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IDENTIFICATION FOR ROBUST CONTROL OF VIBRATING STRUCTURES

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Abstract

This paper aims at introducing the reader to the various issues that arise in the development of a coherent methodology for the development of robust control design on the basis of models identified from data. When a reduced complexity model is identified with the purpose of designing a robust controller, the model is just a vehicle for the computation of controller. The design of the identification and of the controller must be seen as two parts of a joint design problem. One of the control messages of this paper is to show that the global control performance criterion must determine the identification one. On the other hand, the paper summarizes the most important approaches of these iterative schemes of identification for robust control. Finally, an academic example is demonstrated for the applicability of the iterative method.

Keywords: robust control, closed loop identification, iterative control design.

1. Introduction

The model based controller design is a very difficult and complicated process which starts in each case with the idealization of the physical system, then it identifies the mathematical model of the idealized system, finally the controller design is performed on the basis of the mathematical model. The steps of the design are illustrated on the *Fig. 1.*

The design arises some questions to answer but the most fundamental and important among them is to investigate the impact of the modelling errors to the designed controller. Since up till now sufficient qualitative features do not exist, i.e. it is not determinable in each case, which open loop modelling errors have significant influence on the controller.

Robust controller design methods take also into account those features that are ignored during the modeling phase. It means that the designed controllers based on the identified nominal model ensure the system stability and the prescribed performance level in spite of the system uncertainties.

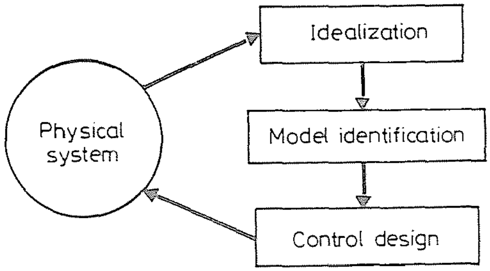

Fig. 1.

The errors of the model identified in open loop and their regions should be taken into account during the controller design process. Although it is difficult to say that which of them are significant and which of them are ignorable from the viewpoint of closed loop design. The following section summarizes the most important modelling principles of the model based controller design and also illustrates them with simple examples (SKELTON, 1989).

Principle 1. Arbitrarily small modelling errors can lead to bad closed-loop performance.
For the system described by the transfer function $P(s) = ((1+s)(1+\varepsilon s))$ let $\varepsilon > 0$ be small. If the fast dynamics are ignored then the control design model becomes $\hat{P}(s) = (1+s)^{-1}$. In our example let $\varepsilon = 0.01$. First we have investigated the step response functions of the system and of the model and the difference between the two response functions. It can be seen on the left side of the *Fig. 2.a* that the ignoration is valid if the system operates in open loop. In the next step the stabilizing controller has to be designed on the basis of the actual system and of the nominal model. The right side of the *Fig. 2.a* illustrates the step response functions of the closed loop in case of negative feedback. The ignoration of the ε dynamics results error in steady state.

Principle 2. Large open loop modelling errors do not necessarily lead to large closed-loop prediction errors.
Consider a plant described by $P(s) = (1+s)^{-1}$ and an approximate model, $\hat{P}(s) = s^{-1}$, which is very bad also from the viewpoint of the open loop identification. The actual system is asymptotically stable, whereas its model is not. The controller designed for the nominal model ensures the stability. *Fig. 2.b* illustrates the step response error functions for the open loop and for the closed loop cases. While the modelling error goes to the infinity in open loop case, it is bounded in closed loop case.

