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IDENTIFICATION OF SYSTEM DYNAMICS OF A

HIGH INCIDENCE RESEARCH MODEL

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Identification of System Dynamics of a High Incidence Research Model

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Abstract: The application of orthogonal nonlinear multivariable identification techniques to model the flight dynamics of a High Incidence Research Model is presented. The system model derived is then shown to be a valid representation of the true system dynamics.

1. Introduction

This paper describes the application of system identification algorithms to obtain a difference equation model to represent the dynamics of a High Incidence Research Model (HIRM) used by the Royal Aerospace Establishment (RAE), Farnborough, UK. in a programme of research into flight dynamics at near departure conditions.

This RAE research programme was initiated in 1982 with the primary objective stated as 'the widening of understanding of the flight dynamics phenomena of control aircraft at high angles of attack. Central to this is the development of mathematical modeling techniques to predict such phenomena at or near departure at low speeds, and to provide data from free-flight and wind-tunnel experiments for this purpose.' [Moss, Ross, Butler; 1982].

The aim of this paper is to demonstrate the suitability of the Nonlinear identification techniques developed at Sheffield University to fulfill the modeling requirements of the above research programme.

Section §2 describes the aircraft model and data collection, section §3 outlines the identification procedures applied and describes the model validation tests, and section §4 gives the results of the parameter estimation algorithms.

2.

The High Incidence Research Model (HIRM)

The HIRM is a three surface unpowered model with a swept wing, a differential canard and stabilator, and an oversized vertical tail. The model is fully instrumented with the measured responses, sampled every 0.012 seconds, transmitted to a ground station. Flight maneuvers are preprogrammed into the system and are executed at specified times after release from the carrier helicopter.

The model was tested at NASA Dryden Flight Research Facility, Edwards California, and was released from a towing helicopter at 3000-4000 meters above ground and speeds of approximately 150 kmh. The model was recovered by deploying parachutes before impact. The data used in this paper was obtained from the flight designated HD8 by RAE.

The Flight variables considered in this paper are:

α,β: *angles of attack and sideslip (radians)*

p,q,r: *rates of roll, pitch, and yaw (radians/second)*

V: *airspeed (meters/second)*

θ: *pitch attitude angle (radians)*

ϕ: *bank angle (radians)*

3. System Identification and Model Validation

Identification was performed using the NMV (identification of Nonlinear MultiVariable systems) package developed at Sheffield University Department of Control Engineering [Billings and Chen; 1988]. The package uses a forward regression orthogonal estimator [Korenberg,Bilings,Liu,McIlroy, 1988] extended to the multivariable case [Billings,Chen,Korenberg; 1989] of the NARMAX (Nonlinear AutoRegressive Moving Average with eXogenous inputs) system representation.

The flight data consisted of 1000 data groups which included a step change in the canard angle at approximately the 250th data set. This step change proved to be insufficiently exciting to allow the canard angle dependence to be accurately estimated and was therefore excluded from the identification by considering a reduced data set consisting of the final 500 data groups with a constant canard deflection.

Identification was performed using the first 400 data groups of the reduced data set, with this full set used for validation of the estimated system models.

Figure 1 shows the time histories of the variables $\alpha,\beta,p,q,r,V,\theta$, and ϕ for the model validation data sets.

Early identification attempts were found to be unsatisfactory due to the near critical stability of the response variables α,β,p,q,r and hence a model for the differentials of these variables was examined. Best results were obtained by using a forward differential approximation, that is replacing the response variable $x(t)$ with $x_d(t) = x(t+1) - x(t)$.

Initially, linear models were identified for the five subsystems and were shown to be adequate representations of p_d and r_d. The other three subsystems were then identified as second degree polynomial models to give the final system representation.

