



MIDWEST APPLIED SCIENCE CORPORATION • WEST LAFAYETTE, INDIANA

1205 Kent Avenue  
McClure Research Park  
Phone 743-2161

FINAL REPORT

ON

THE DEVELOPMENT OF COMPUTATIONAL TECHNIQUES

*etc.*  
*Final Report*  
*Part II*

FOR THE

IDENTIFICATION OF LINEAR AND NONLINEAR MECHANICAL SYSTEMS

SUBJECT TO RANDOM EXCITATION

Part II

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By

Dr. F. Kozin

and

Dr. C. H. Kozin

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A DYNAMICAL MOMENT TECHNIQUE  
FOR THE  
IDENTIFICATION OF SYSTEMS

I. Introduction

The purpose of this report is to describe a new identification technique that appears to be of superior practical significance due to its simplicity both in comprehending and applying the technique.

The technique is based upon relatively straightforward principles of random function analysis, merely involving the estimation of various order moments of the input and output processes.

In a preliminary investigation of the technique for identification of digitally simulated linear systems, the technique produced quite useful approximations to the actual system parameters, with a relatively small number of calculations. Hence, we feel that it warrants further investigation on this basis alone. Even more interesting is that the technique does not appear to be limited to linear systems alone. Since, theoretically, the technique is the same for linear or non-linear systems, that can be described by differential equations with polynomial non-linearities. Of course, it remains to be seen how applicable the technique will be for non-linear systems.

Before describing the technique, we wish to make two points clear relative to this technique and to the general subject of identification of real systems.

First, there exist techniques available for the study of linear systems. The newer techniques may employ cross-correlations or cross-spectral densities for the estimation of the impulse response function or for the frequency response function. These techniques require a random noise source and require the estimation of the functions involved at various time lags or at various frequencies. The techniques that have been used classically employ a simple sinusoidal driver at various frequencies to determine the frequency response of the system. Techniques, such as ours, that require only a parameter estimation are just now emerging. These techniques offer the promise of economy in calculations and time. The establishment of such techniques as practical tools will be of fundamental importance in future complex systems design and development.

References and explanations of the many approaches to this subject may be found in "Identification of Linear and Non-Linear Systems Cross-Correlations Techniques", by Dr. W. Gersch conducted by MASC for NASA-Goddard under NAS5-9741, October 1965.

The second point that must be made concerning the identification of systems is that the methods that have been developed, as well as the method we describe in this report, are methods

that will identify the analytical model or simulated model of the actual physical system. Hence, if the analytical or simulated model is not a satisfactory equivalent or approximation to the system, then clearly one is not identifying the real system.

Thus, any identification scheme is only as good as the analytical model that will be used to describe the physical system.

Of course, identification schemes can be used to help provide a better model to the system, if it is found that the original assumption is poor.

With this understanding of the proper role of identification techniques, we can now proceed to describe our approach.

## II. A General Description of an Identification Technique for Linear Systems.

The basic principle of the technique that we propose is that the system undergoing study is time invariant and is being driven by a statistically stationary, non-white noise random process. This rules out flat wide band noise as inputs. We shall discuss the reason for this requirement below.

We shall assume, furthermore, that for all practical purposes the system is in steady state operation. Thus, the output process is a statistically stationary random process. This implies that all of its moments are constant in time.

Now if we write the general time invariant linear system subjected to random input as

$$\dot{\bar{y}}(t) = A \bar{y}(t) + \bar{x}(t), \quad (2.1)$$

where

$$\bar{y}(t) = \begin{pmatrix} y_1(t) \\ \vdots \\ y_n(t) \end{pmatrix}, \quad \bar{x}(t) = \begin{pmatrix} x_1(t) \\ \vdots \\ x_n(t) \end{pmatrix}, \quad (2.2)$$

$$A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ \vdots & & \vdots \\ a_{n1} & \dots & a_{nn} \end{pmatrix},$$

then the  $\bar{y}$ -process is statistically stationary and, assuming that all moments of the  $\bar{x}$ -process exist, it follows that the moments

$$E \{ y_1^{r_1}(t) \cdot y_2^{r_2}(t) \cdots y_n^{r_n}(t) \cdot x_1^{s_1}(t) \cdots x_n^{s_n}(t) \} \quad (2.3)$$

exist and are constant in time.

Upon multiplying equation (2.1) by  $\bar{y}^T$  (the transpose of the state vector), we obtain

$$\dot{\bar{y}}(t) \bar{y}^T(t) = A \bar{y}(t) \bar{y}^T(t) + \bar{x}(t) \bar{y}^T(t). \quad (2.4)$$

Taking expectations of the equation (2.4) yields

$$E \{ \dot{\bar{y}}(t) \bar{y}^T(t) \} = A E \{ \bar{y}(t) \bar{y}^T(t) \} + E \{ \bar{x}(t) \bar{y}^T(t) \} \quad (2.5)$$

or

$$[E \{ \dot{\bar{y}}(t) \bar{y}^T(t) \} - E \{ \bar{x}(t) \bar{y}^T(t) \}] E \{ \bar{y}(t) \bar{y}^T(t) \}^{-1} = A \quad (2.6)$$

assuming  $E \{ \bar{y}(t) \bar{y}^T(t) \}^{-1}$  exists.

