IDENTIFICATION OF MULTIVARIABLE HIGH-PERFORMANCE TURBOFAN ENGINE DYNAMICS FROM CLOSED-LOOP DATA

Walter C. Merrill
NASA Lewis Research Center
Cleveland, Ohio

First Annual NASA Aircraft Controls Workshop
NASA Langley Research Center
Hampton, Virginia
October 24-26, 1983

A typical engine control design cycle consists of developing a dynamic engine simulation from steady-state component performance data, designing a control based upon this simulation, and then testing and modifying the control in an engine test cell to meet performance requirements. This design cycle has been successful for state-of-the-art engines. However, for more advanced multivariable engines that exhibit strong variable interactions, this procedure will result in substantial trial and error modification of the control during the testing phase. One method to automate the design process and reduce control modification testing and development cost would be to identify accurate dynamic models directly from the closed-loop test data. These identified models would then be used in conjunction with a synthesis procedure to systematically refine the control. Recent advances in closed-loop identifiability (Ref. 1) present a methodology for this direct identification of engine model dynamics from closed-loop test data. This paper describes the application of an identification method (Ref. 2) to simulated and actual closed-loop F100 engine data (Ref. 3). This study was undertaken to determine if useful dynamic engine models could be identified directly from closed-loop engine test data (Ref. 4). (See fig. 1.)

Determine Multivariable Engine Models Directly From Closed-Loop Engine Test Data

Figure 1.- Identification objective.

The F100 engine was tested in the Lewis Research Center altitude test facility to evaluate the F100 Multivariable Control (MVC) law (Ref. 3). During the same test period the "Bill of Material" (BOM) control was also evaluated as a baseline/back-up control model. Thus, there were a variety of closed-loop operating records obtained throughout the flight envelope with a number of different power input requests. (See fig. 2.)

Note that direct control of the engine controls inputs is not possible. Since this is a closed-loop process, input and output noise will be correlated. Normally, this precludes the use of open-loop indentification techniques which require independence of the inputs and outputs. However, sufficient independence can be guaranteed if the PI control changes during a transient or if the simplified engine model generates a full rank, independent desired input. This latter condition is the case for the F100 MVC structure and thus allows a direct application of open-loop identification methodology.