For a nonlinear multivariable system with m outputs and r inputs, The identified model can be shown to be a valid representation of the system dynamics if the prediction error sequences $e_i(t)(i = 1..m)$ are unpredictable from all linear and nonlinear combinations of past inputs and outputs. This will be true if the following correlation tests are satisfied [Billings,Chen,Korenberg; 1989]:

$$\phi_{e_ie_j}(\tau) = \delta(\tau) \qquad i = 1...m \text{ and } j = i...m$$

$$\phi_{u_ie_j}(\tau) = 0 \quad \forall\tau \qquad i = 1...r \text{ and } j = 1...m$$

$$\phi_{e_i(e_ju_k)}(\tau) = 0 \quad \forall\tau \geq 0 \qquad i = 1...m,\ j = i...m \text{ and } k = 1...r$$

$$\phi_{(u_iu_j)e_k}(\tau) = 0 \quad \forall\tau \qquad i = 1...r,\ j = i...r \text{ and } k = 1...m$$

$$\phi_{(u_iu_j)(e_ke_l)}(\tau) = 0 \quad \forall\tau \qquad i = 1...r,\ j = i...r,\ k = 1...m \text{ and } l = k...m$$

1. Results

The identification described above yielded the following model for the system with 5 outputs $(\alpha_d,\beta_d,p_d,q_d,r_d)$ and 8 inputs $(\alpha,\beta,p,q,r,V,\theta,\phi)$:

Model for α_d			
Term	Coefficient	Err	sds
$\alpha_d(t-2)V(t-1)$	-0.01089	0.2174	0.0010
$\alpha_d(t-3)q(t-3)$	-6.602	0.0904	0.6772

Model for α_d (cont)			
Term	Coefficient	Err	sds
$\beta(t-1)p(t-1)$	-0.02015	0.0377	0.0036
$\alpha_d(t-5)$	-0.3548	0.0534	0.0519
$\alpha_d(t-3)\alpha_d(t-9)$	-40.45	0.0121	16.539
$\alpha_d(t-4)q(t-3)$	4.385	0.0097	0.7586
$\alpha_d(t-1)V(t-1)$	0.004068	0.0119	0.0010
$r(t-4)e_\alpha(t-7)$	-3.223	0.0360	0.5948
$e_\alpha(t-2)e_\alpha(t-4)$	90.97	0.0105	33.227
$q(t-2)e_\alpha(t-8)$	-2.321	0.0082	0.9175
$\alpha_d(t-4)e_\alpha(t-7)$	-38.84	0.0046	20.777

Model for β_d			
Term	Coefficient	Err	sds
$p(t-2)$	0.005118	0.5135	0.0002
$\beta_d(t-3)$	-0.4438	0.0737	0.0422
$e_\beta(t-2)$	-0.2773	0.0228	0.0504
$e_\beta(t-4)$	0.2811	0.0207	0.0508
$e_\beta(t-2)e_\beta(t-7)$	-122.9	0.0171	30.972
$e_\beta(t-1)$	0.2448	0.0156	0.0504
$e_\beta(t-7)$	0.1842	0.0095	0.0514
$e_\beta(t-3)e_\beta(t-5)$	74.36	0.0070	29.677
$e_\beta(t-2)e_\beta(t-3)$	56.64	0.0034	29.474
$e_\beta(t-3)e_\beta(t-4)$	67.72	0.0032	29.118

Model for β_d (cont)			
Term	Coefficient	Err	sds
$e_\beta(t-3)e_\beta(t-6)$	74.26	0.0035	31.158
$\beta_d(t-4)e_\beta(t-1)$	34.92	0.0034	16.630
$e_\beta(t-2)e_\beta(t-6)$	54.38	0.0018	31.265
$\beta_d(t-4)e_\beta(t-5)$	28.96	0.0019	16.955
$e_\beta(t-2)e_\beta(t-5)$	-49.26	0.0019	31.46
$p(t-3)e_\beta(t-7)$	-0.1316	0.0017	0.0902

