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A COMPARISON OF MOTOR SUBMODELS IN THE OPTIMAL CONTROL MODEL

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ABSTRACT

Recent interest in the areas of modeling the effects of motion on human operators, and manual control of low bandwidth systems has led to the need for accurate submodels of the low frequency characteristics of the Human Operator (HO). Unfortunately, matching low frequency human response data has been a problem with almost all HO models, the well known Optimal Control Model (OCM) being no exception. This research is an attempt to better understand and hopefully eliminate these problems.

In this paper, properties of several structural variations in the neuromotor interface portion of the OCM are investigated. For example, it is known [1-2] that commanding control-rate introduces an open-loop pole at S=0 and will generate low frequency phase and magnitude characteristics similar to experimental data. However this gives rise to unusually high sensitivities with respect to motor and sensor noise-ratios, thereby reducing the models' predictive capabilities. Relationships for different motor submodels are discussed to show sources of these sensitivities. The models investigated include both pseudo motor-noise and actual (system driving) motor-noise characterizations. The effects of explicit priprioceptive feedback in the OCM is also examined. To show graphically the effects of each submodel on system outputs, sensitivity studies are included, and compared to data obtained from [1-2].

INTRODUCTION

Recently, motion studies [2,3] have shown the major effects of motion to be on low frequency ($\omega < 1$ rad/sec) HO magnitude and phase characteristics. This means that low frequency modeling errors present in the baseline implementation of the OCM must be minimized if the effects of including motion variables are to be felt. It is known [1,2] that changing the structure of the neuro-motor interface portion of the OCM will give the desired low frequency effects. Specifically if the HO commands control rate rather than control, the low frequency phase drooping occurs. However, in order to match human response data over simple vehicle dynamics, large deviations in the motor noise ratios were needed [2]. This clearly degrades the predictive

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power of the model. In this paper sub-models developed in [1,2] will be compared from a sensitivity point of view, in an attempt to better understand the limitations of each approach.

Problem Formulation

In this section structural changes will be made to the baseline OCM (for a more detailed description see Levison [2]). A general form will be developed first, with specific models introduced as special cases to it. In the development which follows, the time delay will be ignored since it has little bearing on our discussion.

The system being controlled is described by the state-space equation

$$\dot{x} = Ax + Bu + Ew \tag{1}$$

where:

x = "true" system state
u = "true" control input

and where displayed system variables are given by

$$y = Cx + Du \tag{2}$$

The system is assumed to be controlled to minimize (in steady-state) a quadratic cost functional

$$J = E\{y' \, Q_y \, y + g \, \dot{u}^2\} \tag{3}$$

based on the (delayed and) noisy information perceived by the HO. This information is assumed to consist of both displayed and proprioceptive variables, i.e.,

$$y_p = Cx + Du + v_y \tag{4a}$$

$$u_p = u + v_u \tag{4b}$$

where:

$$\mathrm{cov}\{v_y\} = V_y + \rho_y \, E\{y^2\} \tag{5a}$$

$$\mathrm{cov}\{v_u\} = V_u + \rho_u \, E\{u^2\} \tag{5b}$$

The control law that minimizes J is given by

$$\dot{u} = -[L_x \;\; L_u] \begin{bmatrix} \hat{x} \\ \hat{u} \end{bmatrix} \triangleq \dot{u}_c \tag{6}$$

where:

$\hat{x}$ = human's best internal estimate of x
$\hat{u}$ = " " " " u

To model any actual noise at the motor end, a driving motor noise is added to (6). Notice control rate is generated rather than control. Thus,

$$\dot{u} = \dot{u}_c + v_{\dot{u}} \tag{7}$$

where:

$$\mathrm{cov}\{v_{\dot{u}}\} = V_{\dot{u}} + \rho_{\dot{u}}\, E\{\dot{u}_c^{\,2}\} \tag{8}$$

However the human's <u>internal</u> representation of the neuromotor interface, Eq. (7), is:

$$\dot{u} = \dot{u}_c + v_p \tag{9}$$

where:

$$\mathrm{cov}\{v_p\} = V_p + \rho_p\, E\{\dot{u}_c^{\,2}\} \tag{10}$$

and typically $\mathrm{cov}\{v_p\} \neq \mathrm{cov}\,\{v_{\dot{u}}\}$.

