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## A USER'S MANUAL FOR THE AUTOMATIC SYNTHESIS PROGRAM (PROGRAM C)

by R. E. Kalman and T. S. Englar

Prepared by
MARTIN-MARIETTA CORPORATION
Baltimore, Md.
for Ames Research Center

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# A USER'S MANUAL FOR THE AUTOMATIC SYNTHESIS PROGRAM 

## (PROGRAM C)

By R. E. Kalman and T. S. Englar

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## PREFACE

ASP, The Automatic Synthesis Program, is a digital-computer program. It is written in FAP and compatible with most IBM 7090-7094 installations.

ASP is an executive program enabling the user to sequence arbitrarily some thirty subroutines. ASP is intended for a person who has some background in modern system theory, especially linear algebra. Such a user can obtain, with the help of ASP, easily and efficiently the numerical solution of most (perhaps all) problems in system theory which involve linear mathematics. Time-varying linear systems are included; in fact they will constitute the most important practical applications. Among others, the following subroutines are included: input-output calculations, the operations of matrix algebra, computation of the exponential of a matrix, the solution of both discrete and continuous-time riccati equations.

The subroutines in ASP are sufficient to solve the most general problem of extremization of quadratic functionals of the state of a linear dynamical system. This includes, in particular, the synthesis of the Kalmanfilter gains and of the optimal feedback gains for minimization of e quadratic performance index, possibly with hard terminal constraints. Use of the program is by no means restricted to these two problems, however, as is evident from the table of contents.

In short, ASP is a very flexible program which can be conveniently and quickly programmed to give the solution to a variety of problems. Input consists of a description of the equations to be solved as well as numbers specifying the system matrices. The programming has been made as "macroscopic" as possible; many special features have been built into the subroutines for the convenience of the user and to lessen numerical difficulties. We hope that the availability of a convenient and reliable program such as this will contribute to greater awareness of the powers of modern system theory, particularly in the areas of control, statistical filtering, and optimization.

After this very terse description, let us outline what ASP is not. It is not an unusually accurate program nor is it a very fast program. Its limitations arise mainly from the fact that integration is done by the matrix exponential (hence all $n^{2}$ couplings are considered whether or not they exist) and because the matrix exponential computation involves scaling problems that do not arise in ordinary numerical integration schemes. We try to compensate for this by automatic scaling. A major cause of time wastage is the compilation of the instruction data every time the deck goes on the machine. That is, the ASP executive routine is not recompiled, but the list of $A S P$ instructions to the executive routine are translated to a system of calling sequences for the ASP subroutines. A binary program could be punched easily from the machine contents, but we have never done enough repetitive work to justify it.

Given these limitations, what uses do we see for ASP?
One of the chief benefits will be educational. This manual contains text-book examples and some more involved practical problems. These illustrate not only the use of ASP but also the steps required to solve these various problems. They provide concrete cases, with real numbers, for the novice in optimal system theory.

ASP is expected to be very useful as an analytic design tool where extreme precision is not required. In addition to the problems discussed in this report, the program has been used satisfactorily on several reentry problems, lunar landing problems, airplane control, and control of large flexible boosters.

Some remarks may be useful here on optimal control as a practical tool. Many engineers have questioned the relevancy of linear optimal control to practical problems because the performance index has no simple relation to the criteria which must be imposed (bounded state variables or bounded control variables, for instance). There are two important considerations here:
(i) It has been our experience that it is usually easy to alter the performance index by experimentation to achieve the desired shape of the trajectory. That is, after a few trials we can usually find an optimal (in the modern sense) control which will appear satisfactory also to the engineer who works with older style criteria.

- (ii) The computation of exact nonlinear control laws is at present prohibitively expensive. It is far more sensible to iterate a general-purpose linear optimization program by trial and error than to write a separate, exact, nonlinear optimization program for each case. This will remain true even when and if nonlinear optimization methods become more generally available. (Note that today (1965) only a Pew special nonlinear optimization procedures have been studied from the point of view of numerical analysis.)

As for the availability of the ASP program, it can be nbtained on request from the Theoretical Guidance and Control Branch, Ames Research Center, NASA, Moffett Field, California. Further details regarding tapes, listings, and check cases can be arranged.