Model for p_d			
Term	Coefficient	Err	sds
$\beta(t-1)$	0.3098	0.5335	0.1603
$r(t-1)$	-0.2546	0.1057	0.0447
$\beta(t-8)$	-0.7513	0.0257	0.1797
$p_d(t-3)$	-0.2486	0.0120	0.0459
$p_d(t-4)$	0.3061	0.0147	0.0505
$p_d(t-1)$	0.1197	0.0148	0.0938
$p_d(t-7)$	0.0948	0.0126	0.0822
$\alpha(t-1)$	-0.0229	0.0062	0.0073
$e_q(t-1)$	-0.9702	0.0108	0.2214
$e_p(t-1)$	0.2120	0.0033	0.1091
$e_p(t-7)$	0.1559	0.0016	0.1002

Model for q_d			
Term	Coefficient	Err	sds
$q_d(t-2)\alpha(t-2)$	-57.60	0.0871	18.816
$q_d(t-3)V(t-9)$	-0.0102	0.0623	0.0022
$\beta(t-2)r(t-4)$	-0.2194	0.0431	0.0493
$q_d(t-5)\alpha(t-5)$	-18.97	0.0237	12.414
$q_d(t-6)q_d(t-6)$	-12.06	0.0215	4.9996
$q_d(t-4)\alpha(t-1)$	0.4394	0.0194	0.1115
$q_d(t-5)\alpha(t-2)$	18.77	0.0163	12.404
$q_d(t-3)r(t-3)$	-3.188	0.0135	0.6994
$q_d(t-8)\beta(t-9)$	-1.658	0.0122	0.8000
$q_d(t-6)\beta(t-1)$	-2.425	0.0134	0.7763
$q_d(t-2)\alpha(t-3)$	56.97	0.0132	18.814
$q_d(t-4)\beta(t-8)$	-1.667	0.0078	0.8731
$q_d(t-7)V(t-8)$	0.8321	0.0070	0.3474
$q_d(t-7)V(t-9)$	-0.8309	0.0093	0.3474
$q_d(t-7)q_d(t-8)$	-18.64	0.0067	7.8930
$e_q(t-3)$	-0.3193	0.0144	0.0962
$q_d(t-3)e_q(t-3)$	-21.67	0.0085	8.4844
$q_d(t-3)e_q(t-7)$	45.66	0.0119	12.416
$q_d(t-7)e_q(t-3)$	-31.59	0.0092	12.952

Model for r_d			
Term	Coefficient	Err	sds
$e_r(t-3)$	-0.03862	0.1926	0.1169
$r_d(t-2)$	-0.4619	0.1190	0.0402
$\beta(t-4)$	-0.1055	0.0270	0.0144
$e_r(t-5)$	-0.1177	0.0160	0.0829
$r_d(t-3)$	-0.5668	0.0147	0.1126
$q(t-2)$	0.03815	0.0090	0.0106
$e_r(t-8)$	-0.2283	0.0035	0.0619
$r_d(t-5)$	-0.3290	0.0091	0.0864
$e_r(t-6)$	-0.2294	0.0113	0.0753

For example the model β_d would be, from the table,

$$\beta_d = 0.005118\, p(t-2) - 0.4438\, \beta(t-3) - \ldots\ldots -0.1316\, p(t-3)e_\beta(t-7)$$

The model validity correlation tests described above consist of 895 individual requirements, each of which is tested with a confidence interval of 95%. The plots of these correlation functions are not shown due to their large number. 27 of the tests were not acceptable at the given confidence interval, However the probability of rejecting the null hypothesis (that a correlation test is true) given that it is in fact true is 5%. Hence the expected number of tests that would fail given that a model was adequate is 44. Therefore the hypothesis that the model is adequate can be accepted.