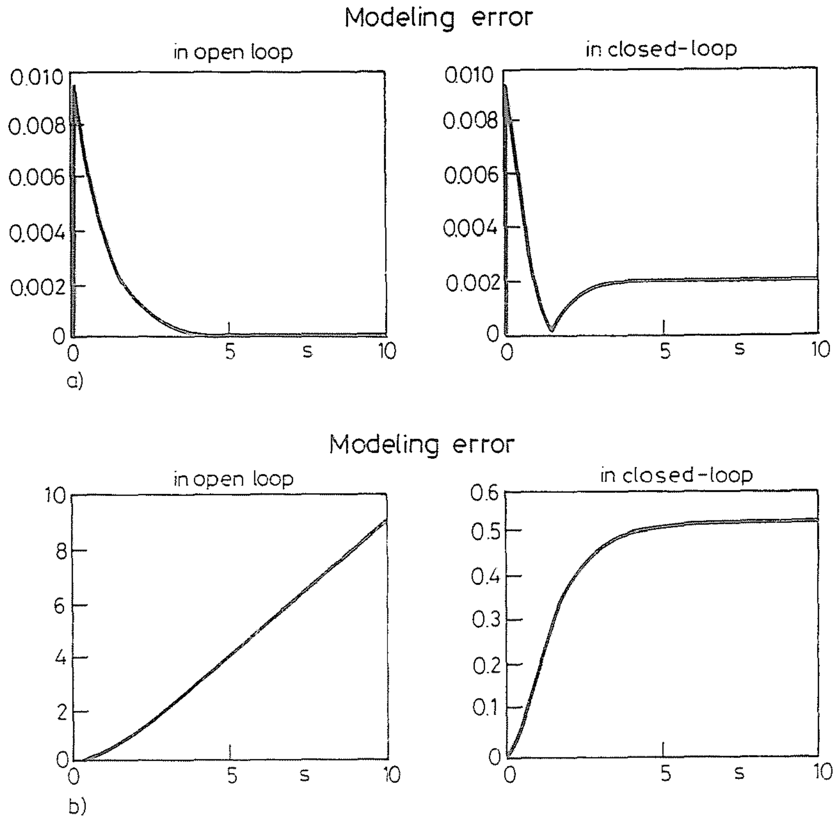

Fig. 2.

The natural consequence of the above modelling principles is that open-loop modelling errors (and hence their bounds) do not generally constitute enough information for successful control design.

In traditional modelling the controller satisfying the prescribed performance level, i.e. which ensures the stabilization in spite of the model uncertainties, is looked for on the basis of the given model set. For this purpose it is necessary to give the control law independently from the model development. Its condition would be that the input signals of the model have to be totally independent from the output signals of the model. But this is impossible since the signals interact because of the feedback. It is therefore to be expected that the separate design of the identifier and of the controller without regard for the effect of the control law on the identified model, or of the identified model on the robustness of the control law, may not lead to a maximization of the global robustness of the identifier/controller schema. This can only be solved by an iterative design procedure.

Principle 3. The modelling and controller design problem cannot be separable and therefore it is iterative.

On the basis of the above discussion the paper is organized as follows. First, the interaction of identification and control will be described. Then one of the most important iterative schema, the Zang schema will be introduced. The latest results of the iterative design methods will be also summarized. Finally, an academic example illustrates the iterative methodology.

2. The Identification/Control Interplay

On the basis of the 3rd modelling principle, this chapter aims to investigate the interaction of identification and robust control. Let y_t be the actual plant output signal, u_t the control signal, v_t the unmeasurable disturbance and let r_t be the given reference signal as it can be seen on *Fig. 3.* Let $P(z)$ mean the transfer matrix of the actual system and $C(z)$ the transfer function of the controller.

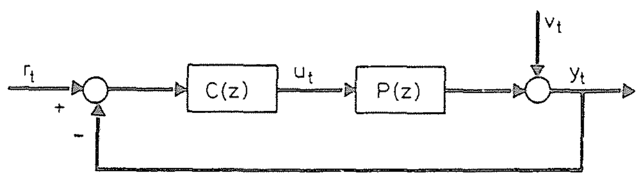

Fig. 3.

The discrete, identified model of the true plant is assumed to be representable as follows

$$y_t = P(z)u_t + v_t, \tag{1}$$

where $P(z)$ is a scalar strictly proper rational transfer function of the true system. We shall make the following assumptions for the design procedure.

- Prior knowledge about the system may have helped the designer to select a parametric model structure or may have given him insight about the achievable bandwidth, but the information about the dynamics of the process is assumed to be derived from data collected on the process.

- The exact model structure is assumed to be unknown, but the designer has a certain parametrized model set,

$$M = \left\{ \hat{P}(z, \Theta), \Theta \in D_\Theta \subset\subset \Re^d \right\}, \tag{2}$$

where $\hat{P}(z, \Theta)$ is a strictly proper transfer function.

The design of the controller $C(z)$ is performed on the basis of a control law and of the $\hat{P}(z, \hat{\Theta})$ nominal model and perhaps of the knowledge of the model uncertainties. Let $L(P, \hat{P})$ mean the estimable, but often assumable uncertainty. Then the control law can be described as follows:

$$C = C\left(\hat{P}, L(P, \hat{P})\right), \tag{3}$$

where $\hat{P}$ means the $\hat{P}(z, \hat{\Theta})$ model and P means the $P(z)$ system.

Let the global control performance criterion of the actual system be as follows:

$$J_{\text{glob}} = J(P, C). \tag{4}$$

It has to be minimized over the class of admissible controllers. In practice $C(z)$ is designed as a function of $\hat{P}(z, \hat{\Theta})$ and $L(P, \hat{P})$, where $\hat{P}(z, \hat{\Theta})$ is assumed to be in the M model set. In case of Linear Quadratic Gaussian (LQG) design, J_{glob} could take the form:

$$J_{\text{LQG}} = J_{\text{glob}} = \lim_{N \to \infty} \frac{1}{N} \sum_{t=1}^{N} \left[(y_t - r_t)^2 + \lambda u_t^2 \right], \tag{5}$$

where λ is a positive weighting factor that reflects the tracking error, (ANDERSON, MOORE, 1989).