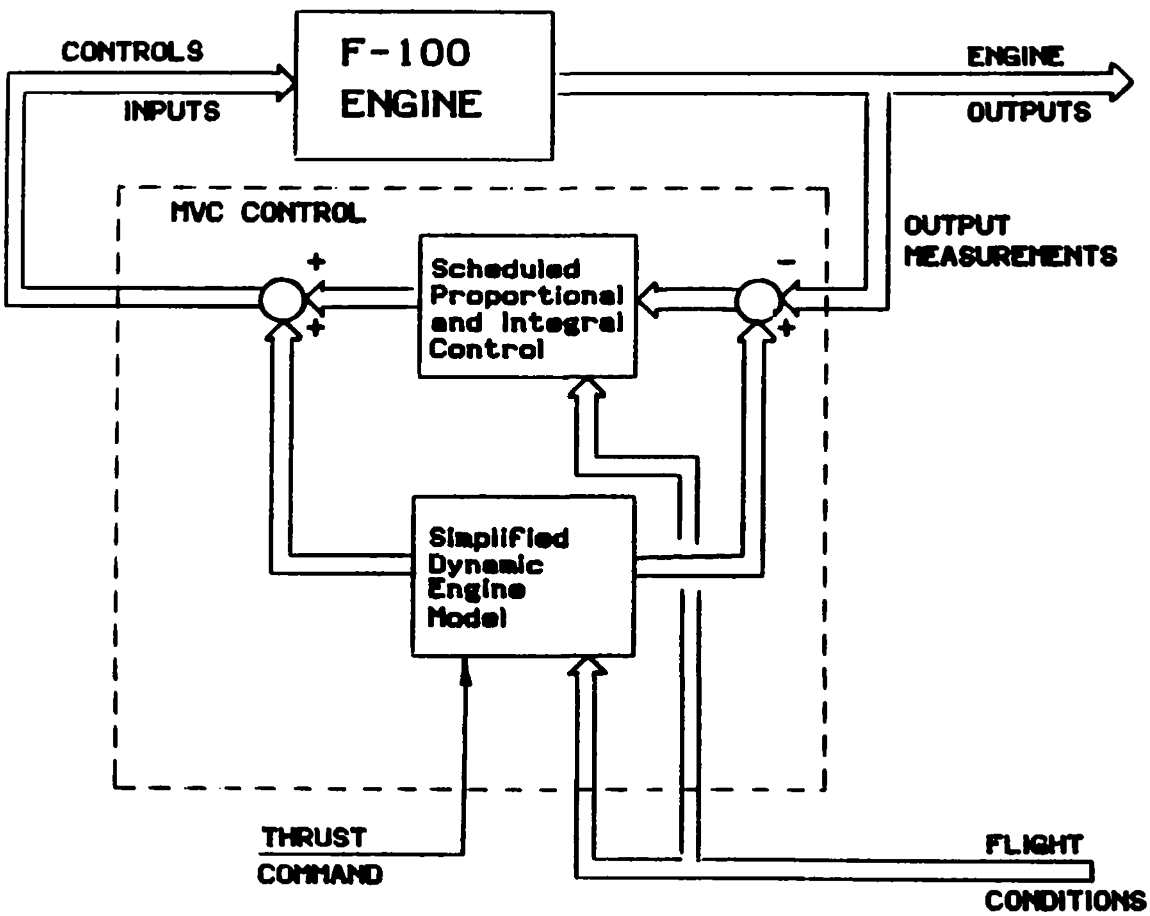

Figure 2.- F100 multivariable control structure.

The Instrumental Variable/Approximate Maximum Likelihood (IV/AML) method is an output error method of time series analysis. It was implemented in a combined iterative/recursive form. The IV/AML method was selected because the method exhibits reasonable convergence for a small number of samples. The IV/AML method is based upon an approximate decomposition of the maximum likelihood solution to the identification problem (fig. 3).

Approach

IV/AML Method of Recursive Time Series Analysis Directly Applied to Closed-Loop Data

Figure 3.- Identification approach.

Engine dynamics at a steady-state operating point are adequately modeled by a linear state space system. For the F100 engine a three-output four-input model written with the "transfer function" form given in Ref. 2 is shown. Engine speeds (N1 and N2) are important dynamic engine variables. Engine exhaust nozzle pressure (PT6) is an indicator of engine thrust. The engine inputs are fuel flow (WF), nozzle area (AJ), compressor inlet variable guide vane position (CIVV) and rear compressor variable stator vane position (RCVV). (See fig. 4.)

$$(zI + A_1)x_k = B_1 u_k$$

$$(zI + C_1)q_k = e_k$$

$$y_k = x_k + q_k$$

$$y = (N1, N2, PT6)^T$$

$$u = (WF, AJ, CIVV, RCVV)^T$$

Figure 4.- Engine model equations.

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The initial values for the A, B, and C matrices of the model were determined from SISO open-loop identification tests performed on an engine simulation. These values were used to start the closed-loop identification procedure. The model structure was taken from a third-order behavioral model developed in Ref. 5. Signal-to-noise ratios were determined from actual closed-loop data. Analysis showed the noise levels to be very low. (See fig. 5.)

- **A,B,C Initial Values From Simulation**
- **Structure From Behavioral Model**
- **Noise Estimates From Data**

  MVC Data 7<SNR<35

  BOM Data 22<SNR<600

Figure 5.- Engine model definition.

The IV/AML method was originally applied to SISO simulated data to determine initial parameter values. The method was then applied to open-loop MIMO simulated data. From these MIMO tests an additional element of A_1 was found to be necessary to satisfactorily model PT6. Also, the noise model was found to be very close to the plant model. The engine model found from this MIMO test was then used to predict engine behavior based upon actual closed-loop engine data.

The F100 engine was tested in the Lewis Research Center altitude test facility to evaluate the F100 Multivariable Control (MVC) law (Ref. 3). During the same test period the "Bill of Material" (BOM) control was also evaluated as a baseline/backup control mode. Thus, there are a variety of closed-loop operating records obtained throughout the flight envelope with a number of different power input requests. The two multivariable data sets used in this report were recorded at an ALT = 10,000 ft, MN = 0.9 condition as the power request was varied (step change) in a small (hopefully linear) range about intermediate engine power. One set corresponds to an MVC control test, the other to a BOM test. Data were sampled at T = 0.05 sec for 10-second transients, which yields 200 points for each record in the data sets. (See fig. 6.)

- Simulation (Open Loop)
  - SISO
  - MIMO
- Test Data (Closed Loop)
  - BOM Control
  - MVC Control
  - T=.05; 200 Points

Figure 6.- Application of instrumental variable/approximate maximum liklihood method.

Normalized WF from the BOM and MVC control tests is shown in figure 7. This is typical of the engine inputs in these tests. Power spectrum analysis of these inputs shows a slightly higher frequency component in the MVC inputs, although more total power is contained in the BOM inputs. However, for both the BOM and MVC inputs most of the power is concentrated below 6 radians/sec.

Note that these inputs are not persistently exciting.