Figure 2 shows the one step ahead predicted outputs defined as

$$\hat{\underline{y}}(t) = \hat{F}[\underline{y}(t-1),\ldots,\underline{y}(t-N_y),\underline{u}(t-1),\ldots,\underline{u}(t-N_u),\underline{e}(t-1),\ldots,\underline{e}(t-N_e)]$$

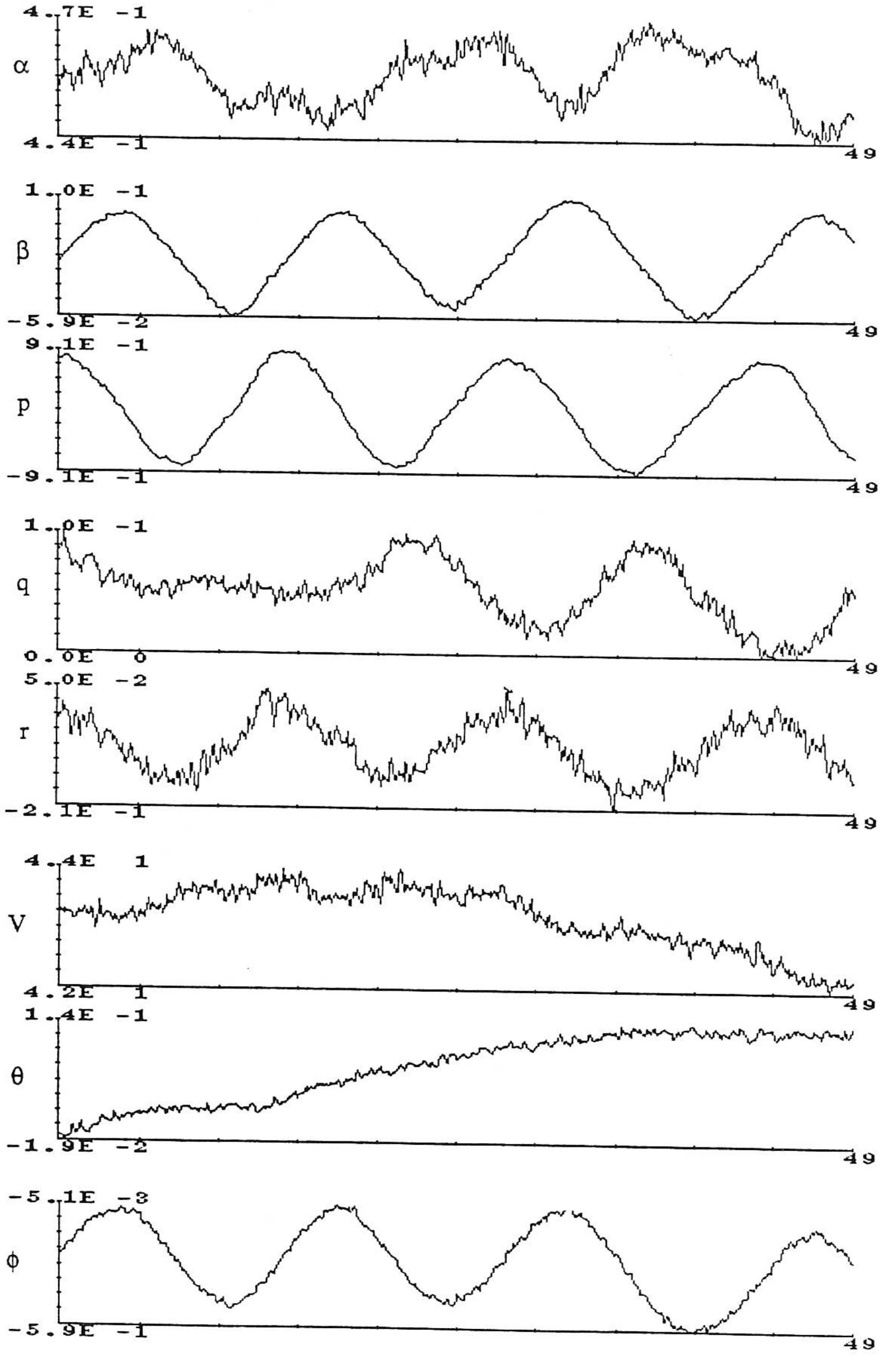
where $\hat{F}$ is the estimated system model (see tables above)