We are indebted to many persons for their efforts, but we particularly wish to thank Mr. Elwood. C. Stewart of Ames Research Center for his interest and assistance and Miss Elsie Cerutti of RIAS for her excellent programming work.

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## INIRODUCTION

This report may be divided ịnto three parts: Chapter I, Chapters II-VIII, and Chapters IX-XVIII.

Chapter I describes the basic mechanics of ASP, its input format, vocabulary, error returns, and idiosyncrasies. For the person who understands his problem, knows what mathematical steps are required in its solution, only Chapter I is needed. In the dictionary, the subroutines are described by specifying the output and how each of the arguments is used. Then referring to the coding sheets at the end of Chapter I, we can determine in which columns the argument names appear. For instance, in the dictionary description of EAT, a matrix PH is output. When using the EAT routine we may call this output by any other two-character symbol, but that symbol must appear in the columns where PH appears in the coding sheets.

Chapters II through VIII describe in detail the more important subroutines available. Generally some theoretical background will be given deriving from basic principles the application of the particular routine to linear systems theory. In addition, the method of computation will be explained with remarks about numerical problems and several check problems given. These chapters will be useful not so much for helping in the actual use of the program but as somewhat more than an introduction to the theory, particularly as it is used in computation. For instance, Chapter VIII provides an ad hoc derivation of the optimal control law for a discretized system with quadratic performance index.

Chapters IX through XVIII are examples in some depth of computation and analysis. The selection of problems solved is far from comprehensive, yet the basic problems of using the subroutines are well covered. The specific ASP programs used appear in the figures for each chapter and when read, should provide a working knowledge of the ASP language. It is our hope that these problem chapters will be an introduction to ASP and a tutorial in linear systems theory from a computational point of view.

## CHAPTER I

## ASP - THE AUTOMATIC SYNTHESIS PROGRAM

1. History. The nature of our work is such that a basic set of matrix subroutines which can be sequenced in a variety of ways would solve many problems. In the original formulation of a program, several approaches were considered. Since there were available at the time many of the necessary subroutines, a programmer could write new connective code very easily for each separate problem in the 709-7094 SOS system. This method has the advantage of immediate availability with very little program verification since the component programs were already checked out. With increased outside interest in the program, it was discovered that many of the IBM compuier installations (e.g., Wright Field) will not accept SOS programs. Consideration was also being given to writing a Fortran program with input which would determine the sub-programs to be utilized. A single program with code accepting decision points to determine flow would be easy to write but the data becomes extremely unwieldy when the number of permutations of routines is large; an even greater difficulty lay in anticipating every type of problem which would be solved. 'Ve decided to adopt a scheme which may be regarded roughly as a matrix formula translator enabling us to write macro-instructions directly in terms of the needed matrix operations. Since so much of the programming had already been done in the SOS system, we decided to keep the SOS infut-output unit and assemble it as the ASP I-D package. Again we ran into difficulty with another computer installation which did not have tape units attached directly to the 7094. Therefore ASP has evolved into a FAP coded-formula translator with Fortran II inputoutput, which may be loaded with the main ASP deck or called off the system tape.
2. I- $\varnothing$ Requirement. Before going into more detail about the main program, several features concerning input-output should be pointed out. Contact is made with the I- $\varnothing$ routines through the following entry points: (TSB), (STB), (TISH), (STH), (SPH), (BST), (RSW), (RIR), (WIR), (FIL), (RTN) and EXIT. It appears possible that with a knowledge of the function of each routine and with more detail on calling sequences and format, one could run this deck at any IBM installation with a 32 K IBM 7090-7094 and any tape units required by the I- $\varnothing$. The format specifications are standard Fortran II as described in Form C28-6066-5. Use is made of the A, H, E, F, and I mode, multiline blocks of print of 120 characters specified by a slash, and column skip specified by an $X$. The logical tape number for input is 5, for output 6. The only nonstandard feature is that the format specification is stored in increasing storage locations. The code which indicates this type of format statement is a 1 in the decrement of the calling sequence.
3. Description of ASP. ASP is composed of two parts, an executive routine, whose function is to read, list, and store alphameric data and a group of independent subroutines which are classified by use as mathematical - those having to do with numerical analysis; data handling - those involved in making storage available, moving information in core or between core and tape; output - those which write alphameric or decimal information; input those which bring in decimal information; and logical - those which provide a means of altering the progress of the program.