Assuming that the true system is known and $\hat{P}(z, \hat{\Theta}) = P(z)$, what is meant by the P_{opt}, optimal transfer function, the minimization of $J(P, C)$ over the class of controllers C for stabilizing the system P leads to the optimal controller C_{opt}, and cost function $J_{\text{opt}}(z)$. This is illustrated in *Fig. 4*.

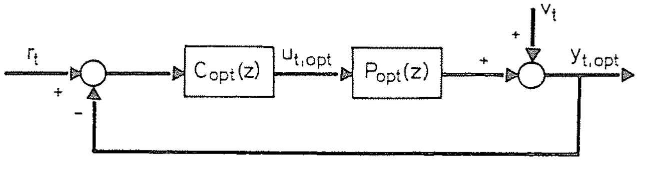

Fig. 4.

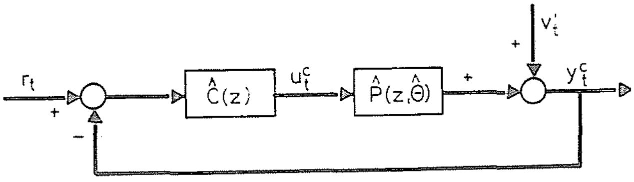

Fig. 5.

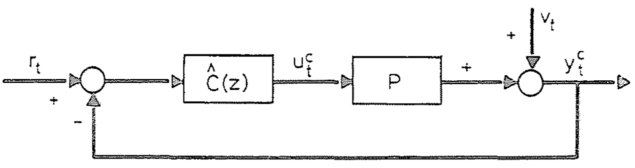

Fig. 6.

$$J_{\text{opt}} = \min_{C(P)} J(P_{\text{opt}}, C) = J(P_{\text{opt}}, C_{\text{opt}}) \tag{6}$$

Of course, this value cannot be reachable, only approximatable since the correct $P_{\text{opt}}(z)$ system model is not known. In the actual situation, the controller C has to be designed on the basis of the identified model $\hat{P}(z, \hat{\Theta})$. Here $\hat{\Theta}$ means an estimated parameter of the parameter set. This method, applied often in practice, applies also the estimation of disturbance v_t. The designed system containing the identified model and the designed controller is illustrated on *Fig. 5.*

In the actual situation $P(z)$ is uncertain, so the design is performed regarding the uncertainties. In this way the minimization of $J(\hat{P}, C)$ leads to the $\hat{C}(\hat{P}, L(P, \hat{P}))$ controller and to the designed cost function:

$$J_{\text{des}} = \min_{\hat{C}(\hat{P}, L(P, \hat{P}))} J(\hat{P}, C) = J(\hat{P}, \hat{C}). \tag{7}$$

In this case (1) takes the following form:

$$y_t^c = \hat{P}(z, \hat{\Theta}) u_t^c + v_t'. \tag{8}$$

If the $\hat{C}$ controller is applied for the actual system in closed loop then it leads to the achieved cost function:

$$J_{\text{ach}} = J(P, \hat{C}). \tag{9}$$

The illustration of the achieved system containing the designed controller can be seen on *Fig. 6.*

At evaluation of the design procedure the achieved cost function has to be taken into account. The error of robust performance criterion in LQG case is as follows:

$$J_{\mathrm{pr}} = \frac{1}{N} \sum_{t=1}^{N} \left[(y_t - y_t^c)^2 + \lambda \, (u_t - u_t^c)^2 \right]. \tag{10}$$

Ideally, one would like the identification and control design to be such that the performance achieved by the designed controller on the actual system is as close as possible to that achieved by the optimal controller. Since C_{opt} is unknown, it is usually impossible to use the closeness of the optimal and the actual loops as a design criterion. Instead, one compares the designed and the actual loops.

The estimated plant model, $\hat{P}$, and the controller, $\hat{C}$ both influence the two terms J_{des} and J_{pr}. Thus, ideally, one should minimize the two terms jointly over the class of admissible plant models and the class of admissible controllers. An obvious suboptimal strategy is to make J_{des} small by controller design for a given plant model, and to keep J_{pr} small by identification design for a given controller. Since J_{des} depends on the estimated plant model, and J_{pr} depends on the designed controller, this strategy can only be applied in an iterative manner, using a succession of local controller designs and local identification designs:

$$\min_{C} J(\hat{P}_i, C) \to \hat{C}_{i+1}, \tag{11}$$

$$\min_{P(\Theta)\in M} J^{\mathrm{pr}}\Big(P(\Theta), \hat{C}_i\Big) \to \hat{P}_{i+1}. \tag{12}$$

This idea is the heart of the iterative identification/controller design methods, (GEVERS, 1993).