$$\underline{y}^T(t) = [\alpha_d(t),\beta_d(t),p_d(t),q_d(t),r_d(t)]$$

$$\underline{u}^T(t) = [\alpha(t),\beta(t),p(t),q(t),r(t),V(t),\theta(t),\phi(t)]$$

$$\underline{e}^T(t) = [e_\alpha(t),e_\beta(t),e_p(t),e_q(t),e_r(t)]$$

FIGURE 1: Input/output time histories for the system.



and $\underline{e}(t)$ is calculated as

$$\underline{e}(t) = \underline{y}(t) - \hat{\underline{y}}(t)$$

as compared to the measured system outputs.

Figure 3 shows the model predicted outputs compared with the measured system outputs, where the model predicted outputs are calculated as

$$\hat{\underline{y}}_{mp}(t) = \hat{F}[\hat{\underline{y}}_{mp}(t-1),\ldots,\hat{\underline{y}}_{mp}(t-N_y),\underline{u}(t-1),\ldots,\underline{u}(t-N_u),\underline{0}, \ldots, \underline{0}]$$

1. Conclusion

A nonlinear model of the dynamics of a HIRM, used in a research programme by RAE, has been identified using the techniques developed at Sheffield University. The model has been shown to be an valid representation of the real system, for both the data used in the identification and for an extended data set, by application of correlation tests and the examination of predicted behavior.

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KORENBERG, M., BILLINGS, S.A., LIU, Y.P., AND MCILROY, P.J., (1988). "Orthogonal Parameter estimation algorithm for Non-linear Stochastic Systems," *Int. J. Control*, vol. 48, no. 1, pp. 193-210.

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FIGURE 2:. One step ahead predicted outputs and measured outputs.