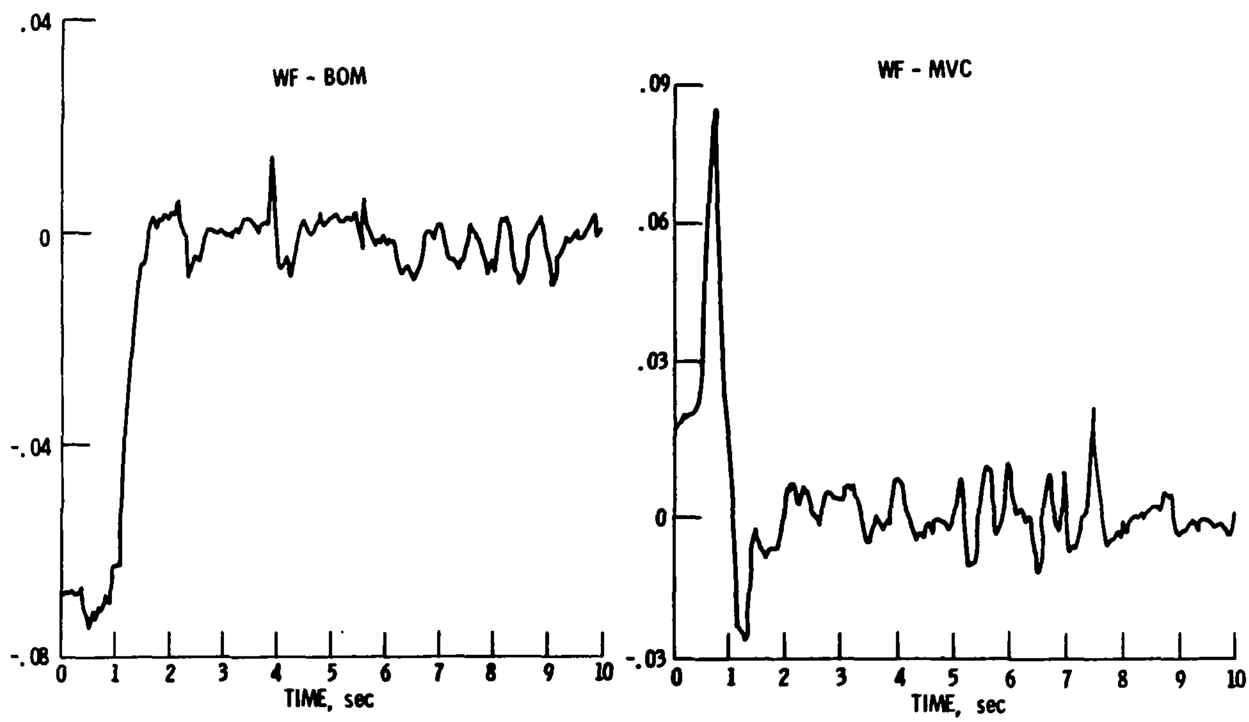

Figure 7.- Typical test inputs.

The control inputs of figure 7 were used in conjunction with the MIMO model identified from the simulation (Model 1) to predict engine output.

Comparing the predicted outputs of model 1 with the actual outputs, it was apparent that model 1 was unacceptable. No output was predicted well for either BOM or MVC data. Figure 8 is typical of the comparison. Slight discrepancies between simulation and test data cannot account for large discrepancies between predicted and actual outputs.