3. Iterative Identification and Control Design by Zangschema

The contribution of the Zang method is the development of an iterative identification/robust control design schema (ZANG, BITMEAD and GEVERS, 1991). This is accomplished by the combination of two novel features:

– The Least Squares (LS) identification of a new model is performed on closed loop data obtained on the actual plant controlled by the previously computed controller, and with a data filter that improves model accuracy at those frequencies where stability and performance dictate that a better model is needed. This allows for performance enhancement at the next controller design stage.

– The control design uses a frequency weighted LQG criterion, where the frequency weightings in the control design stage account for the imperfection of the estimated model. These weightings are derived from spectral estimates of measured closed loop signals. They have the effect of rendering the controller cautious in frequency bands where the data reflects a plant/model mismatch.

The LQG global criterion (5) necessarily leads to a two-degree-of-freedom (TDF) system which is illustrated in *Fig. 7*, (ANDERSON, MOORE, 1989).

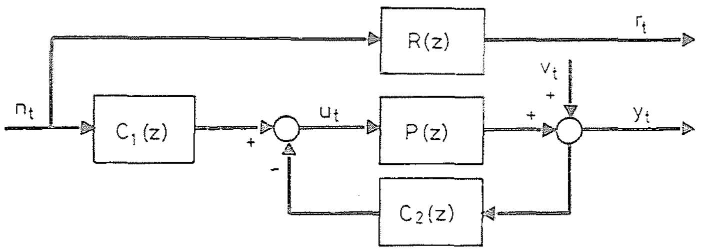

Fig. 7.

In the controller design iteration step the optimal LQ controller is based on the minimization of the designed cost function

$$J_{\text{des}} = \lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} \left[(y_t^c - r_t)^2 + \lambda (u_t^c)^2 \right], \tag{13}$$

where u_t^c is the designed control signal and y_t^c is the output of an identified model. The closed loop system is depicted in *Fig. 7* with the controller, denoted by C_1 and C_2, resulting from the optimization of (13). An LQ optimal control design leads to a TDF controller, $u_t = C_1 n_t - C_2 y_t$. Instead of the traditional route of minimizing (13) it applies the following frequency weighted local LQ tracking criterion:

$$J^c = \lim_{N\to\infty} \frac{1}{N} \sum_{t=1}^{N} \left[\left[F_1(z)\,(y_t^c - r_t) \right]^2 + \lambda' \left(F_2(z) u_t^c \right)^2 \right], \tag{14}$$

where $F_1(z)$ and $F_2(z)$ are linear filters to be chosen, λ' is a constant to be decided. $F_1(z)$ and $F_2(z)$ are selected as

$$F_1(j\omega) = \left(\frac{\Phi_{y-r}}{\Phi_{y^c-r}} \right)^{1/2} \qquad F_2(j\omega) = \left(\frac{\Phi_u}{\Phi_{u^c}} \right)^{1/2}, \tag{15}$$

Here Φ_{y-r}, Φ_{y^c-r} and Φ_{u^c} are the spectra of the corresponding $y-r$, y^c-r, u and u^c signals.

The selection of $F_1(j\omega)$ and $F_2(j\omega)$ is supported by the following observations. If at some frequency, Φ_{y-r} is larger than Φ_{y^c-r}, it means this at that frequency the model fit is poor with the consequence that the achieved tracking performance is worse than expected from the designed system. Hence more emphasis should be put on the tracking penalty at that frequency at the next control design stage, which is reflected by the weighting being larger than 1. If at some frequencies Φ_{y-r} is smaller than Φ_{y^c-r}, it also means that at that frequency the model fit is poor but the presently active controller actually achieves a better tracking performance on the true plant than on the model.