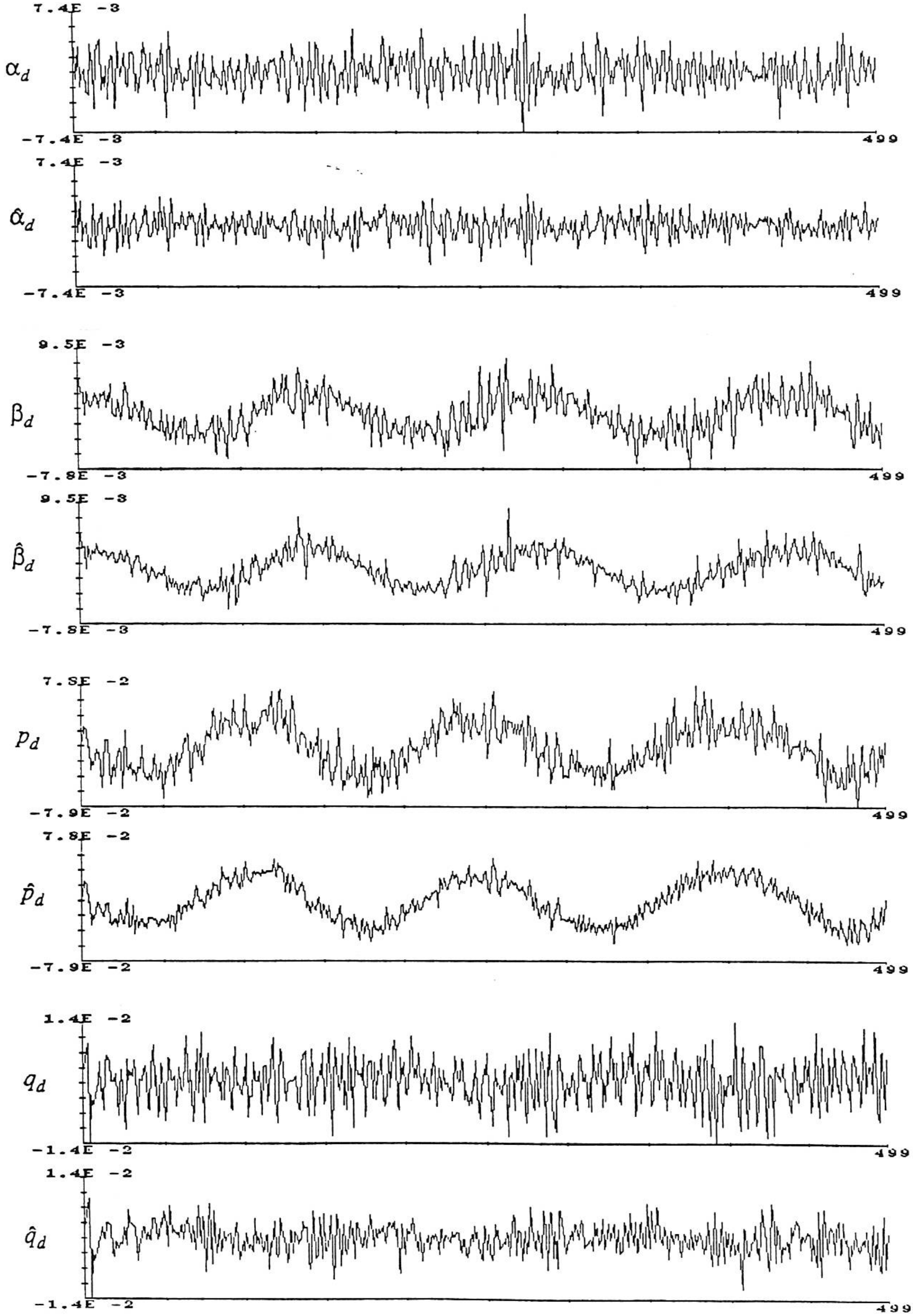

FIGURE 2 (CONT).

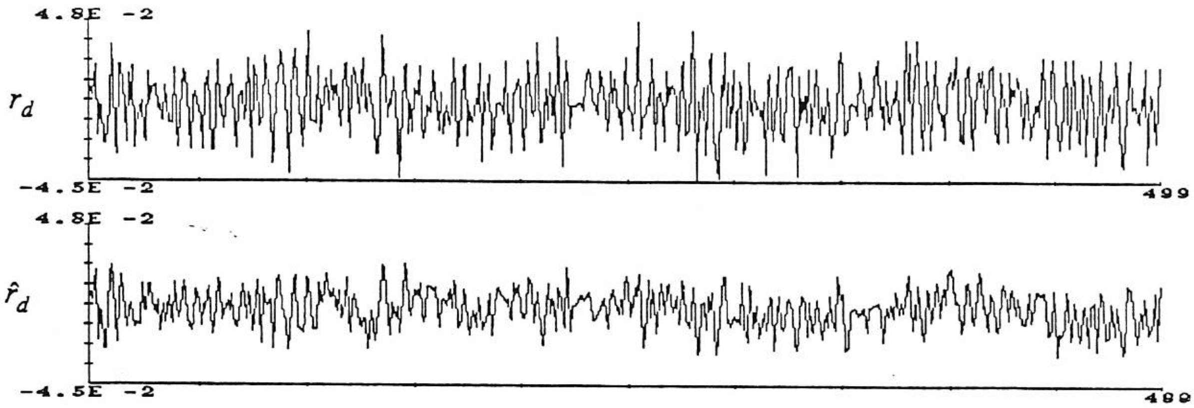

FIGURE 3: Model predicted outputs.