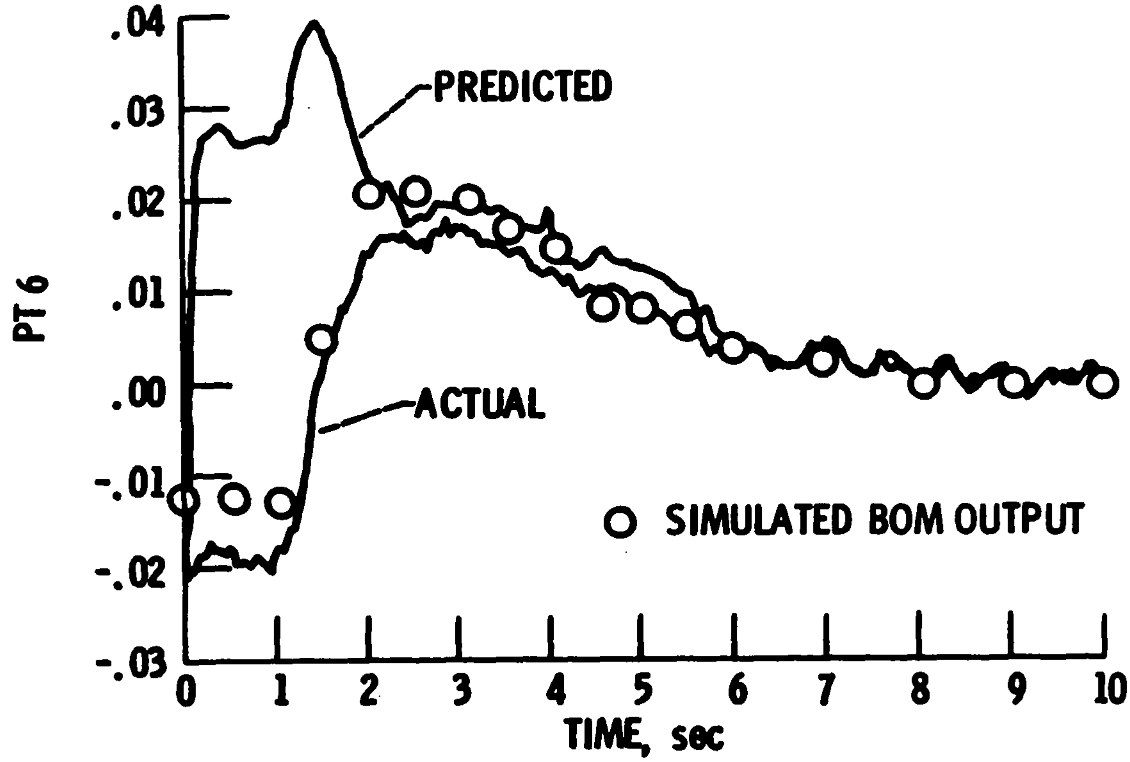

Figure 8.- Identification results for model 1.

To investigate this inability to predict engine response, the IV/AML method was applied directly to the closed-loop data producing models 2 (MVC) and 3 (BOM).

Model 1 was used as a starting point. As illustrated in figure 9, model 3 accurately reproduces the data from which it was generated (BOM). Model 2 results are similar. In fact, the error of all the outputs for models 1, 2, and 3 is less than 1%. However, comparing parameters for models 1, 2, and 3 it can be seen that while A_1 remains essentially unchanged, elements of B_1 do change substantially. This implies a slightly overparameterized model structure which does account for the inability of model 1 to predict BOM and MVC engine data.

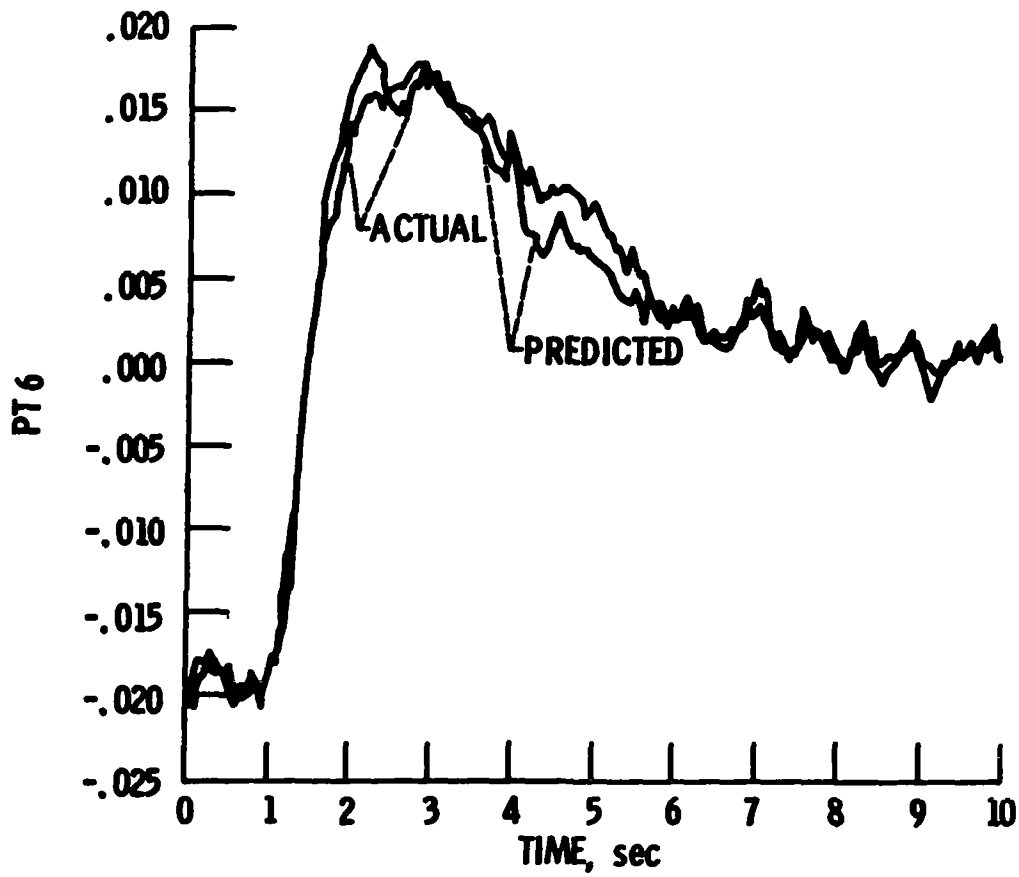

Figure 9.- Identification results for model 3.

A procedure was developed to remove the overparameterization. Three parameters were eliminated and this new structure was applied to the simulation data. The resultant IV/AML identified model is given as model 4. (See fig. 10.)