The emphasis on the tracking penalty at that frequency should therefore be decreased at the next control design stage. For the selection of the weighting functions they made the following suggestions:

$$\Phi_{y^c-r} = \frac{|\hat{P}(C_1 - RC_2) - R|^2 + |\hat{H}|^2}{|1+\hat{P}C_2|^2}, \quad \Phi_{y-r} = \frac{|P(C_1 - RC_2) - R|^2 + |H|^2}{|1+PC_2|^2},$$

$$\Phi_{u^c} = \frac{|C_1|^2 + |C_2\hat{H}|^2}{|1+\hat{P}C_2|^2}, \qquad \Phi_u = \frac{|C_1|^2 + |C_2H|^2}{|1+PC_2|^2}. \tag{16}$$

In the system identification iteration step the true system operates in closed loop with the controller obtained from the previous iteration step by LQG design. In order to recognize the operation of the closed loop system and to take into account the effect of the modified controller a new data set has to be collected. With this data set a new model must be identified on the basis of the following criterion.

$$\bar{V}(\Theta) = \frac{1}{2\pi}\int_{-\pi}^{\pi}\left\{\left|\frac{\left(P\left(e^{j\omega}\right) - \hat{P}\left(e^{j\omega},\Theta\right)\right)}{1+P\left(e^{j\omega}\right)C_2\left(e^{j\omega}\right)}\right|^2 |C_1(e^{j\omega})|^2\Phi_n(\omega) + \right.$$

$$\left.\left|\frac{1+\hat{P}(e^{j\omega},\Theta)C_2(e^{j\omega})}{1+P(e^{j\omega},\Theta)C_2(e^{j\omega})}\right|^2 \Phi_v(\omega)\right\}\frac{|D(e^{j\omega})|^2}{|H(e^{j\omega})|^2}d\omega\,. \tag{17}$$

where the filter $D(z)$ should be chosen to reflect our 'modelling for closed loop control' objective.

The aim of identification for control is to achieve a good closed loop control performance objective. This can be obtained by demanding that the closed loop sensitivity functions of the actual plant, P, and that of the plant model, $\hat{P}$, in feedback with the same controller, be as close as possible one to another. Since the aim is that the identification design be based on signal information only. This requirement has to be translated into the following local identification criterion

$$J_N^{\mathrm{id}} = \frac{1}{N}\sum_{t=1}^{N}\left[(y_t - \hat{y}_t^c)^2 + \lambda(u - \hat{u}_t^c)^2\right]. \tag{18}$$

Here the signals $\hat{y}_t^c$ and $\hat{u}_t^c$ are estimates of the signals y_t^c and u_t^c with the closed loop driven by the same reference source n_t as the actual system, but with no noise added in the loop. The criterion (18) should be compared to the classical closed loop prediction error minimization of (17). The above leads to

$$\begin{aligned} y_t - y_t^c &= \frac{(P-\hat{P})C_1}{(1+PC_2)(1+\hat{P}C_2)}n_t + \frac{1}{1+PC_2}v_t, \\ u_t - u_t^c &= \frac{(P-\hat{P})C_1C_2}{(1+PC_2)(1+\hat{P}C_2)}n_t - \frac{C_2}{1+PC_2}v_t. \end{aligned} \tag{19}$$

Assuming that n_t and v_t are mutually uncorrelated then we have the following frequency domain expression

$$J^{\mathrm{id}} = \frac{1}{2\pi}\int_{-\pi}^{\pi}\left\{\frac{|(P-\hat{P})C_1|^2(1+\lambda|C_2|^2)}{|(1+PC_2)(1+\hat{P}C_2)|^2}\Phi_n + \frac{(1+\lambda|C_2|^2)}{|1+PC_2|^2}\Phi_v\right\}d\omega. \tag{20}$$

A comparison between (20) and (17) immediately suggests that to achieve a minimization of (18), identification should be performed in closed loop with signals filtered through

$$D(z) = \hat{H}(z)G(z)\Big(1+\hat{P}(z)C_2(z)\Big)^{-1}, \tag{21}$$

where $G(z)$ is defined as a stable filter obtained from the following factorization problem

$$G(z)G^*(z^{-1}) = 1 + \lambda C_2(z)C_2^*(z^{-1}). \tag{22}$$

Since the identified plant model $\hat{P}(z,\hat{\Theta})$ appears in this frequency weighting, it would normally only be feasible to adjust this filter using an earlier estimate of $\hat{P}(z,\hat{\Theta})$.

4. State of the Art of the Iterative Design Schemes

The iterative system identification and control design is a dynamically improving research field. It is indicated by the fact that in the two most important control conferences in 1993 two whole sections have been organized for investigation of the present situation of this research field. (*32nd Conf. on Decision and Control, San Antonio, 2nd European Control Conference, Groningen*).

SCHRAMA and VAN DEN HOF (1992), have done a thorough analysis of the iterative design scheme. Both the control and the identification design are performed using coprime factor representations of the plant model and the controller. This representation guarantees that the designed controller is optimally robust against perturbations of the coprime factors. The closed loop identification step is based on the open loop scheme with the help of Hansen representation.

The windsurfer approach improves the performance requirements as the closed loop model becomes closer to the actual closed loop system, (LEE, et al., 1992). It is formulated as the minimization of the H_α norm of the difference between the achieved closed loop transfer function and that of the reference model. The emphasis is put on how to update the reference model as the model and the controller improve.