The executive program described diagramatically in Figure 4 expects as a first card a date card of which there is one and only one in each data deck. Then it begins reading until it finds a card with the operation BEGIN in Columns $7-11$, which signals the executive program that alphameric information follows. This alphameric information is separated into 12, 6 character words, the first of which is a label or heading name, the second word specifies the operation and words 3 through 12 contain the operands. Operands may be referred to by anytwo alphameric characters; followed by
either a comma or blank character; their position following the name of the operation specifies the role each plays in the operation. Resultant matrix storage locations are created in the order in which they appear from left to right. For instance when
PSEUO A, $\quad$ AI, RK,
ADD
is first executed, if conformability requirements are satisfied and $A I, R K$, and $C$ have not been previously defined, they will appear in core in that order. If one of the matrices $A I, R K$ and $C$ have been previously defined and if the size of the new matrix is the same as the size of the core matrix then the resultants will be stored in the defined region.

The alphameric information has a fixed field format. If a matrix identifier is -A (- represents a blank) then any reference to $A$ must be written -A. A- will be defined as a different matrix. The same rule describes the label. The format then can be described in a very general way as follows:

| Columns |  |
| :---: | :--- |
| $1-6$ | labels (may be blank) |
| $7-11$ | operation |
| $13-14$ | operand 1 or blank |
| 15 | blank or comma |
| $16-17$ | operand 2 or blank |
| 18 | blank or comma |
| . | etc. |

Specfically every instruction has an operation in Column 7-11. Whether operand 1 is in Column 13-14 depends on the instruction. See Figs. 1-3 for the specific location of the matrix identifiers.

In addition to the fixed format restriction there is a limit of 120 for the number of matrix identifiers. If this limit is exceeded error statement number 5 is printed.

Certainly every operation does not require 10 words for the operands. Therefore a test is made to eliminate anything beyond the first completely blank word. This implies certain restrictions on the use of double-blank as an identifier. Such a use is not recommended. This alphameric data from the second word to the first blank word is stored downward unchanged in a reserved block behind the program. Two words precede the stored data, a machine instruction which acts as a transfer to the 30 subprograms and a control word with the number of operands for this instrusesion. This is done for every alphameric data cand except the EEGII. Observe then, that the data is stored to look like a series of call statements with their respective arguments, thereby acting as a stored program. One is able to change the direct flow through the stored program by use of the IF instruction which in turn uses the label that was in Columns $1-6$ of an alphameric data card. If word 1 is not blank it is stored in a vector (dimension 40) of labels along with the address of the core location which contains the transfer for that operation.

The END instruction signals the end of the instruction data; and a transfer is made to the first stored data point. Since the input tape is now positioned after the END record any LOAD given in the stored program will cause the input tape to be read for decimal information from that point. To summarize, the data deck is in the following order: 1) Date, 2) BEGIN, 3) any of the 30 numeric, input or output statements, 4) END, 5) decimal data for the LOAD instructions or instruction in the order that the LOAD will be executed. For information about the decimal data see LOAD in the dictionary which follows.

Every subprogram has two entry points. The first entry point uses the symbolic material, which is stored following the transfer instruction, to determine the location of the first element of the operands. A number is stored, in place of the alphameric symbol, which defines the position of
that matrix in the ordered matrix storage area. This part of the subprogram also defines a matrix region for the resultant and examines the operations for conformability. If the region has already been defined, the size of the defined region is compared with the size of the resultant matrix. If the sizes are not equal error statement number 8 is printed and execution is deleted. An error statement is also written if the matrices are not conformable. Finally "the transfer to entry point 1 " instruction is replaced by a "transfer to entry point 2". The second part of the subprogram performs the numerical calculation. It is this part of the subprogram which is repeated if the operation is in the range of an executed IF instruction. Care must be exercised in storing results in previously defined areas. The row and column dimensions of the one may not be the same as the row and column dimensions of the other; thus allowing undetected nonconformable operations in any of the repeated operations since the confomability check is made in the first part of the subprogram.