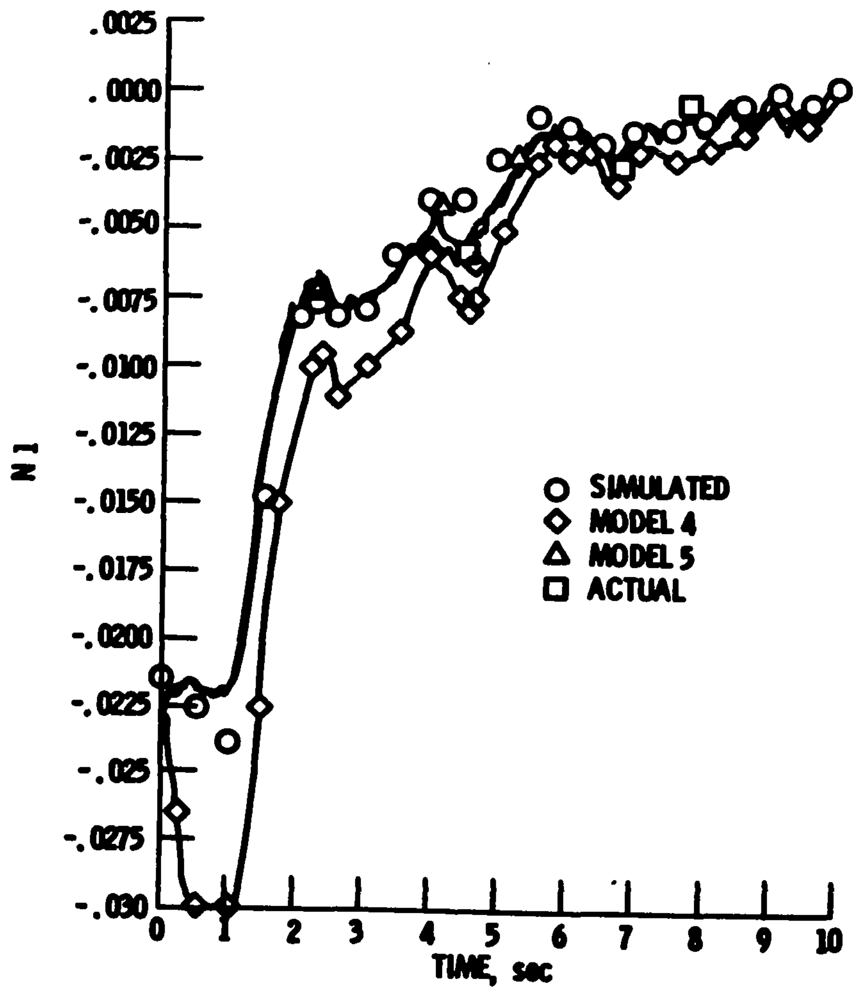

Figure 10.- Identification results for models 4 and 5.

When used to predict BOM and MVC output data, model 4 was still unsatisfactory. Model 4 did predict N1(MVC), N2(MVC), and N2(BOM). However, N1(BOM) and especially PT6 for both data sets were not predicted well. The error in PT6 is somewhat expected from sensor and input bandwidth consideration. The N1(BOM) error was not expected, however. Figure 11 compares predicted N1 data using model 4 to actual closed-loop N1(BOM) data. Model 4 predicted N1 grossly follows the trend of the simulated data. Thus, it appears that the dynamic portion of model 4 is correct. However, there must then be large discrepancies in some of the model 4 gain terms. These discrepancies are somewhat perplexing since model 4 predicted N1(MVC) but not N1(BOM).