In LIU and SKELTON (1990), the q-Markov Cover theory is used in the identification step to identify a model of the closed loop system with the previously designed controller operating in the loop. A minimum energy controller with output variance constraint is used in the control design step.

Remarks on iterative approaches:

– The methods are predicted on the ability to perform experiments on the closed loop system resulting from a control design.

– They each utilize closed-loop identification methods and couple the identification and control objectives.

– In each approach is also implicit a global control objective associated with the achieved loop.

– These iterative schemes decompose the global criterion to local design criterion in the ith iteration, the C_i controller from the set of C controllers is designed starting from the P_i actual model by the minimization of the $J(\hat{P}_i, C)$. They perform again an identification step but on the basis of the minimization of $J(P, C_i)$.

The unsolved problems in the different iterative schemes point out the most important direction of this research:

– The stopping criteria of these iterative schemes are not enough effective therefore they cannot be automatizable.

– Till the end of 1993 there were no publications about the iterative schemes of the multi input, multi output (MIMO) systems.

5. Example

The present example illustrates the execution of the software implemented in Matlab for model based estimation of the controller of a MIMO system and for closed loop design. The simulation of the input/output time series is based on the airplane design example in SAFONOV, et al. (1981), where the continuous state space representation of the 2 input, 2 output system is as follows:

$$A = \begin{bmatrix} -0.0226 & -36.6170 & -18.8970 & -32.0900 & 3.2509 & -0.7626 \\ 0.0001 & -1.8997 & 0.9831 & -0.0007 & -0.1708 & -0.0050 \\ 0.0123 & -11.7200 & -2.6316 & 0.0009 & -31.6040 & 22.3960 \\ 0 & 0 & 1.0000 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & -30.0000 & 0 \\ 0 & 0 & 0 & 0 & 0 & -30.0000 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 30.0000 & 0 \\ 0 & 30.0000 \end{bmatrix}$$

$$C = \begin{bmatrix} 0 & 1.0000 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1.0000 & 0 & 0 \end{bmatrix}$$

$$D = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

The input-output time series of the actual sampled system, which is the start point of the identification for robust control design, can be seen on *Fig. 8*.

On the basis of the time series the identification of the open loop system has been executed. The structure of the transfer matrix has been determined by estimation on each equation on the basis of Akaike Information Criteria (AIC). As a result of the structure estimation the order of the autoregressive operator and the order of the input variables have been also selected as equal to 2.

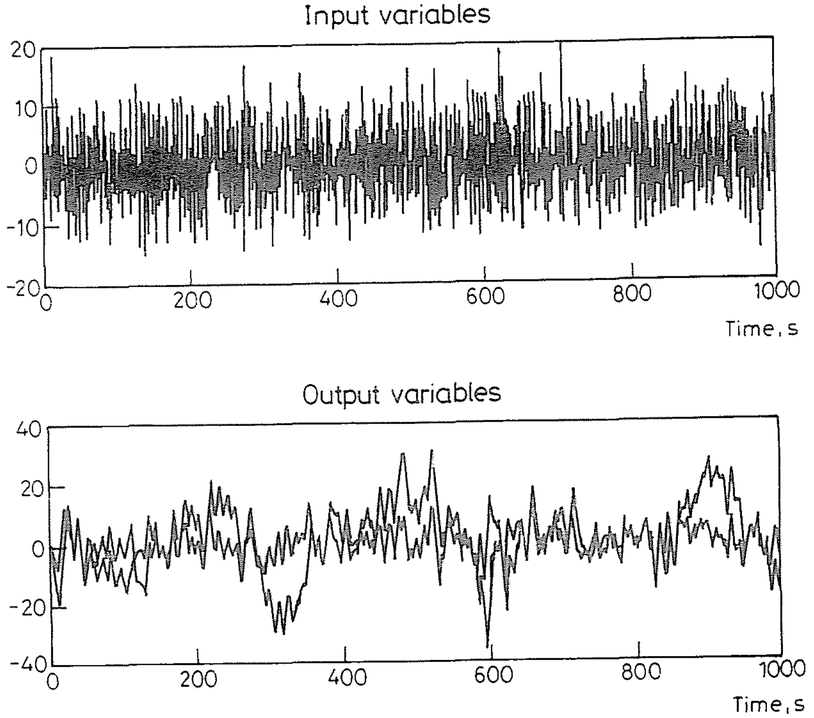

Fig. 8.

$$AR(1) = \begin{bmatrix} -6.2945 & 4.2693 \\ -5.7430 & 3.4354 \end{bmatrix} \qquad INP(1) = \begin{bmatrix} -0.0846 & 0.0525 \\ -0.0791 & 0.0567 \end{bmatrix}$$

$$AR(2) = \begin{bmatrix} 4.5810 & -4.2652 \\ 4.8169 & -4,4317 \end{bmatrix} \qquad INP(2) = \begin{bmatrix} -0.0790 & 0.0969 \\ -0.0877 & 0.1086 \end{bmatrix}$$

The controller has been designed in two steps on the basis of the identified model in accordance with the separation theory of the LQG method. In the first step the control law has been designed assuming he knowledge of the x states. In the second step the observer has been designed which estimates the state vector on the basis of the measured or observed input/output signals.