The pseudo motor noise v_p does not act as a driving noise to the system, but instead degrades performance by making estimation sub-optimal [2].

Implementing these changes gives rise to the structure shown in Fig. 1.

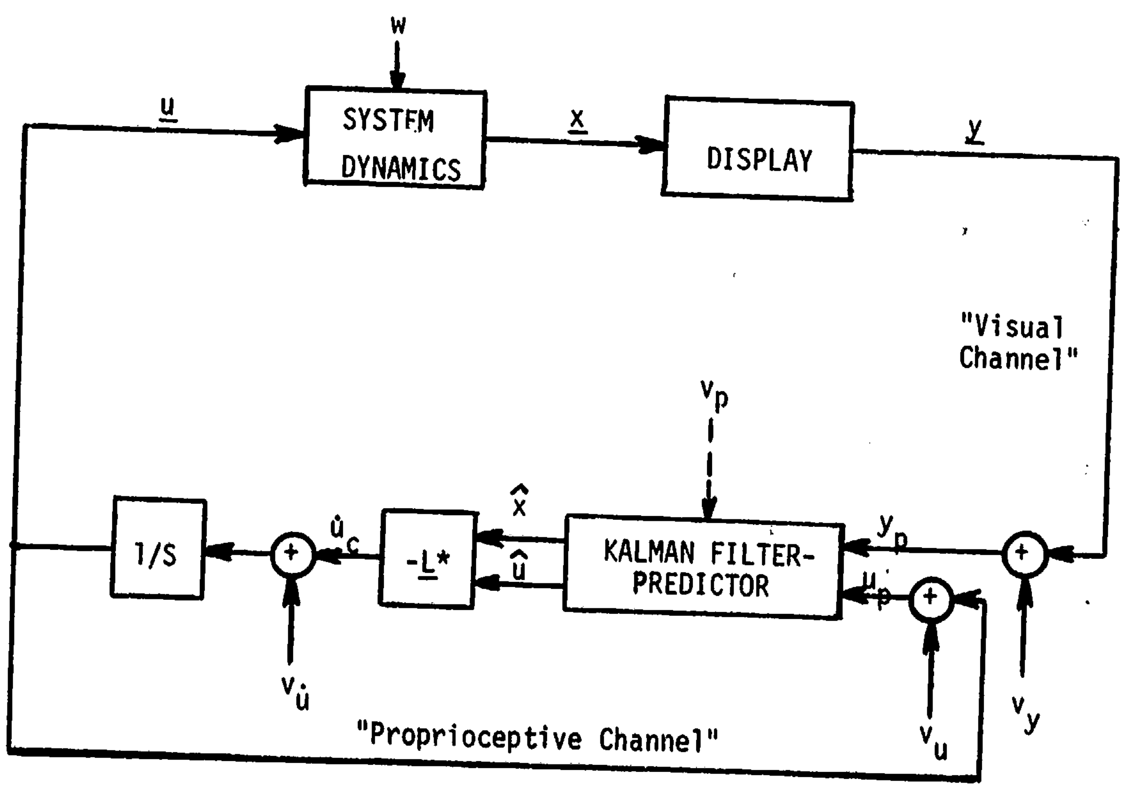

FIG.1 REVISED OPTIMAL CONTROL MODEL.