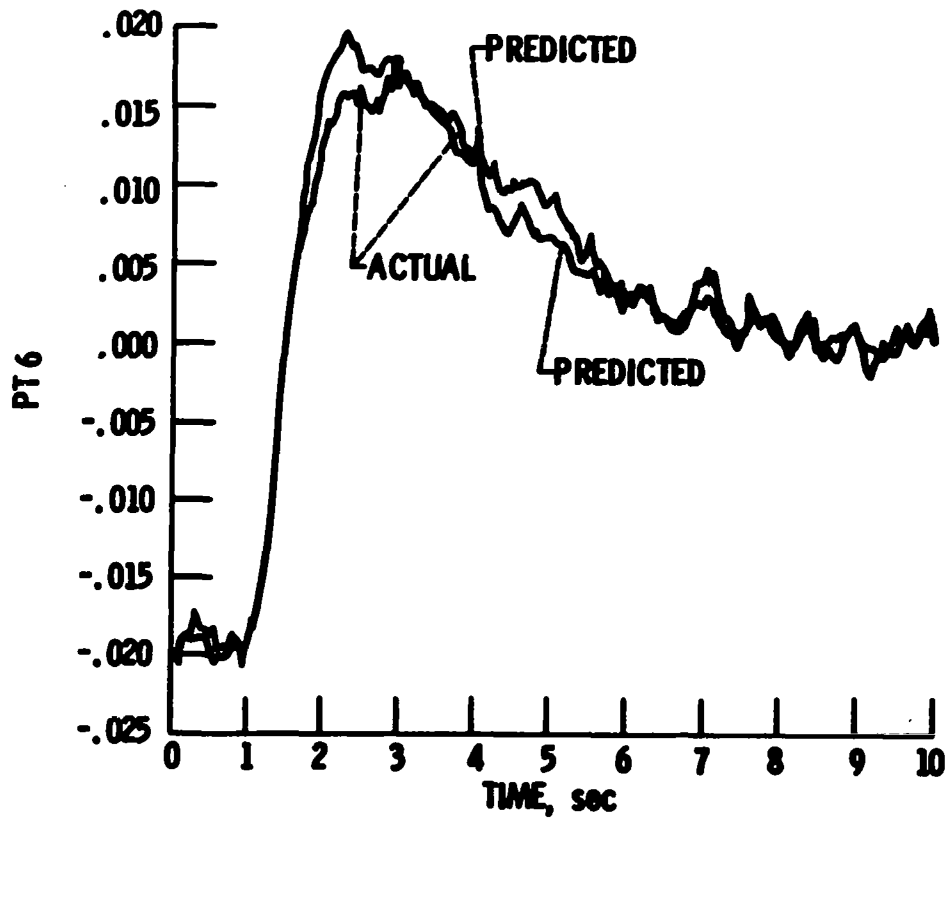

Figure 11.- Identification results for model 5, PT6.

Recall, however, that the BOM inputs are larger in magnitude than the MVC inputs and that model 4 represents linearized dynamics. Thus, some nonlinear effects may be inherent in the BOM data. This explanation is not entirely satisfactory since N2(BOM) and N2(MVC) were both predicted. Further work to resolve this problem is required. The IV/AML identification method was again utilized to further refine the model parameters for the structure of model 4 using the two sets of experimental closed-loop data. The purpose of this final iteration is to identify a single model that can accurately predict both sets of engine test data and, hopefully, simulation data as well. (See fig. 12.)

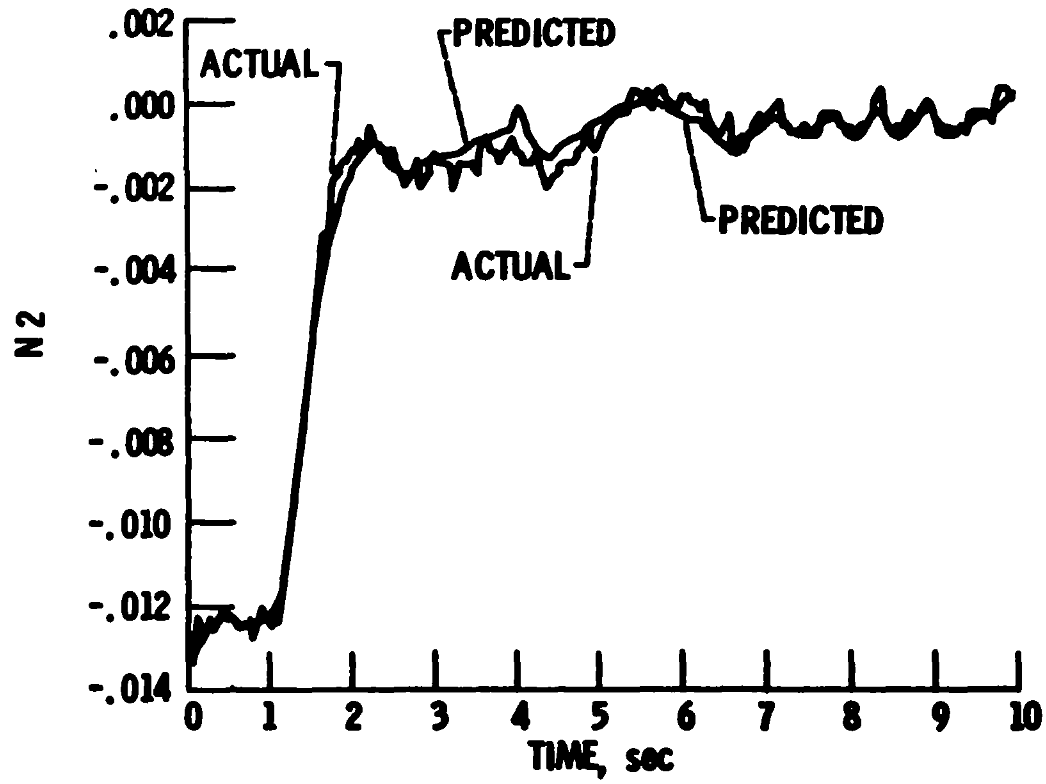

Figure 12.- Identification results for model 5, N2.