The control law connect the system states and the system input on the basis of the K_c state feedback constant matrix. The optimal state feedback Kalman filter in Linear Quadratic (LQ) sense is as follows.

$$K_c^T = \begin{bmatrix} 0.0343 & -0.1974 & 0.0510 & 0.0271 \\ 0.1385 & -0.2622 & 0.1367 & 0.0339 \end{bmatrix}$$

The observer Kalman filter has modified the singular value function and the sensitivity function of the optimal controller, which is illustrated on *Fig. 9.* The solid line means the actual while the dashed the optimal frequency functions.

$$K_f = \begin{bmatrix} -1.2970 & -16.1719 & 2.3684 & -288.0535 \\ 0.8456 & 10.8289 & -1.3444 & 195.3601 \end{bmatrix}$$

The aim of the Loop Transfer Recovery (LTR) is that the estimated singular value frequency functions, obtained by the modified observer Kalman filter, have to approach the optimal singular functions as close as possible, STEIN, Athans, 1987. Applying the weighting factor it has resulted, that the obtained singular functions have approached well the optimal singular functions. The observer Kalman gain selected on the basis of the LTR can be described by the following parameters.

$$K_f = 10^3 \begin{bmatrix} -0.0025 & -0.0704 & 0.0111 & -2.0572 \\ 0.0016 & 0.0513 & 0.0140 & 1.4462 \end{bmatrix}$$

The estimated singular value and characteristic functions obtained by the LTR with the optimal functions can be seen on *Fig. 10.*

Applying the designed controller in the real circumstances the simulation of the time series of the input/output signals have been repeated. At the next steps of the simulation the system model has to be identified again on the basis of the input/output signals simulated in closed loop, then the LQG controller has to be designed again on the basis of the nominal model estimated in the previous step. In Matlab it is possible to repeat automatically the identification and control design with the previous parameters. In practice it means that the estimation of the model parameters is performed applying the knowledge of the previous structure, and that the value of the weighting factor is known in the LTR of the control design.

Summary

This paper aimed to investigate the novel, iterative approach of robust control design based on identified dynamic models of multi input, multi output systems applying the present results published in the international research literature. The motivation of this research is that the identification and control of a closed loop system have to be performed in their interaction instead of independently in order that the designed closed loop system can perform the robust stability and performance criterions, which has been summarized in the first two chapter. The Zang method has been investigated in more detail among the iterative schemes. Finally the exe-