The particular submodels considered in this study are as follows:

Driving Noise Models:

1) $cov\{v_p\} = cov\{v_{\dot{u}}\}$, i.e., optimal estimation occurs, driving motor noise equal to $v_{\dot{u}}$
   - proprioceptive information available
2) Same as model (1), except no proprioceptive information available

Pseudo noise models:

3) $v_{\dot{u}} = 0$, i.e., sub-optimal estimation occurs, only pseudo noise present
   - proprioceptive information available
4) Same as model (3) except no proprioceptive information available

SENSITIVITY RESULTS

Data from [1,2] was matched using each of the aforementioned models. Only K/S and K/S**2 dynamics were considered. The reader is referred to the sensitivity studies included in [1] so a comparison can be made to the baseline model.

K/S Dynamics

The following nominal parameters were found to give reasonable matches to the data, and will be used as a basis for the K/S sensitivity work. Notice that proprioceptive feedback is not needed for K/S dynamics; this agrees with findings in [1,2]. Therefore, for K/S dynamics we need only consider two models, driving noise and pseudo noise.

Model	SNR	SNR-u	MNR	TD	TN
1 & 3	-20	-∞	-40	.17	.08
2 & 4	-20	--	-40	.17	.08

SNR $\triangleq \rho_y$

SNR - u $\triangleq \rho_u$

MNR = $\rho_{\dot{u}}$ or ρ_p

TD = τ, TN = L_u^{-1}

It was found that the trends discussed in [1] for SNR, TD and TN were the same for all the models considered. The only exception to this was for the driving noise models, where the low frequency remnant curves were slightly higher.

