# ENGINE IDENTIFICATION FOR ADAPTIVE CONTROL*

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## SUMMARY

This paper describes an attempt to obtain a dynamic model for a turbofan gas turbine engine for the purpose of adaptive control. The requirements for adaptive control indicate that a dynamic model should be identified from data sampled during engine operation. The dynamic model identified was of the form of linear differential equations with time-varying coefficients. A turbine engine is, however, a highly nonlinear system, so the identified model would be valid only over a small area near the operating point, thus requiring frequent updating of the coefficients in the model. Therefore it is necessary that the identifier use only recent information to perform its function. The identifier selected minimized the square of the equation errors. Known linear systems were used to test the characteristics of the identifier. It was found that the performance was dependent on the number of data points used in the computations and upon the time interval over which the data points were obtained. Preliminary results using an engine deck for the QCSEE indicated that the identified model predicted the engine motion well when there was sufficient dynamic information, that is when the engine was in transient operation.

## INTRODUCTION

Identification is an essential part of any adaptive control strategy. It is necessary to determine the current performance characteristics of a plant in order to adaptively modify the overall system to better satisfy a given performance index. The work described herein focused upon the development of identification techniques which have characteristics suitable for use as part of an adaptive control system. A detailed description of this work is available in reference 1.

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## DESCRIPTION OF THE METHOD

The method is illustrated by applying the technique to a simple second order system described by

$$\ddot{x} + a\dot{x} + bx = cu$$

The objective is to identify the coefficients a, b, and c from measurements of the input, u, and output, x, as well as measurement or computation of the derivatives, $\dot{x}$ and $\ddot{x}$. An error, e, is defined and forms the basis for an equation error identification scheme

$$e = \hat{c}u = \ddot{x} - \hat{a}\dot{x} - \hat{b}x$$

where $\hat{a}$ denotes the estimated or identified value of the coefficient a. The estimates are chosen such that for N discrete samples, the index of performance

$$IP = \frac{1}{2}\sum_{i=1}^{N} e_i^2$$

is minimized to provide best values of the coefficients in a least squares sense. Partial derivatives are taken with respect to each coefficient which yield

$$\frac{\partial IP}{\partial \hat{a}} = \sum_{i=1}^{N} e_i \frac{\partial e_i}{\partial \hat{a}} = 0$$

$$= \sum_{i=1}^{N} e_i \dot{x}_i = 0$$

or

$$\sum_{i=1}^{N} (\hat{c}u - \ddot{x} - \hat{a}\dot{x} - \hat{b}x)_i \dot{x}_i = 0$$

Evaluating the other partial derivatives and performing some rearrangement gives the vector equation

$$
\begin{bmatrix} -\hat{a} \\ -\hat{b} \\ \hat{c} \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{N} \dot{x}_i^2 & \sum_{i=1}^{N} \dot{x}_i x_i & \sum_{i=1}^{N} \dot{x}_i u_i \\ \sum_{i=1}^{N} \dot{x}_i x_i & \sum_{i=1}^{N} x_i^2 & \sum_{i=1}^{N} x_i u_i \\ \sum_{i=1}^{N} \dot{x}_i u_i & \sum_{i=1}^{N} x_i u_i & \sum_{i=1}^{N} u_i^2 \end{bmatrix}^{-1} \begin{bmatrix} \sum_{i=1}^{N} \ddot{x}_i u_i \\ \sum_{i=1}^{N} \ddot{x}_i x_i \\ \sum_{i=1}^{N} \ddot{x}_i \dot{x}_i \end{bmatrix}
$$

The symmetry of the matrix on the right-hand side (aided by the negation of $\hat{a}$ and $\hat{b}$) is attractive for the required inversion.

The method can be utilized off-line where many samples from operating records can be used in the summations. Previous investigations (2, 3) have successfully used this method to identify parameters in dynamic systems. A more challenging use for the method lies in on-line applications. The most challenging application is in the area of adaptive control where it is essential to obtain a description (model) of the system in real time so that the adaptation can be effected.

To employ this identification scheme in real-time the practitioner must make three choices:

1. a model form whose coefficients are to be determined
2. a sampling interval, $\Delta t$, between the times when the input, output, and required derivatives are sampled
3. the number of samples, N, which are to be used by the identification algorithm.

## AN ILLUSTRATIVE EXAMPLE

The method was applied to a known system described by the differential equations

$$
\dot{x}_1 = ax_1 + bx_2
$$

$$
\dot{x}_2 = cx_1 + dx_2 + u
$$

with two fixed coefficients, $a = 0$, $b = 1$, and with the coefficients c and d being time varying. The input, u, was a square wave. The identification technique was used to identify these four coefficients. [A generalization of the technique for multiple input/multiple output systems is presented in (1)].