At present one can communicate with ASP by the following vocabulary

## Mathematical

1. EAT
2. ETPHI
3. TRNSI
4. RICAT
5. PSEUO
6. SAMPL
7. INVRS
8. DECOM
9. AD D
10. S U B T
11. M U L T
12. TRANP
13. N O R M
14. TRACE
15. P I Z E K
16. JUXTC
17. J U X T R

## Data Handling

Output
18. S AVE
24. PRINT
19. EQUAT
25. RINT
20. BLOT
21. REW
22. WEF
23. $B S R$
26. WRITE
27. P U N CH

Input
28. LOAD
29. $B R I N G$

## Logical

30. I F
31. BEGIN
32. END

## DICTIONARY

1. EAT. This program computes $P H=e^{T \cdot F}$ and $B=\int^{T} e^{t F} d t ; \quad P H$ and $B$ will be printed if PRINT is punched in columns 85 to 29 . $F$ can be $30 \times 30$.
2. ETPHI. This program computes $\mathrm{PH}=\mathrm{e}^{\mathrm{T} \cdot \mathrm{F}}$; PH will be printed if PRINT is punched in columns 25 to $29, F$ can be $30 \times 30$.

EIPHI has the option that if a matrix symbol is contained in column 22 to 24 the value of $t$ which will be used will not be the input $t$ but a value $\frac{t}{2^{k}} \leqq \frac{10}{\|F\|}$. The value $\frac{t}{2^{k}}$ will be stored in core, identified by the symbor in $22,23$.
-3. TRNS I. This program computes $y(t)$ and $u(t)$ according to the difference equations

$$
\begin{gathered}
x\left(t+\tau_{1}\right)=\operatorname{Px}(t)+G u(t) \\
u(t)=J R-K x\left(t_{0}+i \tau_{2}\right), i \tau_{2} \leqq t-t_{0}<(i+1) \tau_{2}
\end{gathered}
$$

where

$$
y(t)=H x(t)
$$

where $x\left(t_{0}\right)=X$ and $i$ is a positive integer.
Rather than describe the output in detail we have included a sample T R N S I output as Fig. 19.

Print of $t$, the first two components of $R, Y$, and the first three components of $u$ is done at intervals of $\tau_{1}$. The control computation is done at intervals of $\tau_{2}$ with $\tau_{2}$ some positive integral multiple of $\tau_{1}$ and these steps are marked by an asterisk. Because there is room for only 7 components of $y$, the $H$ matrix should have less than 8 rows.

The problem terminates when the final time $t_{f}$ is reached.
The matrix $T$ has elements $\tau_{2}, \tau_{1}, t_{o}$, and $t_{f}$ in that order.
4. R I CAT. This program computes $P(t)$ and $K(t)$ by the difference equation

$$
\begin{aligned}
P(t+\tau) & =\left[\theta_{21}+\theta_{22} P(t)\right]\left[\theta_{11}+\theta_{12} P(t)\right]^{-1} \\
K(t) & =C P(t)
\end{aligned}
$$

with $P(0)=Z$ and

$$
\left[\begin{array}{ll}
\theta_{11} & \theta_{12} \\
\theta_{21} & \theta_{22}
\end{array}\right]=\mathrm{PH}
$$

In addition to the given equation there is an option in which if there is a matrix name $X$ in Column 28-30 the computation for $P(1)$ and only $P(1)$ will be

$$
P(1)=\left[\theta_{21} X+\theta_{22} P(0)\right]\left[\theta_{11} X+\theta_{12} P(0)\right]^{-1}
$$

If this option is used, $\left[\theta_{11} X+\theta_{12} P(0)\right]\left[\theta_{11} X+\theta_{12} P(0)\right]^{-1}$ is automatically printed.

This program also computes

$$
A L=\frac{\Sigma\left|P_{i i}(t+\tau)-P_{i i}(t)\right|}{\Sigma\left|P_{i i}(t+\tau)\right|}
$$

Computation continues until $t+\tau$ is equal to or greater than $T_{F}$, an input number, or until AL is less than $\epsilon$, an input number. Printing is controlled as follows. $p_{1}$ controls the intermediate printing of $K, p_{2}$ controls the intermediate printing of $P, p_{3}$ controls final $K$ and $P$ print. If

0 there is no intermediate print
$\mathrm{p}_{1}$ or $\mathrm{p}_{2}$ is
$M$ there is a print every Mth iteration
if
0 there is no final $K$ and $P$ print $p_{3}$ is

I there is a final $K$ and $P$ print.