Effects of MNR

From Fig. 2 it is clear that motor noise mainly affects the low fre-

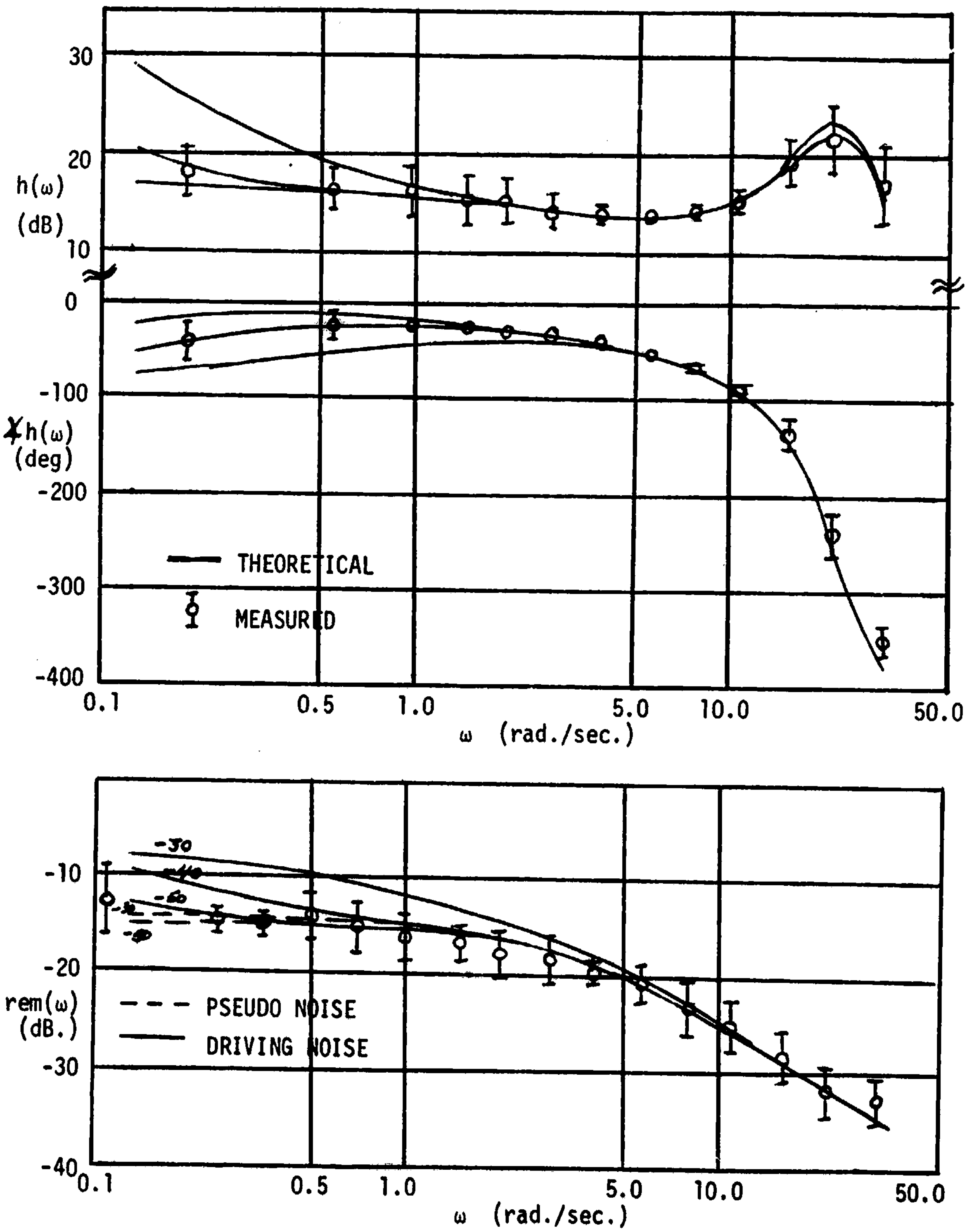

FIG.2 EFFECTS OF MNR ON K/S DYNAMICS.

quency portion of the magnitude, phase and remnant curves. There are basically two reasons for this. First, the shape of the low frequency portion is due to the integrator at the motor end (where in the baseline OCM, $1/(T_N S+1)$ was present). Secondly, the sensitivity is due to the degradation of estimation performance as the motor noise is increased. Because the level of the driving noise is so low, the linear part of the HO model (Bode plot) is the same whether pseudo noises or driving noises are used. Notice that the driving noise has a dominant affect only on the low frequency remnant.

All scores increase with increasing motor noise. Scores using the pseudo model are fairly insensitive to motor noise, since it is the degraded estimation which causes them to change. Scores using the driving model are much more sensitive to motor noise, since increasing the motor noise increases the remnant in the system.

K/S**2 Dynamics

The following is the nominal parameter set found for K/S**2 dynamics.

Model	SNR	SNR-u	MNR	TD	TN
1 & 3	-20	-25	-40	.21	.1
2 & 4	-20	---	-54	.21	.1

Here, as in K/S dynamics, trends discussed in [1] for SNR, TD, and TN also hold for our revised models. Below we discuss only the effects of MNR & SNR on control.

Effects of MNR

No Proprioceptive Information (models 2 & 4)

Looking at Figure 3 it is clear that the motor noise affects the low frequency Bode plots in a manner similar to that found for K/S dynamics. Again, more remnant power is shifted to the low frequencies for model 2 than for model 4.

Notice that model 4 matches the low frequency remnant very poorly (this could be improved slightly by increasing the noise on displayed error) and may be interpreted as a major shortcoming of this model since we desire a nominal set of parameters.