The relation (2.6) presents a general form of the solution of the general problem for the linear system.

It is easily seen that  $E \{ \bar{y}(t) \bar{y}^T(t) \}$  is symmetric and, furthermore, since for any  $(\alpha_1, \dots, \alpha_n)$ ,

$$E \{ \left| \sum_{i=1}^n \alpha_i y_i(t) \right|^2 \} \geq 0, \quad \text{it follows that } E \{ \bar{y}(t) \bar{y}^T(t) \}$$

is non-negative definite.

If the system equations are linearly independent, we shall expect that  $E\{\bar{y}(t)\bar{y}^T(t)\}$  is positive definite and that its inverse exists. Thus, the matrix A is identified by estimation of the correlation matrices in Equation (2.6).

For our applications, we wish to be less general and somewhat more specific. We are assuming that the  $\bar{y}$ -process is a stationary, mean square differentiable process. Such a process is generated, for example, by passing a stationary mean square continuous process (i.e. a process whose covariance is continuous at the origin) through the time invariant linear system. This is the reason that we are ruling out wide band white noise processes. For, by passing a wide band, essentially white-noise, through the system the mean square differentiable property will cease to hold which, as can be shown, yields a bias to our estimations.

By our stationarity assumptions, it follows that the following moments, for the components of the vector  $\bar{y}$ -process,

$$E\{y_i^n(t)\} \quad \text{and} \quad E\{y_i^n(t)y_j^m(t)\} \quad (2.7)$$

exist and are constant in time.

Hence, it follows that

$$\frac{d}{dt} E\{y_i^n(t)\} = 0 \quad (2.8)$$

$$\frac{d}{dt} E\{y_i^n(t) y_j^m(t)\} = 0.$$

Due to our assumption of mean square differentiability, the derivatives in Equation (2.8) can be taken inside the expectations to give

$$a) \quad E \{y_i^{n-1}(t) \dot{y}_i(t)\} = 0 \tag{2.9}$$

$$b) \quad n E\{y_i^{n-1}(t) \dot{y}_i(t) y_j^m(t)\} + m E\{y_i^n(t) y_j^{m-1}(t) \dot{y}_j(t)\} = 0$$

In particular it follows that, for  $n=m=1$  in 2.9b),  $n=2$  in 2.9a)

$$a) \quad E \{y_i(t) \dot{y}_i(t)\} = 0 \tag{2.10}$$

$$b) \quad E \{y_i(t) \dot{y}_j(t)\} + E \{\dot{y}_i(t) y_j(t)\} = 0.$$

The first equality in Equation (2.10) states the well-known fact that a stationary process and its derivative are uncorrelated at any given time.

With these last few statements, we can now show how to identify a few specific linear systems.



### III. Examples

In the following examples the  $x$ -process is a stationary mean square continuous, non-white, random process and the  $y$ -process is the stationary solution.

#### Example 1. A First-Order System

Consider the system

$$\dot{y}(t) = -a y(t) + x(t) \quad (3.1)$$

Upon multiplying Equation (3.1) by  $y(t)$  and taking the expectations we have

$$E\{y(t) \dot{y}(t)\} = -a E\{y^2(t)\} + E\{y(t) x(t)\}. \quad (3.2)$$

But, by (2.10) it follows that

$$a = \frac{E\{y(t) x(t)\}}{E\{y^2(t)\}}. \quad (3.3)$$

#### Example 2. An Oscillator

Consider the second order system

$$a) \quad \dot{y}_1(t) = y_2(t) \quad (3.4)$$

$$b) \quad a \dot{y}_2(t) + b y_2(t) + c y_1(t) = x(t)$$

Upon multiplying 3.4b) by  $y_1(t)$ ,  $y_2(t)$ ,  $y_2^2(t)$  respectively and taking the expectations, we obtain

$$\begin{aligned} a E\{y_1(t) \dot{y}_2(t)\} + b E\{y_1(t) y_2(t)\} + c E\{y_1^2(t)\} &= E\{y_1(t) x(t)\} \\ a E\{y_2(t) \dot{y}_2(t)\} + b E\{y_2^2(t)\} + c E\{y_1(t) y_2(t)\} &= E\{y_2(t) x(t)\} \quad (3.5) \\ a E\{y_2^2(t) \dot{y}_2(t)\} + b E\{y_2^3(t)\} + c E\{y_2^2(t) y_1(t)\} &= E\{y_2^2(t) x(t)\} \end{aligned}$$

But, by equations (2.10) and (3.4a), we have

$$\begin{aligned} E\{y_2(t) \dot{y}_2(t)\} &= E\{y_2^2(t) \dot{y}_2(t)\} = 0 \\ E\{y_1(t) y_2(t)\} &= E\{y_1(t) \dot{y}_1(t)\} = 0 \quad (3.6) \\ E\{y_1(t) \dot{y}_2(t)\} &= -E\{\dot{y}_1(t) y_2(t)\} = -E\{y_2^2(t)\}. \end{aligned}$$

The equations 3.5) may now be written as

$$\begin{aligned} -a E\{y_2^2(t)\} + c E\{y_1^2(t)\} &= E\{y_1(t) x(t)\} \\ b E\{y_2^2(t)\} &= E\{y_2(t) x(t)\} \quad (3.7) \\ b E\{y_2^3(t)\} + c E\{y_2^2(t) y_1(t)\} &= E\{y_2^2(t) x(t)\} \end{aligned}$$

from which a, b, c can be solved.