- PC is a matrix with fixed point elements $p_{1}, p_{2}, p_{3}$, and $\beta$ (in that order). $D$ is a matrix with elements $\epsilon, \tau$ and $T_{F}$.

Where $\beta$ is 0 if the Riccati equation is known to be linear and nonzero otherwise.
5. PSEU O. This program computes the pseudo-inverse of $P$, storing it in $P I$ and the rank $r$ of $P$, storing it in RK. The final pivotal element and

$$
\rho=\min \left(\frac{\left\|\left(B^{\#} B-I\right) B\right\|}{\|B\|}+\frac{\left\|\left(B^{\#} B-I\right) B^{\#}\right\|}{\left\|B^{\#}\right\|}\right) p_{2}^{r}
$$

(see Chapter $V$ and dictionary entry 15) are also available as the second and third elements of the 3 element matrix RK. Pseuo will use the pizer in the machine and the $\rho$ computation to determine the rank of $P$, if a 1 is punched in Column 18; otherwise the pseudo inverse of $P$ will be computed with a pizer as read in by the PIZER instruction and no iteration as determined by $\rho$. Computation therefore will cease when rank is maximal or any diagonal element is less than the product of pizer and the maximum diagonal element. If the matrix $P$ is nonnegative definite symmetric, $a+s i g n$ should be punched in Column 16; this will save time and improve accuracy, since it will drop the symmetrizing steps. PI will be printed if PRINI is punched in Column $25-29$ and $\rho$ as a function of rank, will follow PI if a 1 appeared in Column 18.
6. SAMPL. This program computes $P\left(t_{o}+N \tau\right)$ and $K\left(t_{o}+N \tau\right)$ by the difference equations

$$
\begin{aligned}
P(t+\tau) & =F\left[P(t)-P(t) G^{\prime}\left(G P(t) G^{\prime}+R\right)^{\#} G P(T)\right] F^{\prime}+Q \\
K(t) & =F P(t) G^{\prime}\left[G P(t) G^{\prime}+R\right]^{\#}
\end{aligned}
$$

with $P\left(t_{o}\right)=P O$.

The pseudo-inverse in these equations is computed using the value of pizer which has been stored by the PIZER instruction and no $\rho$ iteration as described above.

Computation continues until the number of steps exceeds $N$, an input number, or until $A L$ is less than $\epsilon$, an input number. Printing is controlled as follows; $p_{1}$ controls the intermediate printing of $K$, $p_{2}$ controls the intermediate printing of $P, P_{3}$ controls the final $K$ and $P$ print. If

0 there is no intermediate print
$p_{1}$ or $p_{2}$ is
$M$ there is a print every Mth iteration

0 there is no final print if $p_{3}$ is

1 there is a final print.
$D$ is a matrix with first element $\epsilon$ and second element $\tau$.
$P C$ is a matrix with fixed point elements $p_{1}, p_{2}, p_{3}$, and $N$ (in that order).
7. INVRS. The program finds $Y=P^{-1}$, provided $P$ is not a scalar. To invert scalars, PSEUO must be used. (See p. 21 , Error 1 when det $P=0$.
8. D E C O M. For any nonnegative definite symmetric, n-dimensional matrix $B$ of rank (in the sense of $P S E U O$ ) $r$, this program returns matrices $T, E_{r}$ and $E$ such that $T$ is nonsingular, $E$ is an n-dimensional matrix as defined by $E=T B P^{\prime}$ and $E_{r}$ is some $r$ columns of the n-dimensional identity matrix where $E_{r_{r}} E_{r}^{\prime}=T B T^{\prime}$. In addition the matrix $S=T^{-1}$, the permutation matrix $P$ such that
$P E E^{\prime} P^{\prime}=\left[\begin{array}{ll}I_{r} & 0 \\ 0 & 0_{n-r}\end{array}\right]$ and a $3 \times 1$ matrix $R K$ with $r$, final pivotal
element, and $\rho$ (in that order) are also provided. If a 1 is punched in column 18, the machine pizer will be used and the rank of $B$ will be determined by the computation $\rho=\min \left\|S E E^{\prime} S^{\prime}-B\right\| p_{2}{ }^{r}$. If column 18 is blank, computation will cease when rank is maximal or any diagonal elemeint is less than the product of pizer and the maximum diagonal element.