Figures 1 through 4 show the results from four of the test cases that were conducted to illustrate the nature of the method. In figure 1 it can be seen that the actual coefficient c varies linearly with time while d varies in a sinusoidal fashion. Note also that the coefficients vary slowly compared to the period of the input square wave which is 0.5 seconds. The identified values for c and d do a reasonably good job of tracking the actual parameter values in figures 1, 2, and 3. In figure 1 the identification window, $N\Delta t$, is 0.8 seconds and the identified values tend to follow approximately half of this time behind the actual values. The identification window is doubled in figure 2 by retaining 16 data points for the identification rather than 8. The time lag between the actual and the identified coefficients is again approximately half of the identification window. Figure 3 illustrates the use of a smaller time interval, 0.05 seconds as compared with 0.1 seconds in figures 1 and 2, to reduce the identification window. The results shown in figure 3 are identical to those of figure 1 where both identification windows are 0.8 seconds.

Figure 4 illustrates the degradation of performance which results when insufficient information is provided for identification. For this case the input period was increased to 4 seconds, the approximate settling time of the system being identified. With this slow input the system approaches steady state before the input square ware changes state. As the system approaches steady state, the derivative terms required in the identification algorithm approach zero and numerical difficulties are encountered adversely affecting the computed values for c and d. Immediately following the reversal of the input, the algorithm quickly recovers and moves toward the correct result but the lack of sufficient dynamic information precludes the attainment of satisfactory identification. With this lack of dynamic information no combination of sampling interval and number of data points will produce satisfactory results. If such a condition was encountered in practice, a number of alternatives could be employed including suspension of the parameter identification while retaining previous results. Another possibility would be to change the model form for the identification to a lower order, possibly even a static model, until sufficient dynamic information is again available for use.

## APPLICATION OF THE METHOD TO A TURBINE ENGINE MODEL

Engine performance data were obtained from a digital simulation of the QCSEE (Quiet, Clean, Shorthaul Experimental Engine). This simulation includes a 16th order model (including sensors and actuators) and the nonlinearities for such items as the compressor maps based upon curve fits to typical engine characteristics.

One of the objectives of this preliminary work was to obtain reduced order linear models, probably with time-varying coefficients, which could be used to describe the engine. It was felt that these models would be applicable about an operating point and that they may be capable (with suitable identification) to track the engine under transient conditions. Initial efforts were tried using a second-order model to account for the two spool speeds in the QCSEE since it was felt that these would be the dominant energy storage elements. These attempts were not fruitful. It was necessary to add a third state, the compressor outlet temperature, to "account" for a thermal energy storage.

Some promising results were obtained with a third-order model using as states the compressor spool speed, NH, the fan spool speed, NL, and the compressor exit temperature, T3. The three inputs to the engine, fuel flow, WFM, fan blade angle, BETA, and the fan nozzle exhaust area, A18, formed the input vector. The engine was excited by a ramp variation in the power level angle from 40° to 45° to 40° over a period of one second. Figure 5 shows the result from one of these preliminary runs. The plots show the variations of the three eigenvalues associated with the state variables. As expected the dominant (slowest) eigenvalue is associated with the fan spool speed and the fastest is associated with the thermal state variable. While no actual verification of the numerical values obtained from the identification has been made, the trends and approximate magnitudes of the results are encouraging.

## CONCLUSION

The identification method appears promising for utilization in an adaptive control strategy. The algorithm is attractive for implementation on an onboard computer if models of low order can be used to adequately describe the engine dynamics. No attempt has been made to date to examine a combination of scheduled gains with adaptive trim which may be necessary to follow rapid acceleration/deceleration transients or to operate the system in the absence of adequate dynamic information.

## REFERENCES


1. Arnett, E. M., "On-Line Linear Model Identification Applied to a Gas Turbine Engine." M.S. Thesis, Purdue University, August 1978.

2. Ward, E. D., and Leonard, R. G., "Automatic Parameter Identification Applied to a Railroad Car Dynamic Draft Gear Model," ASME Paper 74-WA/AUT-1.

3. Warner, D. E., "Linear Parameter Identification Applied to a Gas Turbine Engine," M.S. Thesis Purdue University, May 1976.

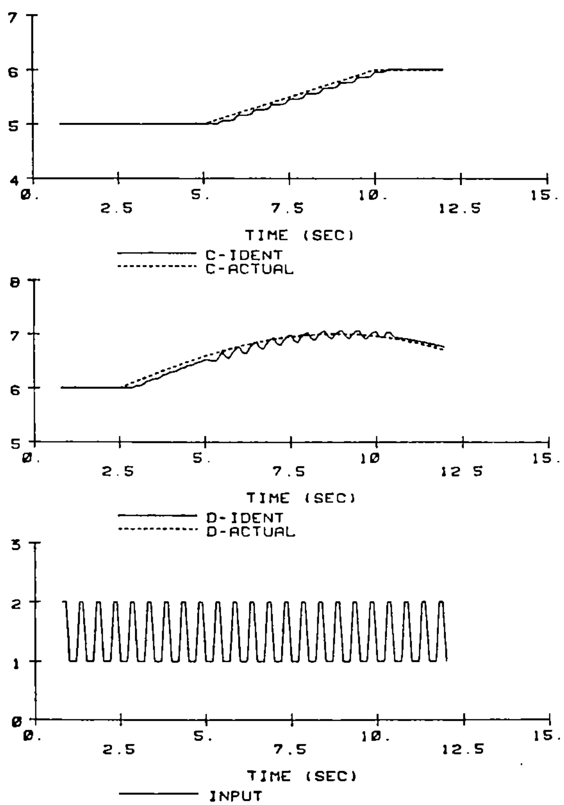


Figure 1. - Identified and actual coefficients for known system with $\Delta t = 0.1$ and $N = 8$.