Again model 4 was used as an initial condition in the IV/AML method applied to the BOM and MVC data. Models 5 and 6 resulted. Both models 5 and 6 fit their respective data sets quite well. Figures 10 to 12, for example, show a good fit of the BOM data by outputs predicted using model 5. Similar comparisons to MVC data were obtained using model 6. More importantly, when the BOM model 5 is used to predict the MVC data, the comparison given in Figures 13 to 15 is quite reasonable. Thus, model 5 (or equivalently model 6) represents a model which predicts a class of inputs and can be used with confidence in a control design procedure.

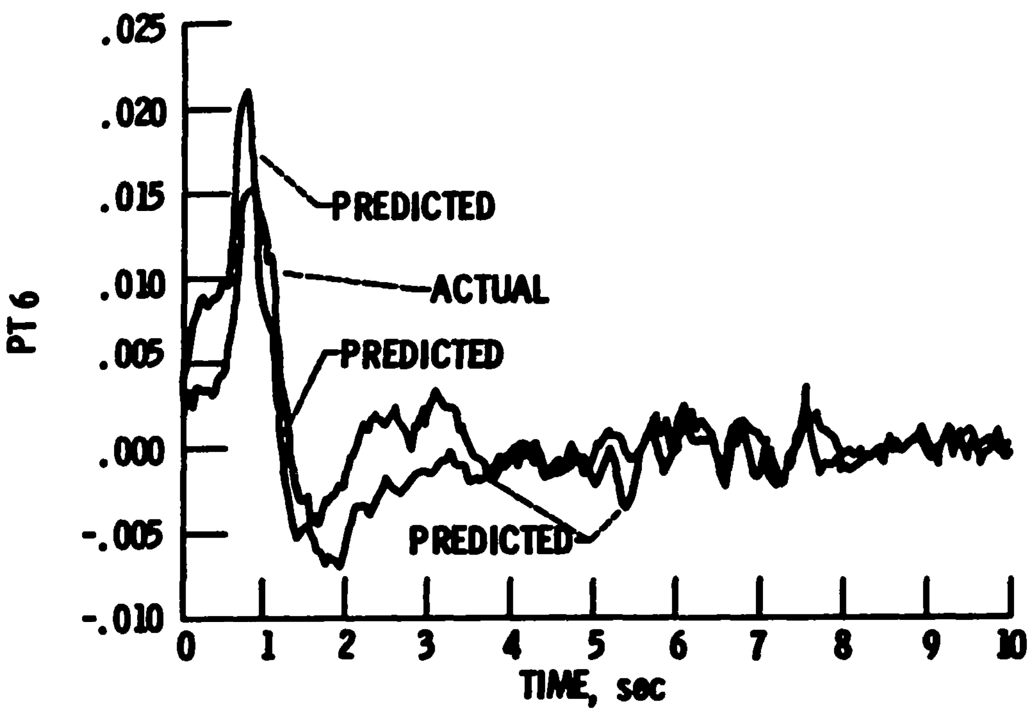

Figure 13.- Identification results for model 5 predicting multivariable control data, PT6.

The IV/AML method was applied to both open-loop simulation and closed-loop test data of an F100 turbofan engine. The method accurately and consistently identified models from both the simulation and test data. Due to the structure of the BOM and MVC control laws, the engine model is strongly system identifiable and consequently a direct identification approach was used on the closed-loop data.

A third-order model structure was derived and found to be overparameterized. Three parameters were eliminated by sensitivity considerations. The simplified structure was found acceptable for fitting both simulation and test data. Test model accuracy is limited to 6 radians/sec since spectral analysis of the inputs shows limited signal strength above this frequency.

