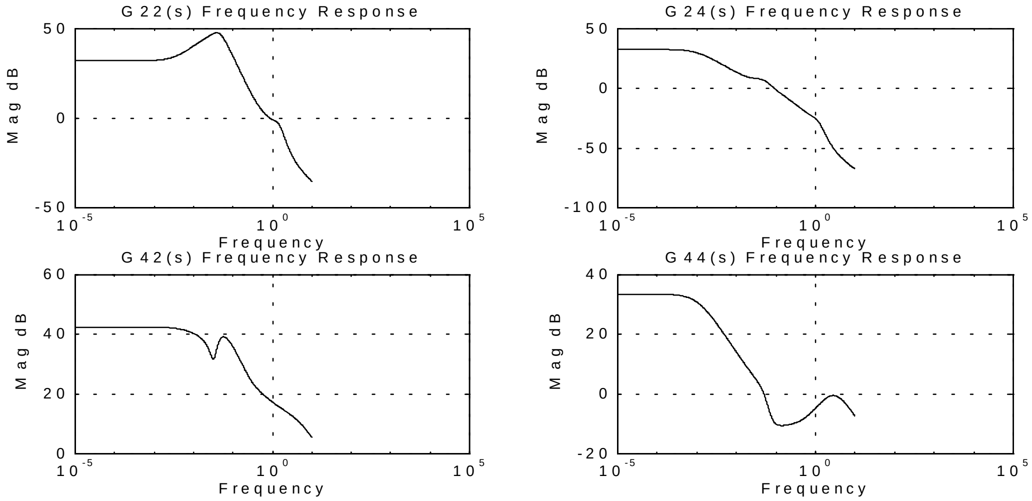

Figure 3. The Open Loop Plant Frequency Responses.

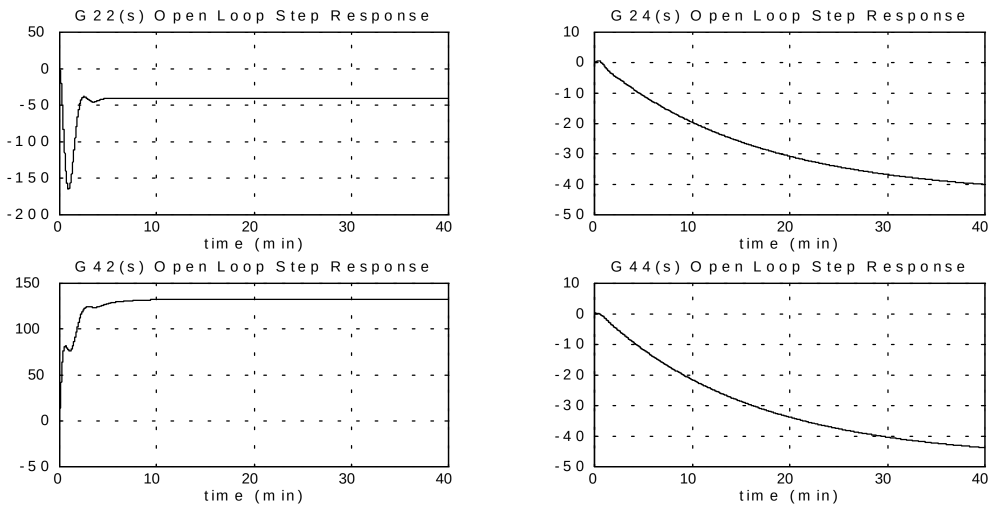

Figure 4. The Open Loop Plant Step Responses.