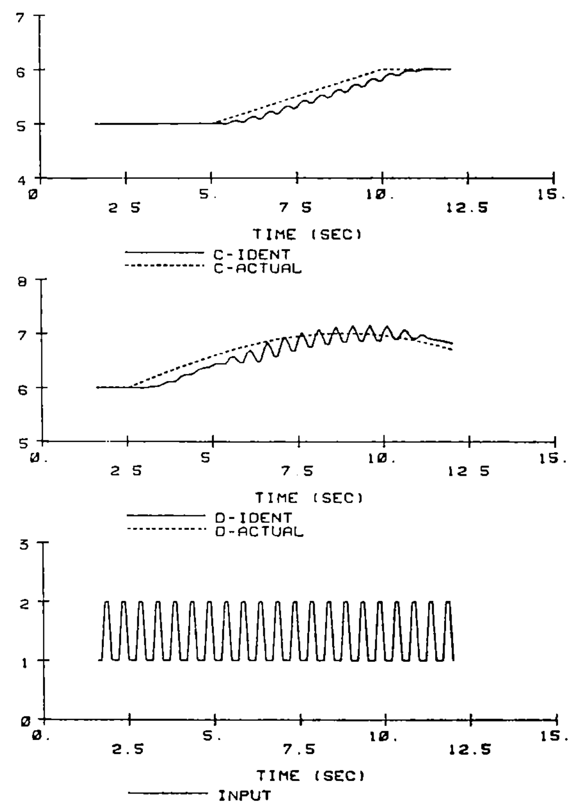


Figure 2. - Identified and actual coefficients for known system with $\Delta t = 0.1$ and $N = 16$.

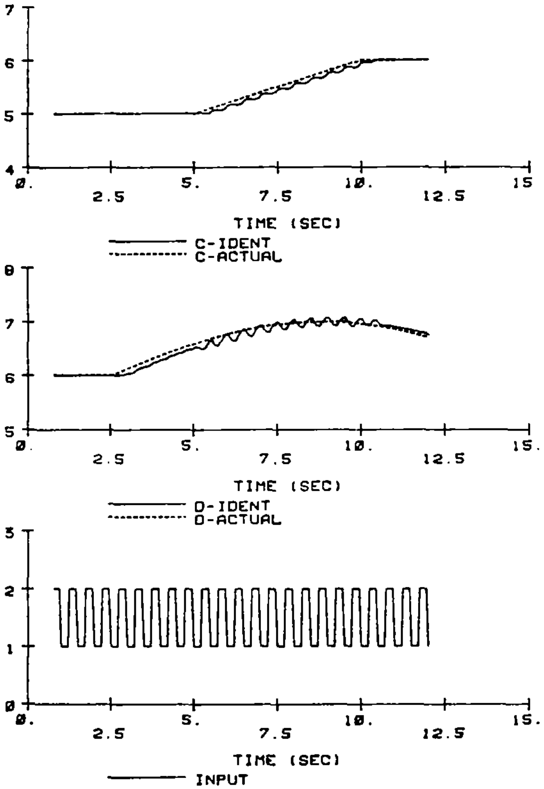


Figure 3. - Identified and actual coefficients for known system with $\Delta t = 0.05$ and $N = 16$.

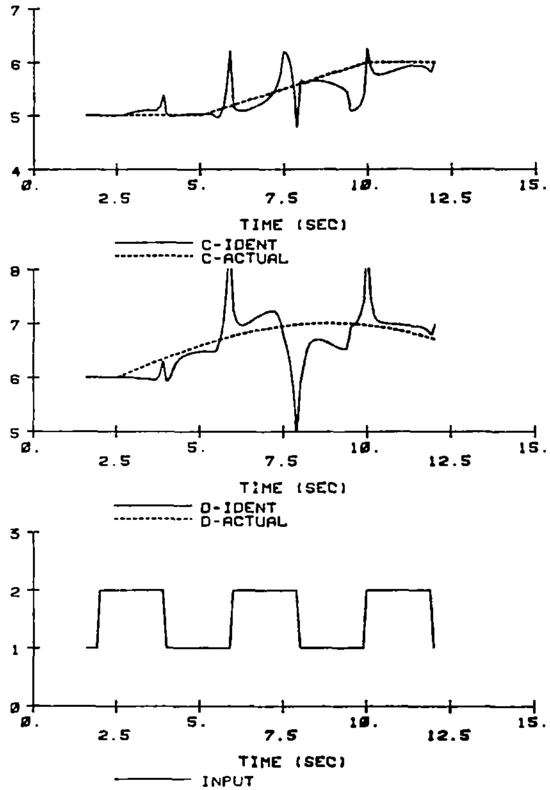


Figure 4. - Identified and actual coefficients for known system with $\Delta t = 0.1$ and $N = 16$.