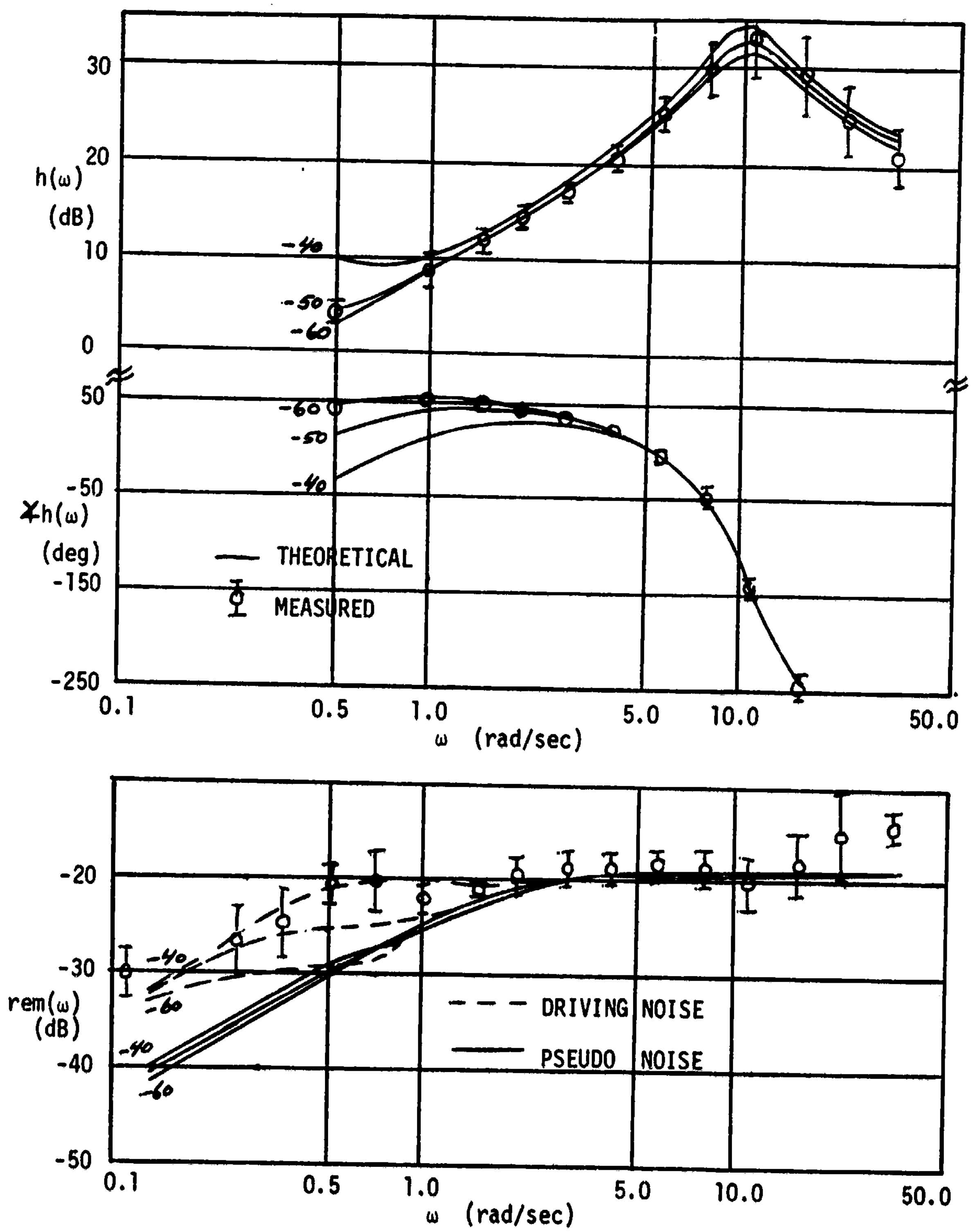

FIG.3 EFFECTS OF MNR ON K/S**2 DYNAMICS (MODELS 2 & 4).