Example 3. A Coupled Oscillator

We now consider the system

$$\begin{aligned}
 \dot{y}_1(t) &= y_2(t) \\
 \dot{y}_2(t) &= -a y_2(t) - b y_1(t) + c[y_4(t) - y_2(t)] + d[y_3(t) - y_1(t)] \\
 \dot{y}_3(t) &= y_4(t) \\
 \dot{y}_4(t) &= -c[y_4(t) - y_2(t)] - d[y_3(t) - y_1(t)] + x(t).
 \end{aligned}
 \tag{3.8}$$

The second equation of (3.8) is multiplied by  $y_1, y_2$  and the resulting equations are averaged. The fourth equation of (3.8) is multiplied by  $y_3, y_4$  and the resulting equations are averaged.

On the basis of (2.10) and (3.8), the following four equations will result.

$$\begin{aligned}
 -E\{y_2^2\} &= -b E\{y_1^2\} + c E\{y_1 y_4\} + d[E\{y_1 y_3\} - E\{y_1^2\}] \\
 0 &= -a E\{y_2^2\} + c[E\{y_4 y_2\} - E\{y_2^2\}] + d E\{y_2 y_3\} \\
 E\{y_4^2\} + E\{x y_3\} &= -c E\{y_2 y_3\} + d[E\{y_3^2\} - E\{y_1 y_3\}] \\
 E\{x y_4\} &= +c[E\{y_4^2\} - E\{y_4 y_2\}] - d E\{y_1 y_4\}
 \end{aligned}
 \tag{3.9}$$

The set of four linear algebraic equations in four unknowns given by (3.9) are easily solved to determine the parameters (a,b,c,d).

Thus, it is easily established that

$$c = \frac{\begin{vmatrix} E\{y_4^2\} + E\{xy_3\} & E\{y_3^2\} - E\{y_1y_3\} \\ E\{xy_4\} & -E\{y_1y_4\} \end{vmatrix}}{B}$$

$$d = \frac{\begin{vmatrix} -E\{y_3y_2\} & E\{y_4^2\} + E\{xy_3\} \\ E\{y_4^2\} - E\{y_4y_2\} & E\{xy_4\} \end{vmatrix}}{B}$$

where

$$B = \begin{vmatrix} -E\{y_3y_2\} & E\{y_3\} - E\{y_1y_3\} \\ E\{y_4^2\} - E\{y_4y_2\} & -E\{y_1y_4\} \end{vmatrix}$$

Similar expressions yield a,b, as well.

#### IV. Numerical Examples

In this section we present the results of parameter identification obtained by digitally simulating each of the examples above.

The systems digitally simulated are

$$a) \quad \dot{y}(t) = -y(t) + x(t)$$

$$b) \quad \begin{cases} \dot{y}_1(t) = y_2(t) \\ \dot{y}_2(t) = -4y_2(t) - 16y_1(t) + x(t) \end{cases} \quad (4.1)$$

$$c) \quad \begin{cases} \dot{y}_1(t) = y_2(t) \\ \dot{y}_2(t) = -5y_2(t) - 100y_1(t) + x(t) \end{cases}$$

$$d) \quad \begin{cases} \dot{y}_1(t) = y_2(t) \\ \dot{y}_2(t) = -3y_2(t) - 9y_1(t) + 4[y_4(t) - y_2(t)] + 16[y_3(t) - y_1(t)] \\ \dot{y}_3(t) = y_4(t) \\ \dot{y}_4(t) = -4[y_4(t) - y_2(t)] - 16[y_3(t) - y_1(t)] + x(t) \end{cases}$$

The digital simulation of the input process, the  $x(t)$ -process, is a stationary gaussian process generated by taking a moving average of the form

$$x_N = \sum_{i=0}^{K-1} c_i v_{N-i}, \quad (4.2)$$

$$N = 0, 1, 2, 3, \dots,$$

where the  $v$ 's are independent identically distributed gaussian random variables generated by the usual computer routines, and the  $c$ 's are weights chosen to obtain a specific covariance function.

For our example we chose  $K = 10$ ,

$$c_i = 0.1 \quad \text{for} \quad i = 0, 1, 2 \dots 9.$$

The moments calculated were simple arithmetic averages taken over the first 1300 output values, the second 1300 output values, and so on. The complete details of the digital simulation are given in Appendix A.

For the system,(4.1a), the first three groups of 1300 data points yield the estimates.

<u><math>E\{y^2\}</math></u>	<u><math>E\{xy\}</math></u>	<u><math>a</math></u>
5.6892	6.0682	1.0667
4.4014	4.8197	1.0950
3.3332	4.7634	1.0992

FIGURE 1.