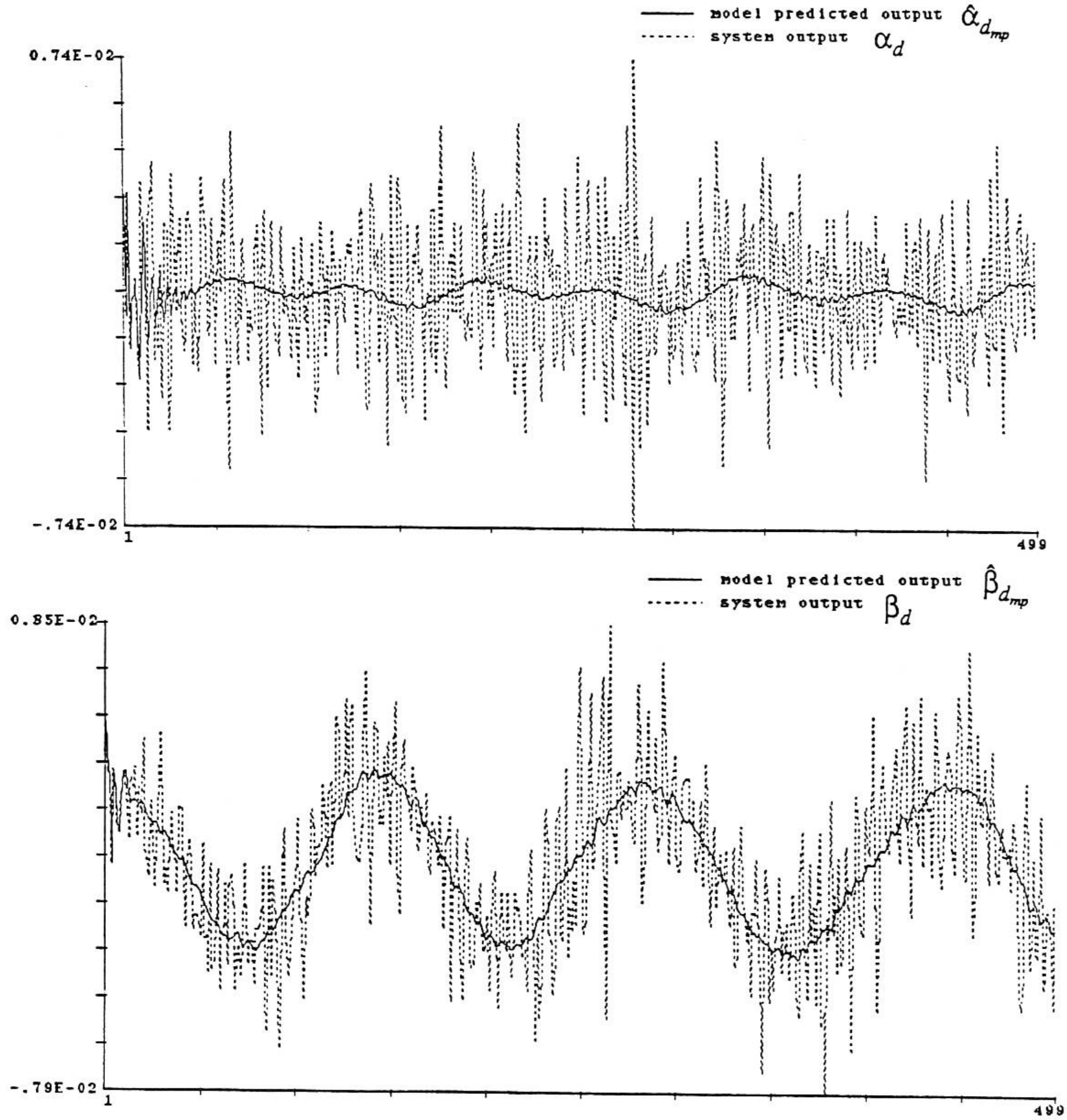

FIGURE 3 (CONT).