Some care must be exercised in using DECOM in a loop since $E_{r}$ may change its dimensions. This of itself is not a problem since $E_{r}$ is stored in a sufficiently large area, $n \times n$, but if $E_{r}$ is transposed and the dimension of $E_{r}^{\prime}$ increases as iterations continue, then $E_{r}^{\prime}$ will destroy the storage following itself. This usually is not a serious restriction on programming.
9. A D D. This program computes $C=A+B$. These matrices can be $30 \times 30$.
10. S U B T. This program computes $C=A-B$. These matrices can be $30 \times 30$.
11. M U LT. This program computes $C=A B$ if 1) $A$ and $B$ are conformable or 2) A is a scalar. The output of this program can have 900 elements.
12. TRANP. This program computes the transpose $B=A^{\prime}$.
13. NORM. This program computes $N A=\left\{\operatorname{Max}_{i} \Sigma\left|a_{i j}\right|, \operatorname{Max}_{j} \Sigma\left|a_{i j}\right|\right\}$. The input to this routine can be a $30 \times 30$ matrix.
14. TRACE. This program computes $T B=$ trace $B=\sum_{i=1}^{n} b_{i i}$.
15. P I Z ER will store two constants $P_{1}$ and $P_{2}$ which are used in the PSEUO, DECOM, and SAMPL instructions. The program values of the two constants are $10^{-2}$ and 1 unless the P I Z ER instruction stores other values. For a complete description of their use see Chapters V and VII.
16. JUXTC. This program takes the $m$ by $n$ matrix $A$, the $m$ by . $p$ matrix $B$, and forms the $m$ by $(n+p)$ matrix

$$
C=\left[\begin{array}{ll}
A & B]
\end{array}\right.
$$

JXXTC can not be used in a loop if the output dimensions are changing.
17. JUXTR. This program takes the $m \times n$ matrix $A$, the $p \times n$ matrix $B$, and forms the $(m+p)$ by $n$ matrix

$$
C=\left[\begin{array}{l}
A \\
B
\end{array}\right]
$$

JUXIR can not be used in a loop if the output dimensions are changing.
18. SAVE. This routine will write the given matrices on any of 9 units or channels as defined by the I $\ddagger \mathrm{U}$ tables of the installation monitor system. In Column 18 is punched a number 1 through 9 which is used as an entry to a table common to all the tape instruction. This table will contain a logical tape number which in turn is used by the Fortran $I \not \partial U$ to select a tape channel and unit. The logical tape number as stored in the present version of ASP corresponds to the B channel units 1 through 9. The table is as follows:

Actual channel in FORIRAN II I $\varnothing$

| 1 | 8 | B-1 |
| :--- | :--- | :--- |
| 2 | 2 | $\mathrm{~B}-2$ |
| 3 | 3 | $\mathrm{~B}-3$ |
| 4 | 7 | $\mathrm{~B}-4$ |
| 5 | 10 | $\mathrm{~B}-5$ |
| 6 | 12 | $\mathrm{~B}-6$ |
| 7 | 14 | $\mathrm{~B}-7$ |
| 8 | 16 | $\mathrm{~B}-8$ |
| 9 | 18 | $\mathrm{~B}-9$ |