For the system's (4.1 b,c),the first three groups of 1300 data points yielded (see following page),

	$E\{y_1^2\}$	$E\{y_1 y_2\}$	$E\{y_2^2\}$	$E\{y_1 x\}$	$E\{y_2 x\}$	$a$	$b$
System (4.1-b)	.0637	.0004	.4862	.5841	2.0500	4.2172	16.8006
	.0710	.0009	.5657	.6340	2.3313	4.1210	17.3080
	.0678	.0000	.5450	.5936	2.2500	4.1280	16.7810
System (4.1-c)	.0029	.0001	.0881	.2098	.4074	4.6190	103.72
	.0028	.0001	.0773	.2094	.3719	4.8120	103.27
	.0028	.0001	.0873	.2065	.4084	4.673	103.74

FIGURE 2

For system (4.1d), the correlation matrices and parameter estimates on the first two runs are

<u>Run I</u>	<u>y<sub>1</sub></u>	<u>y<sub>2</sub></u>	<u>y<sub>3</sub></u>	<u>y<sub>4</sub></u>
y <sub>1</sub>	.2253			
y <sub>2</sub>	.0000	.8223		
y <sub>3</sub>	.3216	.0839	.4700	
y <sub>4</sub>	-.0837	1.1044	.0004	1.6038
x	.1418	1.8412	.5172	3.5491
Parameter Estimates	a=3.1790	b=9.194	c=4.3044	d=16.7258

<u>Run II</u>				
y <sub>1</sub>	.2465			
y <sub>2</sub>	-.0004	.9255		
y <sub>3</sub>	.3505	.0924	.5105	
y <sub>4</sub>	-.0929	1.2505	.0004	1.8117
x	.1000	2.1328	.4837	3.9482
Parameter Estimates	a=3.1708	b=9.2560	c=4.2525	d=16.8094

FIGURE 3



## V. Comments and Conclusions

It is immediately obvious that the estimates obtained in the examples above are quite practical being less than 10%, and in most cases less than 5%, in error. The most significant feature of the estimates above is that their bias is almost always positive. That is, they do not fluctuate about the true value, but in fact they are almost all greater than the true value. We believe that this bias is a function of the nature of the noise input into the system. It can be demonstrated that if the noise input to the system approximates white noise into the system then the bias will increase. Hence, the noise source to the system should be smoothly filtered.

Exactly how the noise source effects the parameter estimates, remains to be studied and understood. It is our belief at this time, however, that a real system should be subjected to noise obtained from various filters to determine the robustness of the resulting system parameter estimates.

The stationarity assumption used, Equation (2.8), appears to be quite realistic in the simulated systems. Upon checking Figures 1, 2, 3, we see that the random functions and their derivatives possess correlation values that are orders of magnitude less than the other cross-correlations.

At this time we can only reiterate our sincere belief that this technique can be developed into one of significant engineering value both for linear and non-linear systems.

APPENDIX A

This section describes briefly the computer program used to simulate a system of five (or less) first order differential equations and to compute the second order moments to be used for calculating the parameters of the system as described in Section III.

The method of Runge-Kutta integration is used in Subroutine RK3 to simulate a system of first order differential equations which are supplied by Function Subroutines FN1, FN2, FN3, FN4, and FN5. The external excitation to the system is a filtered white Gaussian noise which is generated by Subroutines GENR, GAUSS, and RANDU. The filtering process used in the Subroutine GENR is a weighted sum of NF number of independent noise samples generated by Subroutines GAUSS and RANDU. The second order moments are estimated in Subroutine MOMENT, the method used there is to calculate the sample moments of N samples, that is, sample moment  $m_{jk} = \frac{1}{N} \sum_{i=1}^N Y_i(j) Y_i(k)$ .

Autocorrelation of the variables up to 9 lags are calculated in Subroutine AUTCOR in order to check the smoothness of the noise input as compared to system. As mentioned in Section II, the noise must have smooth correlation function in order for the method to be valid.

Different systems can be simulated by using different Function Subroutines FN1, FN2, FN3, FN4 and FN5. Different choices of the number of samples, the input noise level, the filter constants and the sampling interval are controlled by 7 input cards. The description and the formats of the 7 input cards are as follows.

	Col. No.	Format	Description
1st Card	1	I1	0 if the simulated sample points are not to be printed. 1 if the simulated sample points are to be printed.
	2 - 3	I2	Number of runs desired.
	4	I1	0 if each run starts from zero initial point. 1 if success runs are desired.
2nd Card	1 - 10	I10	Any odd integer up to 9 digits for the first entry to Subroutine GAUSS.
	11 - 20	F10.1	Standard deviation of the noise.
	21 - 30	F10.1	Mean value of the noise.
3rd Card	1 - 2	I2	Number of filter coefficients.
4th Card	1 - 80	16I5.1	Filter coefficients, as many cards as needed should be used.
5th Card	1 - 10	F10.1	Sample interval for integration.
6th Card	1 - 2	I2	Number of intervals between values of samples stored for calculation. 1 is used for the results in Section IV.
7th Card	1 - 4	I4	Number of sample points, N, desired for each run, $N \leq 1300$ . If larger number is desired, the dimension of y in the Main Program has to be changed accordingly. Note that the average of the moments estimated from successive K runs is equivalent to the moments estimated from KxN number of samples.

The output consists of:

- A) The mean value of each variable.
- B) The second order moment matrix.
- C) The autocorrelation up to 9 lags for each variable.
- D) Sample points simulated if desired.

The prime reason for the simplicity of the program included in this appendix is that it was used mainly to check the moment estimates and establish the overall credibility and practicality of the technique for identifying simple simulated systems.