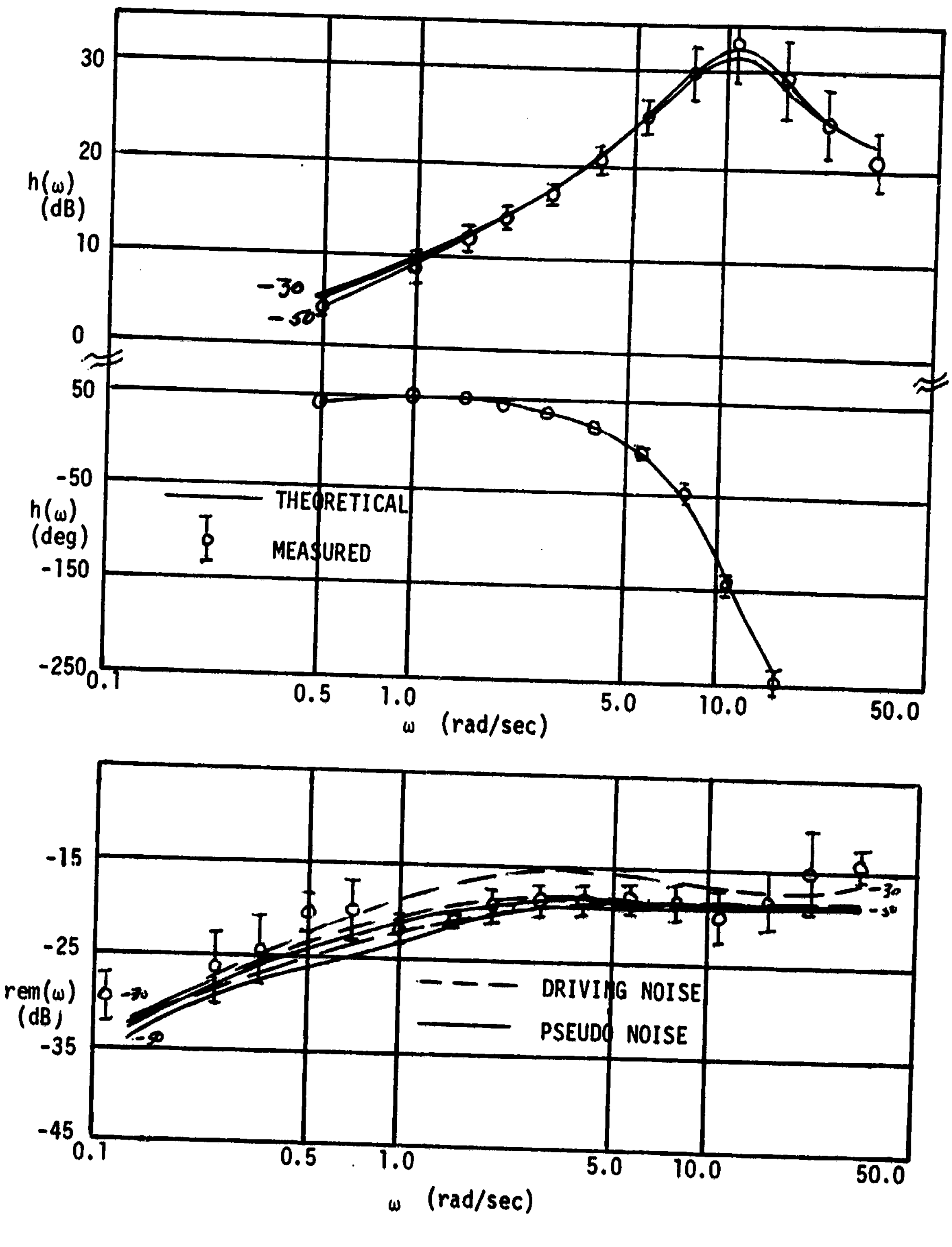

FIG.4 EFFECTS OF MNR ON K/S**2 DYNAMICS (MODELS 1 & 3).

With Propioceptive Information (Models 2 & 4)

The effects of including proprioceptive feedback can be seen by comparing Figs. 3 & 4. Again remnant is higher for driving motor noises, but it is spread out over a wider band of frequencies. This may be due to the circulation of remnant in the feedback loop. Although not shown, the scores for model 1 were always higher and more sensitive than those for model 3, and seemed to match the data better.

Notice that the sensitivity of the model to changes in the motor noise has been reduced dramatically by including proprioceptive feedback. Because the model now has observations of control and control rate to use in forming an estimate of control, estimation stabilizes and improves.

Effects of SNR (Models 1 & 3)

Figure 5 shows the low frequency remnant for model 3 much closer to that of model 1. Notice if the sensor noise is too large (>-15dB), the model ignores this observation and models 1 & 3 effectively become models 2 & 4. Since knowledge of the control signal is important in this task, it is clear that the model should be, and is, sensitive to the quality of this information. The low frequency effects result primarily from the movement of the estimator poles.