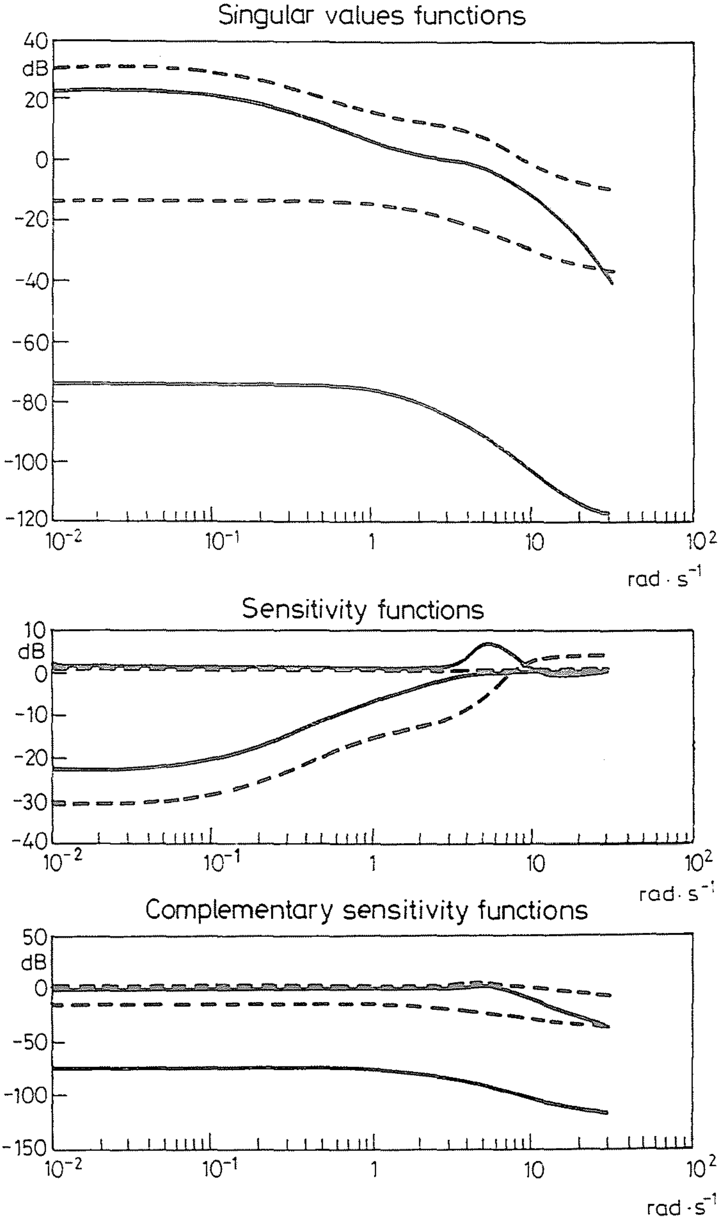

Fig. 9.

cution of the software implemented in Matlab for model based controller design has been showed.

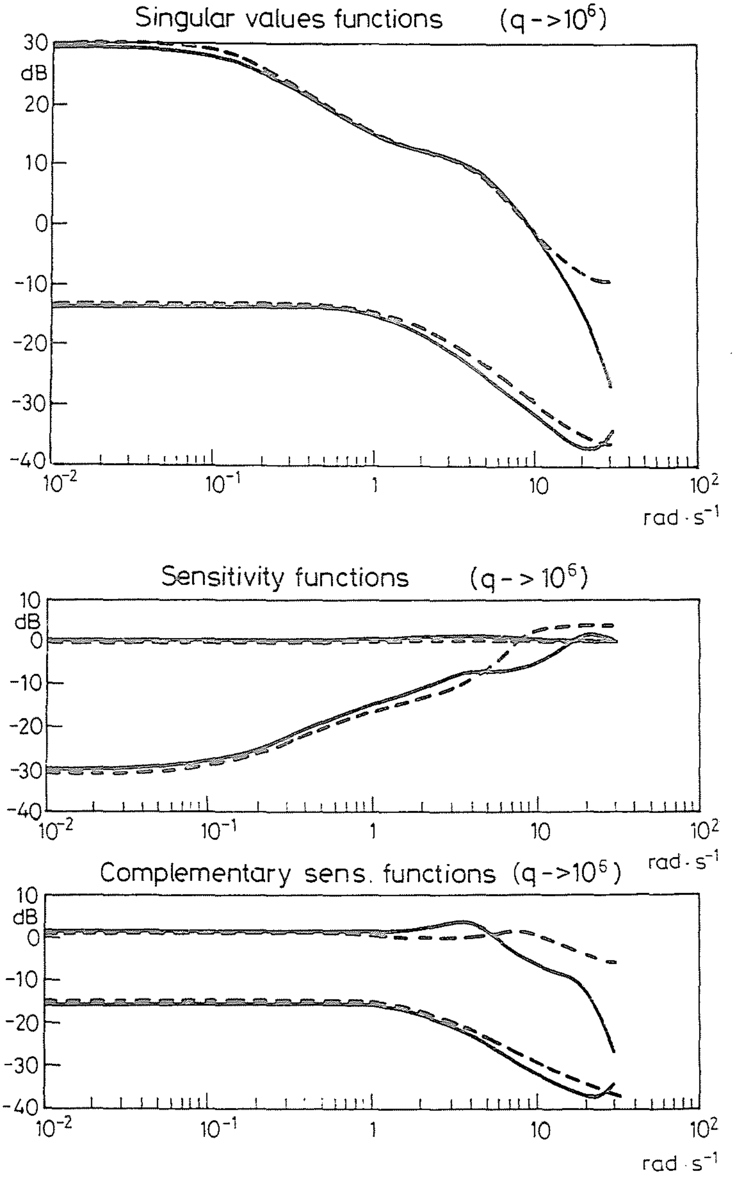
Singular values functions (q->10^6)
30
dB
20
10
0
-10
-20
-30
-40
10^-2
10^-1
1
10
10^2
rad · s^-1
Sensitivity functions (q-> 10^6)
10
dB
0
-10
-20
-30
-40
10^-2
10^-1
1
10
10^2
rad · s^-1
Complementary sens. functions (q->10^6)
10
dB
0
-10
-20
-30
-40
10^-2
10^-1
1
10
10^2
rad · s^-1

Fig. 10.

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