This program, therefore, must be considered as preliminary in that we have not allowed for an arbitrary number of degrees of freedom and we have not included the final arithmetic calculations of the estimated system parameters.

The studies included within this report are the initial investigations of the identification technique. Future investigations of this technique will include the composition of a comprehensive program that will accommodate linear systems of n-degrees of freedom and will carry the calculations to the final arithmetic stages providing a print out of the parameter estimates for prescribed classes of systems.

```

DIMENSION Y(6,1300),X(1300),YI(6),FC(20),FMON(6),SMDN(6),XMDN(21)
1 EXTERNAL FN1, FN2, FN3, FN4, FN5, FN6
READ(5,500) IO, NR, IR
READ(5,501) IX, S, AM
READ(5,502) NFC, (FC(I), I=1, NFC)
READ(5,503) STEP, KS, NV
KR=NR
DO 15 I=1, NFC
CALL GAUSS(IX, S, AM, V)
15 FI=0
DO 10 I=1, 6
YI(I)=0
17 DO 20 J=1, NV
CALL GENR(F, FC, NFC, FX, IX, S, AM)
20 X(J)=F
CALL RK3(FN1, FN2, FN3, FN4, FN5, FN6, STEP, TI, YI, KS, NV, Y, X)
25 YI(J)=Y(J, NV)
TI=TI+NV*KS*STEP
DO 30 J=1, NV
Y(6, J)=X(J)
CALL MOMENT(Y, 6, NV, 1, FMON, SMDN, XMDN)
WRITE(6,604)
WRITE(6,602) (FMON(J), J=1, 6)
DO 40 J=1, 6
CALL LOC(J, 1, J1, 6, 6, 1)
CALL LOC(J, J, J1, 6, 6, 1)
40 WRITE(6,601) (XMDN(K), K=J1, JJ)
DO 45 I=1, 6
CALL AUTCOR(Y, I, 6, NV, 10, R)
45 WRITE(6,605) (R(J), J=1, 10)
IF(IO) 50, 55, 50
50 WRITE(6,601) ((Y(J, I), J=1, 6), I=1, NV)
55 KR=KR-1
IF(KR) 100, 100, 60
IF(IR) 17, 5, 17
FORMAT(11, 12, 11)
501 FORMAT(110, 2F10.1)
502 FORMAT(12/16F5.1)
503 FORMAT(F10.1/12/14)
501 FORMAT(F10.3)
601 FORMAT(1H0, 6E16.8)
602 FORMAT(1H1, 7X, Y1, 16X, Y2, 16X, Y3, 16X, Y4, 16X, Y5, 16X, X)
604 FORMAT(1H0, 10E11.3)
605 STOP
100 END

SUBROUTINE AUTCOR(X, NOVAR, NV, NO, KS, R)
DIMENSION X(1), R(1)
DO 10 J=1, KS
R(J)=0.0
NOKS=NO-KS+1
DO 50 I=1, NOKS
IJ=(I-1)*NV+NOVAR
DO 50 K=1, KS
IK=(I+K-2)*NV+NOVAR
R(K)=R(K)+X(IJ)*X(IK)
50 DO 60 K=1, KS
R(K)=R(K)/FLOAT(NOKS)
60 RETURN
END
FUNCTION FN1(T, Y1, Y2, Y3, Y4, Y5, Y6, X)
FN1=-Y1+X
RETURN
END
FUNCTION FN2(T, Y1, Y2, Y3, Y4, Y5, Y6, X)
FN2=Y3
RETURN
END
FUNCTION FN3(T, Y1, Y2, Y3, Y4, Y5, Y6, X)
FN3=-4.0*Y3-16.0*Y2+X
RETURN
END
FUNCTION FN4(T, Y1, Y2, Y3, Y4, Y5, Y6, X)
FN4=Y5
RETURN
END
FUNCTION FN5(T, Y1, Y2, Y3, Y4, Y5, Y6, X)
FN5=-5.0*Y5-100.*Y4+X
RETURN
END
FUNCTION FN6(T, Y1, Y2, Y3, Y4, Y5, Y6, X)
FN6=0.

```

END

001 RK3  
002 RK3  
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.....  
SUBROUTINE RK3  
PURPOSE  
INTEGRATES A SYSTEM OF SIX FIRST ORDER DIFFERENTIAL  
EQUATIONS AND PRODUCES A TABLE OF INTEGRATED VALUES  
USAGE  
CALL RK3(FN1,FN2,FN3,FN4,FN5,FN6,H,XI,YI,K,N,VAL,F)  
DESCRIPTION OF PARAMETERS  
FN1-FN6 -SIX USER-SUPPLIED FUNCTION SUBPROGRAMS GIVING  
DY/DX AS A FUNCTION OF {X,Y1,Y2,Y3,Y4,Y5,Y6}  
H -STEP SIZE  
XI -INITIAL VALUE OF X SIX CONTAINING THE INITIAL VALUES  
YI -VECTOR OF LENGTH SIX CONTAINING THE INITIAL VALUES  
FOR Y1,Y2,Y3,Y4,Y5,Y6  
K -THE DESIRED NUMBER OF STEPS OF SIZE H BETWEEN  
VALUES OF THE INTEGRALS STORED IN VAL  
N -THE NUMBER OF VALUES TO BE STORED IN VAL. THE  
FINAL VALUE OF X WILL BE XI+(N\*K\*H).  
VAL -RESULTANT SIX BY N MATRIX CONTAINING THE INTEGRATED  
VALUES OF THE SIX EQUATIONS  
F - INPUT TO THE SYSTEM, ARRAY OF N