Sensitivity of Scores

Relative RMS error is plotted in Fig. 6 as a function of MNR. Because RMS error is the most sensitive score, Fig. 6 shows that including proprioceptive feedback reduces the sensitivity of all the scores.

Review

From the sensitivities studies it was seen that in general:

- All predicted scores were lower than measured ones for pseudo noise
- All system measures were more sensitive to driving motor noise than to pseudo noise
- This sensitivity can be reduced by including an observation of control
- The level of sensor noise on control induces the low frequency effects
- The integrator at the motor end confines the remnant power to the low frequencies

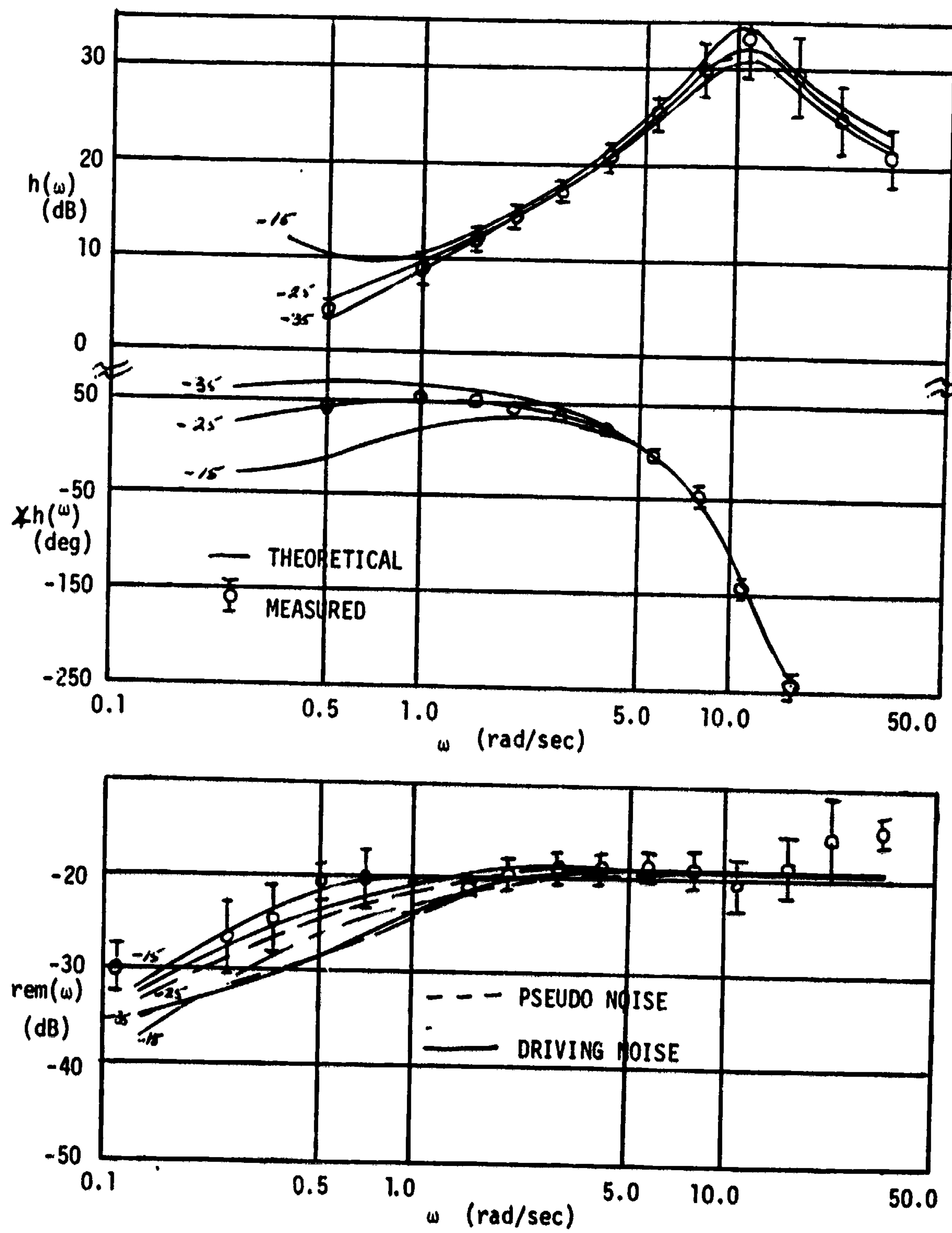

FIG.5 EFFECTS OF SNR-U ON K/S**2 DYNAMICS (MODEL 1 & 3).

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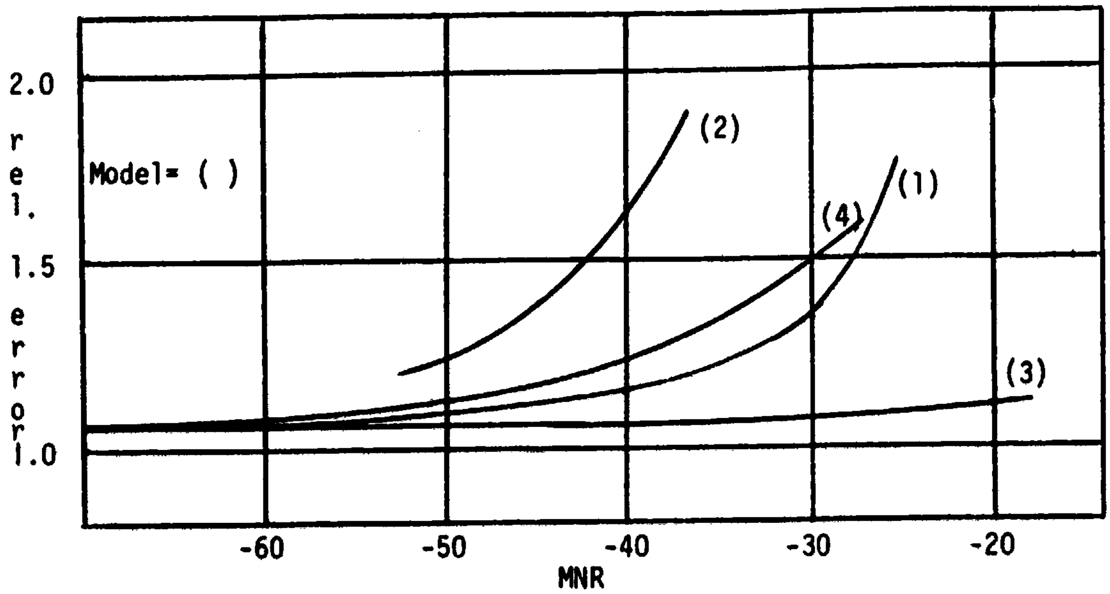

FIG. 6: SENSITIVITY OF RMS ERROR (K/S**2 TASK)

- It is difficult to match K/S**2 data, with a nominal set of parameters, using models 2 & 4

FINAL COMMENTS

Sensitivity studies have shown that including observations on control can reduce model sensitivity to driving motor noises. Also it was shown that a sensor noise added to control does not greatly affect the uncorrelated part of the model. Nominal parameters were found that could match K/S & K/S**2 dynamics, provided that observations on control are included for K/S**2 but not for K/S. If the model is allowed to allocate attention freely among all observed variables, this may provide a scheme for determining the sensor noises. One hypothesis is that this essentially forms a decision step (perhaps as part of the learning process) in the HO model, where it must evaluate the benefits of all the cues it has available to it and then decide on a subset which will be useful for control purposes.

More work needs to be done in order to find a good rule for picking the sensor noises. Testing models 1 and 3 over a wider set of system dynamics is also important to see if our findings are true in general or just a special case.

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