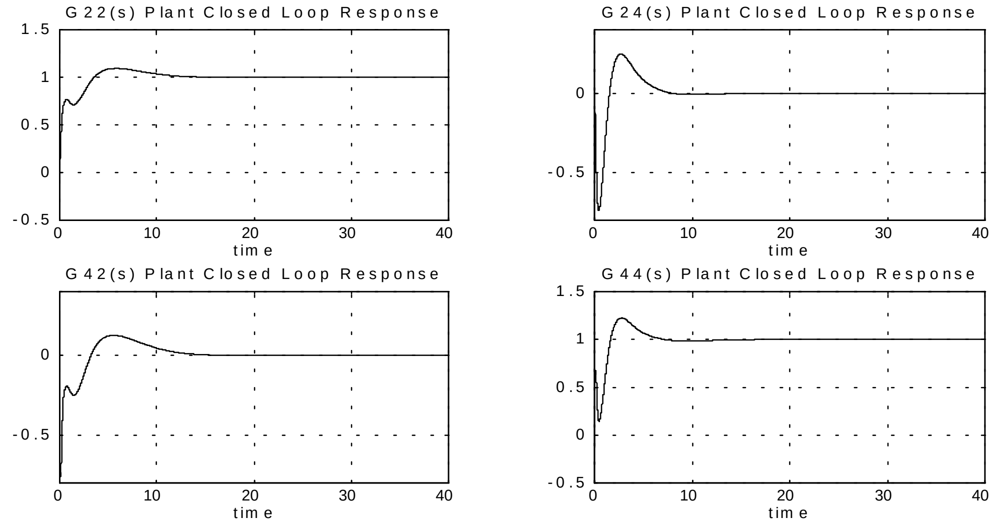

Figure 5. The Closed Loop Plant Step Responses.

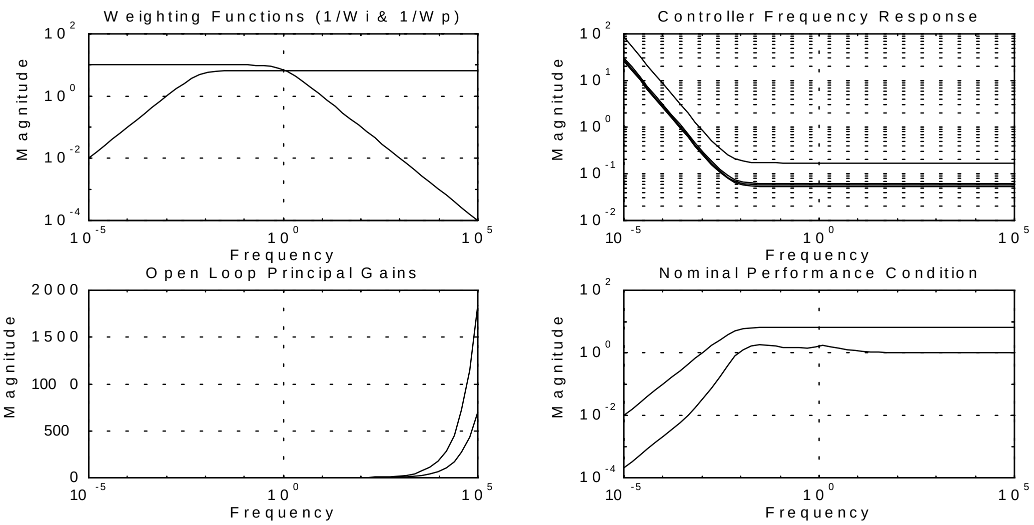

Figure 6. Frequency Domain Analysis.

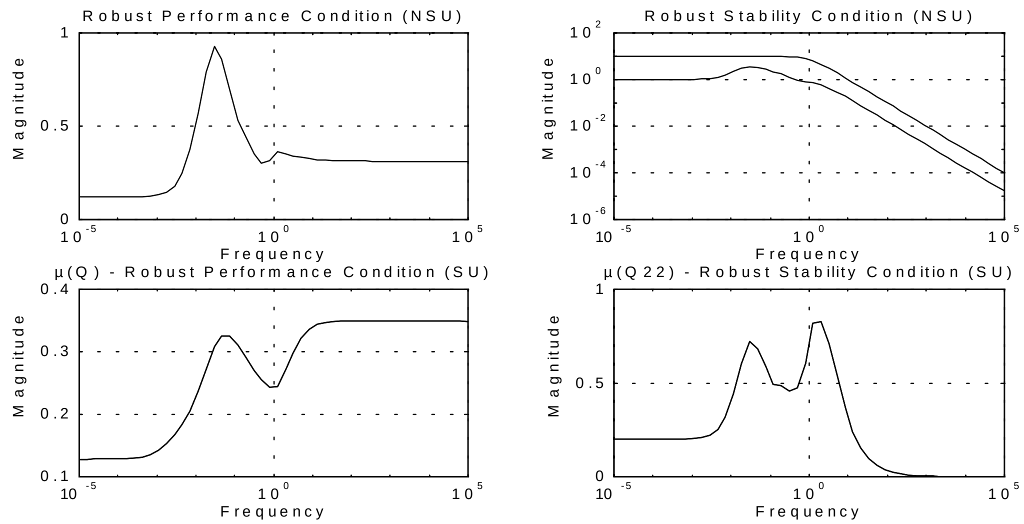

Figure 7. Control Robustness Validation.