REMARKS  
NONE  
SUBROUTINES AND FUNCTION SUBPROGRAMS REQUIRED  
FN1,FN2,FN3,FN4,FN5,FN6 AS NOTED ABOVE  
CALLING PROGRAM MUST HAVE FORTRAN EXTERNAL STATEMENT  
CONTAINING NAMES OF FUNCTION SUBPROGRAMS LISTED IN CALL TO  
RK3

METHOD  
EXTENSION OF FOURTH ORDER RUNGE-KUTTA INTEGRATION ON A  
RECURSIVE BASIS AS SHOWN IN F.B. HILDEBRAND, 'INTRODUCTION  
TO NUMERICAL ANALYSIS', MCGRAW-HILL, NEW YORK, 1956

.....  
SUBROUTINE RK3(FN1,FN2,FN3,FN4,FN5,FN6,H,XI,YI,K,N,VAL,F)  
DIMENSION YI(6),Y(6),S1(6),S2(6),S3(6),S4(6),VAL(1),F(1)

IF A DOUBLE PRECISION VERSION OF THIS ROUTINE IS DESIRED, THE  
C IN COLUMN 1 SHOULD BE REMOVED FROM THE DOUBLE PRECISION  
STATEMENT WHICH FOLLOWS.

1 DOUBLE PRECISION H,XI,YI,VAL,Y,S1,S2,S3,S4,H2,X,T,XA,A1,A2,A3,  
A4,A5,A6,FN1,FN2,FN3,FN4,FN5,FN6

THE C MUST ALSO BE REMOVED FROM DOUBLE PRECISION STATEMENTS  
APPEARING IN OTHER ROUTINES USED IN CONJUNCTION WITH THIS  
ROUTINE.

USER FUNCTION SUBPROGRAMS FN1-FN6 MUST BE IN DOUBLE PRECISION

.....  
H2=H/2.  
X=XI  
DO 10 I=1,6  
Y(I)=YI(I)  
DO 70 LL=1,N  
L=(LL-1)\*6  
DO 69 JJ=1,K

COMPUTE K SUB 0

DO 30 I=1,6  
GO TO (21,22,23,24,25,26),I  
21 T=FN1(X,Y(1),Y(2),Y(3),Y(4),Y(5),Y(6),F(LL))  
22 T=FN2(X,Y(1),Y(2),Y(3),Y(4),Y(5),Y(6),F(LL))  
23 T=FN3(X,Y(1),Y(2),Y(3),Y(4),Y(5),Y(6),F(LL))  
24 T=FN4(X,Y(1),Y(2),Y(3),Y(4),Y(5),Y(6),F(LL))  
25 T=FN5(X,Y(1),Y(2),Y(3),Y(4),Y(5),Y(6),F(LL))  
26 T=FN6(X,Y(1),Y(2),Y(3),Y(4),Y(5),Y(6),F(LL))

026 RK3  
027 RK3  
028 RK3  
029 RK3  
030 RK3  
031 RK3  
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033 RK3  
034 RK3  
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081 RK3  
082 RK3  
083 RK3  
084 RK3  
085 RK3



```

10 FX(K+1)=FX(K)
CALL GAUSS(IX,S,AM,V)
FX(1)=V
F=0
DO 20 I=1,NEC
F=F+FC(I)+FX(I)
RETURN
END
20

```

```

.....
SUBROUTINE GAUSS
PURPOSE
  COMPUTES A NORMALLY DISTRIBUTED RANDOM NUMBER WITH A GIVEN
  MEAN AND STANDARD DEVIATION
USAGE
  CALL GAUSS(IX,S,AM,V)
DESCRIPTION OF PARAMETERS
  IX - IX MUST CONTAIN AN ODD INTEGER NUMBER WITH NINE OR
      LESS DIGITS ON THE FIRST ENTRY TO GAUSS. THEREAFTER
      IT WILL CONTAIN A UNIFORMLY DISTRIBUTED INTEGER RANDOM
      NUMBER TO THE SUBROUTINE FOR USE ON THE NEXT
      ENTRY TO THE SUBROUTINE.
  S - THE DESIRED STANDARD DEVIATION OF THE NORMAL
      DISTRIBUTION.
  AM - THE DESIRED MEAN OF THE NORMAL DISTRIBUTION
  V - THE VALUE OF THE COMPUTED NORMAL RANDOM VARIABLE
REMARKS
  THIS SUBROUTINE USES RANDU WHICH IS MACHINE SPECIFIC
SUBROUTINES AND FUNCTION SUBPROGRAMS REQUIRED
  RANDU
METHOD
  USES 12 UNIFORM RANDOM NUMBERS TO COMPUTE NORMAL RANDOM
  NUMBERS BY CENTRAL LIMIT THEOREM. THE RESULT IS THEN
  ADJUSTED TO MATCH THE GIVEN MEAN AND STANDARD DEVIATION.
  THE UNIFORM RANDOM NUMBERS COMPUTED WITHIN THE SUBROUTINE
  ARE FOUND BY THE POWER RESIDUE METHOD.
.....
SUBROUTINE GAUSS(IX,S,AM,V)
A=0.0
DO 50 I=1,12
CALL RANDU(IX,IY,Y)
IX=IY
A=A&Y
50 V=(A-6.0)*S&AM
RETURN
END