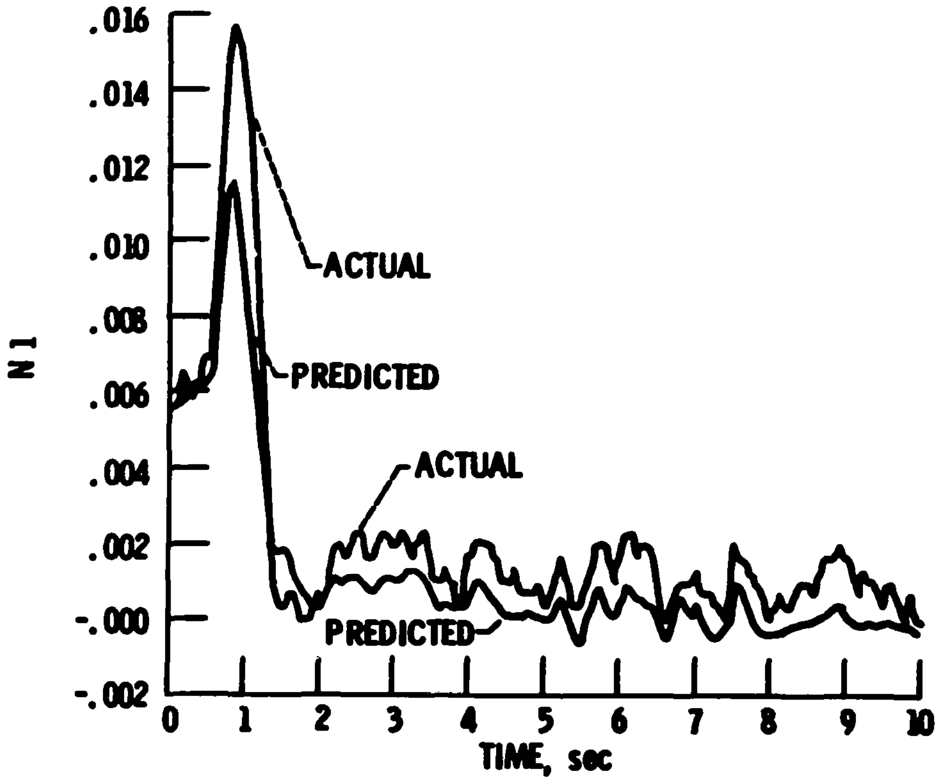

Figure 14.- Identification results for model 5 predicting multivariable control data, N1.

Comparisons showed that models identified from simulated data generally predicted N1(MVC), N2(MVC), and N2(BOM) test response adequately. However, predictions of PT6(MVC) and PT6(BOM) were poor and N1(BOM) showed some discrepancies in dynamics. The PT6 differences are attributed to the low-frequency content of the test input signals (∿6 radians/sec), the bandwidth of the sensor, and the high-frequency nature of the PT6 mode. However, the difference in N1 is attributable to a difference in simulated versus actual engine performance. This conclusion is accurately portrayed in a comparison of identified models.

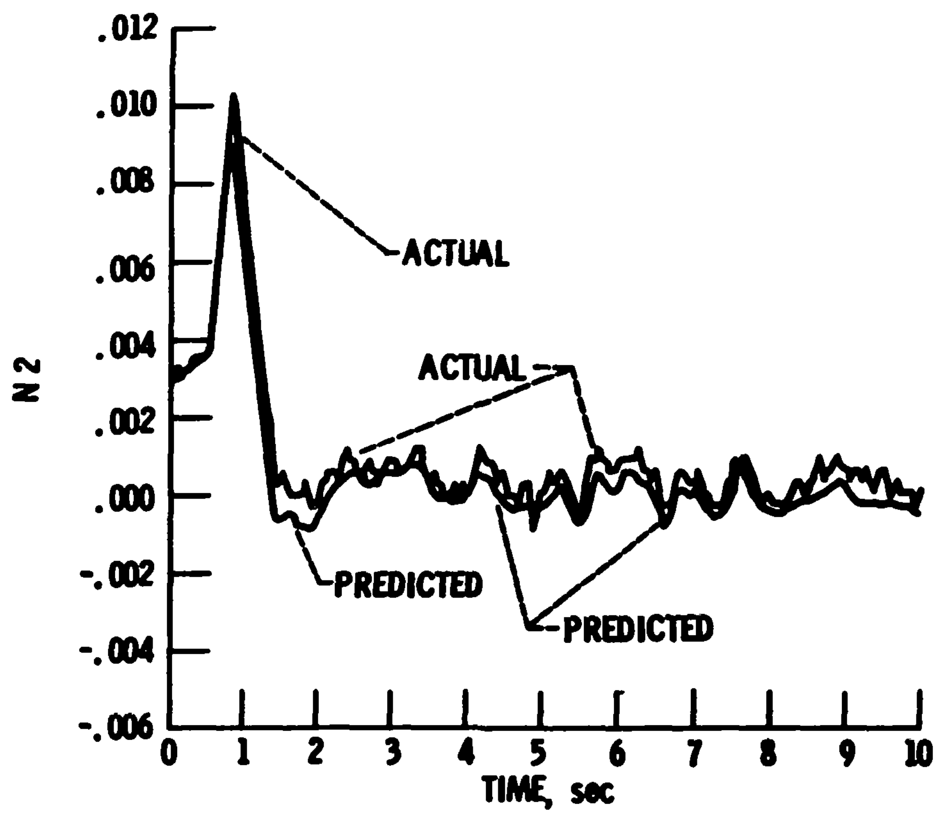

Figure 15.- Identification results for model 5 multivariable control data, N2.

Finally, a simplified model determined from BOM data accurately predicted not only BOM but also MVC test response data. This ability to predict engine performance for a class of inputs generates confidence in controls designed from this model. Thus, it is concluded that useful dynamic engine models can be obtained from closed-loop test data using the IV/AML identification method. This identification technique, then, represents the first step in an automated engine control design process. (See fig. 16.)

- Basic IV/AML Worked Well
- Engine Model is SSI
- Third-Order Model Structure
- Simulation Predicts Test Data
- Models From Simulation do not Predict N1 (BOM) and PT6 (BOM & MVC)
- BOM Model Predicts MVC Data

Figure 16.- Conclusions.

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