One SAVE instruction can be used to store as many as 9 matrices, giving each a tape name which can be different from the core name. In the sample, matrices $A, B$, and $C$ are being saved on tape 5 and are being called $D, E$, and $F$ respectively. Operation is as follows: The unit reads the tape until a record with the code word END is encountered, backspaces over that record, writes the matrices, writes a record with the code END and then backspaces over this last record. Some initialization therefore is necessary before the first occurrence of the SAVE instruction. This initilization can be REW, WEF, REW.
19. E Q U AT. This instruction replaces completely except for identification the matrix in the second half of the word with the matrix in the first half, if the sizes are equal. In the example Fl will be replaced by $F 2$, F3, by F4. If F1 is undefined at the time of the instruction, F2 will be stored in a second area and given the identification Fl. F2 under any situation will still be defined in storage. This instruction will handle as many as 10 pairs of matrices.
20. B L O T. This instruction erases the matrix $F$ and every matrix stored after $F$, thus making the storage area available for reuse. This instruction cannot be used in a loop and will result in error statement 12 if an attempt is made to execute a given $B$ L OT instruction a second time.
21. RE W. This instruction will rewind (to tape beginning) any one of nine tapes as designated by the table shown in the $S A V E$ instruction (in the example, tape 5). The tape number is punched in Column 18.
22. WEF. This instruction will write a record with the code word END on any one of nine tapes as designated by the table shown in the $S A V E$ instruction (in the example, tape 5). The tape number is punched in Column 18.
23. BSR. This instruction will backspace 1 to 9 records (in the example 3) on any one of 9 tapes as designated by the table shown in the SAVE instruction (in the example tape 5). The number of records is punched in Column 15, the tape number in Column 18.
24. PRINT. This instruction will print up to ten matrices in one execution, printing each matrix, one row per line in a five-digit format, with its row size, column size, exponent, and a three character title. In the example, for instance, the matrix called CF in core will be printed With title C I F. If several matrices can be contained completely on a page, PRINT will not eject to a new page for each matrix.

In addition to the above, there is an option in which every matrix title following the first on the list will be printed in functional notation using the first element of the first matrix on the list as the argument. To use this option put the argument name in the first word as usual (Columns 13, 14) but leave the three character title region blank (Columns 16, 17, 18).
25. RINT. This instruction will print up to ten matrices in one execution. Printing is done row-wise, six elements per line to the end of the row, in an eight decimal place floating point format if the column size is greater than 6. Otherwise each row beings on a separate line. Several matrices are printed per page if they can be completely contained on a page. As in PRINT, the row size, column size, and a three character title are printed. Also as in PRINT, the instruction can print the title in functional notation.
26. WRITE. This instruction enables the person using the program to print comments during the course of the program. These comments can use Colume 14-72 and might tell what the program is doing at various points. They are not necessary to a knowledge of the output, however, because the entire input data deck is printed by ASP. A page eject may be accomplished by a WRITE instruction with a 1 in Column 13, a line eject by 0 in Column 13. A non-blank character must appear before Colunn 18; otherwise that card is ignored.
27. P UNCH. Just as PRINT and RINT, the punch instruction will handle a maximum of ten matrices in one execution, punching cards in a form which is compatable with the LOAD routine. For each matrix will be punched a row and colum card with the identifying matrix name in Columns 4-6. There is also an option in which matrices 2 through 10 can be identified as a function of matrix 1 . This option in addition to the identification in Columns $4-6$ will punch the first element of matrix 1 in Column 24 to 38 of the row and column card of matrices 2 through 10. This number is not loaded onto the computer on a LOAD instruction. It is merely an additional identification for the programmer. To use this option leave Columns 16-18, of matrix identification 1 blank.
28. L O A D. This instruction may read into core from the input tape up to $\dot{c} 0$ matrices at one execution. If more than 20 matrices must be entered, L O A D instructions may be given at any time in the flow of a problem.

The decimal data for the LOAD is written after the END which defines that particular problem that uses the decimal data. The first card for every input matrix is a card with the row and column size punched in Colurans 11, 12 and 17 , 18 respectively. As in all FORTRAN I- $\varnothing \varnothing$ routines the fixsd zoint numbers (no decimal point) must be right justified; that is if the row-column sizes are single digits they much be punched in Columns 12 a..i 3 respectively. Following the row-column card are the elements punc $-\alpha$ per card with a field width of 15 between 1 and 75 .

This instruction will also load into a previously defined area if the size of the matrix to be loaded is the same as the size of the previously defined area. Otherwise for every different identifier in the LOAD instruction, there wil工 be read a set of decimal data, stored in the following order: matrix identification, row size, column size, $a_{1,1} a_{1,2}, \cdots, a_{m, n}$.