```

```

.....
SUBROUTINE RANDU
PURPOSE
  COMPUTES UNIFORMLY DISTRIBUTED RANDOM REAL NUMBERS BETWEEN
  0 AND 1.0 AND RANDOM INTEGERS BETWEEN ZERO AND
  2**31. EACH ENTRY USES AS INPUT AN INTEGER RANDOM NUMBER
  AND PRODUCES A NEW INTEGER AND REAL RANDOM NUMBER.
USAGE
  CALL RANDU(IX,IY,YFL)
DESCRIPTION OF PARAMETERS
  IX - FOR THE FIRST ENTRY THIS MUST CONTAIN ANY ODD INTEGER
      NUMBER WITH NINE OR LESS DIGITS. AFTER THE FIRST ENTRY,
      IX SHOULD BE THE PREVIOUS VALUE OF IY COMPUTED BY THIS
      SUBROUTINE.
  IY - A RESULTANT INTEGER RANDOM NUMBER REQUIRED FOR THE NEXT
      ENTRY TO THIS SUBROUTINE. THE RANGE OF THIS NUMBER IS
      BETWEEN ZERO AND 2**31
  YFL - THE RESULTANT UNIFORMLY DISTRIBUTED, FLOATING POINT,
      RANDOM NUMBER IN THE RANGE 0 TO 1.0
REMARKS
  THIS SUBROUTINE IS SPECIFIC TO SYSTEM/360
  THIS SUBROUTINE WILL PRODUCE 2**29 TERMS
  BEFORE REPEATING
SUBROUTINES AND FUNCTION SUBPROGRAMS REQUIRED
  RANDU

```



```

METHOD
POWER RESIDUE METHOD DISCUSSED IN IBM MANUAL C20-8011,
RANDOM NUMBER GENERATION AND TESTING

```

```

RANDU0034
RANDU0035
RANDU0036
RANDU0037
RANDU0038
RANDU0039
RANDU0040
RANDU0041
RANDU0042
RANDU0043
RANDU0044
RANDU0045
RANDU0046
RANDU0047

```

```

SUBROUTINE RANDU(IX,IY,YFL)

```

```

IY=IX*65539
IF(IY)5,6,6
5 IY=IY&2147483647&1
6 YFL=YFL*.4656613E-9
RETURN
END

```

```

SUBROUTINE MOMENT(A,NV,NO,IXM,FMON,SMON,XMON)

```

```

A- DATA MATRIX,NV BY NO
NV- NO OF VARIABLES
NO- NO OF OBSERVATIONS
IXM- INDEX FOR CROSS MOMENTS
FMON- FIRST MOMENTS ARRAY OF NV
SMON- SECOND MOMENTS ARRAY OF NV
XMON- CROSS MOMENTS ARRAY OF (NV*(NV+1))/2
DIMENSION A(1),FMON(1),SMON(1),XMON(1)
INITIALIZATION

```

```

10 DO 10 J=1,NV
FMON(J)=0
SMON(J)=0
DO 20 J=1,NV
DO 20 L=1,J
CALL LOC(J,L,K,NV,NV,1)
20 XMON(K)=0

```

```

CALCULATE FIRST MOMENTS

```

```

30 DO 30 I=1,NO
DO 30 J=1,NV
IJ=(I-1)*NV+J
FMON(J)=FMON(J)+A(IJ)
40 DO 40 J=1,NV
FMON(J)=FMON(J)/NO

```

```

CALCULATE SECOND MOMENTS

```

```

45 IF(IXM)60,45,60
DO 50 I=1,NO
DO 50 J=1,NV
IJ=(I-1)*NV+J
SMON(J)=SMON(J)+A(IJ)*A(IJ)
50 DO 55 J=1,NV
SMON(J)=SMON(J)/NO
55 GO TO 100

```

```

CALCULATE CROSS MOMENTS

```

```

60 DO 70 I=1,NO
DO 70 J=1,NV
DO 70 L=1,J
CALL LOC(J,L,K,NV,NV,1)
IJ=(I-1)*NV+J
IL=(I-1)*NV+L
XMON(K)=A(IJ)*A(IL)+XMON(K)
70 KN=(NV*(NV+1))/2
DO 75 K=1,KN
75 XMON(K)=XMON(K)/NO
100 RETURN
END

```

```

001 SUBROUTINE LOC
002
003
004
005 COMPUTE A VECTOR SUBSCRIPT FOR AN ELEMENT IN A MATRIX OF
006 SPECIFIED STORAGE MODE
007
008 USAGE
009 CALL LOC (I,J,IR,N,M,MS)
010
011 DESCRIPTION OF PARAMETERS
012 I - ROW NUMBER OF ELEMENT
013 J - COLUMN NUMBER OF ELEMENT
014 IR - RESULTANT VECTOR SUBSCRIPT
015 N - NUMBER OF ROWS IN MATRIX
016 M - NUMBER OF COLUMNS IN MATRIX
017 MS - ONE DIGIT NUMBER FOR STORAGE MODE OF MATRIX
018 0 - GENERAL
019 1 - SYMMETRIC
020 2 - DIAGONAL
021
022 REMARKS
023 NONE
024
025 SUBROUTINES AND FUNCTION SUBPROGRAMS REQUIRED
026 NONE
027
028 METHOD
029 MS=0
030 MS=1
031 MS=2
032
033 SUBSCRIPT IS COMPUTED FOR A MATRIX WITH N*M ELEMENTS
034 IN STORAGE (GENERAL MATRIX)
035 STORAGE IS COMPUTED FOR A SYMMETRIC MATRIX WITH N*(N+1)/2 IN
036 ELEMENT (UPPER TRIANGLE OF SYMMETRIC MATRIX). IF
037 CORRESPONDING ELEMENT IN UPPER TRIANGLE, SUBSCRIPT IS
038 SUBSCRIPT IS COMPUTED FOR A MATRIX WITH N ELEMENTS
039 IN STORAGE (DIAGONAL ELEMENTS OF DIAGONAL MATRIX).
040 IF ELEMENT IS NOT ON DIAGONAL (AND THEREFORE NOT IN
041 STORAGE), IR IS SET TO ZERO.
042
043 .....
044 SUBROUTINE LOC(I,J,IR,N,M,MS)
045
046
047
048
049
050
051
052
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056
057
058
059
060
061

```

```

SUBROUTINE LOC
PURPOSE
COMPUTE A VECTOR SUBSCRIPT FOR AN ELEMENT IN A MATRIX OF
SPECIFIED STORAGE MODE
USAGE
CALL LOC (I,J,IR,N,M,MS)
DESCRIPTION OF PARAMETERS
I - ROW NUMBER OF ELEMENT
J - COLUMN NUMBER OF ELEMENT
IR - RESULTANT VECTOR SUBSCRIPT
N - NUMBER OF ROWS IN MATRIX
M - NUMBER OF COLUMNS IN MATRIX
MS - ONE DIGIT NUMBER FOR STORAGE MODE OF MATRIX
0 - GENERAL
1 - SYMMETRIC
2 - DIAGONAL
REMARKS
NONE
SUBROUTINES AND FUNCTION SUBPROGRAMS REQUIRED
NONE
METHOD
MS=0
MS=1
MS=2
SUBSCRIPT IS COMPUTED FOR A MATRIX WITH N*M ELEMENTS
IN STORAGE (GENERAL MATRIX)
STORAGE IS COMPUTED FOR A SYMMETRIC MATRIX WITH N*(N+1)/2 IN
ELEMENT (UPPER TRIANGLE OF SYMMETRIC MATRIX). IF
CORRESPONDING ELEMENT IN UPPER TRIANGLE, SUBSCRIPT IS
SUBSCRIPT IS COMPUTED FOR A MATRIX WITH N ELEMENTS
IN STORAGE (DIAGONAL ELEMENTS OF DIAGONAL MATRIX).
IF ELEMENT IS NOT ON DIAGONAL (AND THEREFORE NOT IN
STORAGE), IR IS SET TO ZERO.
.....
SUBROUTINE LOC(I,J,IR,N,M,MS)

```

```

10 IX=I
11 JX=J
12 IF(MS=1) 10,20,30
13 IF(MS=2) 10,20,30
14 GO TO 36
15 IF(IX=JX) 22,24,24
16 IF(IX=JX) 22,24,24
17 GO TO 36
18 IF(IX=JX) 24,24,36
19 GO TO 36
20 IF(IX=JX) 24,24,36
21 IF(IX=JX) 24,24,36
22 IF(IX=JX) 24,24,36
23 IF(IX=JX) 24,24,36
24 IF(IX=JX) 24,24,36
25 IF(IX=JX) 24,24,36
26 IF(IX=JX) 24,24,36
27 IF(IX=JX) 24,24,36
28 IF(IX=JX) 24,24,36
29 IF(IX=JX) 24,24,36
30 IF(IX=JX) 24,24,36
31 IF(IX=JX) 24,24,36
32 IF(IX=JX) 24,24,36
33 IF(IX=JX) 24,24,36
34 IF(IX=JX) 24,24,36
35 IF(IX=JX) 24,24,36
36 IF(IX=JX) 24,24,36
37 IF(IX=JX) 24,24,36
38 IF(IX=JX) 24,24,36
39 IF(IX=JX) 24,24,36
40 IF(IX=JX) 24,24,36
41 IF(IX=JX) 24,24,36
42 IF(IX=JX) 24,24,36
43 IF(IX=JX) 24,24,36
44 IF(IX=JX) 24,24,36
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51 IF(IX=JX) 24,24,36
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54 IF(IX=JX) 24,24,36
55 IF(IX=JX) 24,24,36
56 IF(IX=JX) 24,24,36
57 IF(IX=JX) 24,24,36
58 IF(IX=JX) 24,24,36
59 IF(IX=JX) 24,24,36
60 IF(IX=JX) 24,24,36
61 IF(IX=JX) 24,24,36
END

```