This instruction will handle matrices of size $30 \times 30$.
29. BRING. This routine will read up to 9 matrices from any one of 9 tapes as defined by the tables in the SAVE instruction. The tape number is punched in Column 18. In the example the matrices which are identified on tape 5 as $F, G$, and $H$ are being read into core as $F, G$, and $P H$.

Operation is as follows. The tape unit reads forward from its location at the time of the instruction until it finds the first required matrix. It then reads in that matrix and searches forward (without rewinding) for the next matrix. If a matrix is not found an exit is made from the machine and error statement number 7 is printed; the program does not continue. Thus not all matrices on a tape need be brought, but those which are must appear in the same relative order as they are stored on tape.

This means that to recover the first matrix saved on a tape, an REW instruction must precede the BRING instruction. The operation was programed in this manner so that a sequence of matrices all having the same identification symbol could be successively brought into core.
30. IF. This is the only instruction able to alter the course of the program. In the example, if the first element of 14 is greater than or equal to the first element of $F$, a transfer is made to an instruction which is labeled HEAD 1 in Column 1 to 6. If the condition does not exist, a transfer is made to HEAD 2 or if the area comprised of Colums $25-30$ is bler the next executed instruction will be the one following the $I F$ instruc. . .

An unconditional transfer can be made by comparing the same matrix.
The headings in Columns $1-6$ may be any size character symbol and may be punched in Columns $1-6$ of any data card except decimal data and the BEGIN control card. In case the heading required by an IF statement does not exist, then a problem exit will be made. Error statement number 4 will be printed.

Another restriction to the IF statement is the number of headings for each problem. If there are more than 40 headings, error statement number 13 will be printed.

A sample heading appears on the IF statement itself.
31. BEGIN. This instruction marks the beginning of a problem in the data deck. It precedes the first operation data card of every problem. BEGIN instructs the translator that Hollerith information follows. If the BEGIN card should be omitted the data will be read without processing until a BEGIN is found or to the end of the data. As an example of the use of this instruction see Fig. 5.
32. E N D. This instruction must directly follow the last operation card of any problem. It instructs the executive program to return to the first operation command and begin executing the program data. If the END card should be omitted the executive program will attempt to read the decimal data as Hollerith information and return with error statement 2.

Following is a list of program limitations and error statements internal to ASP. If an ASP error should be encountered, after writing an error statement transfer is made to the executive program which will begin by reading again without processing until the operation BEGIN is found. In addition to the ASP error statements the FORTRAN I- $\varnothing$ will indicate such errors as illegal decimal data on the input tape or redundancy on either input tape or the tapes being used by ASP itself. If Fortran errors are encountered the program will exit to the monitor.

Of the following limitations number 1 is the only one which the user of ASP cannot remedy in general. The others can be controlled by taking advantage of the replacement capability or the BLOT instruction or even storing matrices on tape in one problem (as defined by BEGIN and END)
and then developing a new problem following the first (with a second BEGIN • and END) which calls these matrices from tape.

1) All matrices, except as specifically exempted in the dictionary, must have their larger dimension less than 16 . There is no general error return for using too large a matrix.
2) There is a limit of 120 on the number of matrices of any size winich can be carried in core. If the number is exceeded, error statement number 5 is printed.
3) The program reserves a block of 11,000 words of core storage for the matrices and the operation instructions. If the problem is too large, error statement number 6 will be written.

## ERROR STATEMENIS

1) ERROR RETURN FOR INVERSE IN (X X X X X X X X X X X X),

In the operations which require inverses, RICAT, DECOM, INVRS, if the matrix is singular the above will be printed with the symbol in parentheses identifying the operation ahd the first six characters following the operation.
2) ERROR IN OPERATION ( $\mathrm{X} \times \mathrm{XXXXXXXXXXX}$ ).

This statement will be written if the executive program does not recognize the operation as one of the thirty (excluding BEGIN and END).
3) ERROR IN IDENIIFICATION (X X X X X X X X X X X X) will be printed out, with the symbol in parentheses identifying the operation (and the first six characters following the operation) in which a non-existent matrix has been requested.
4) ERROR IN IDENTIFICAITION (HEAD 1).

This will be printed if the non-existent heading (HEAD I) is requested in an $I F$ instruction.
5) NUMBER OF MATRIX SYMBOLS EXCEEDS 120 AT (X X X X X X X X X X X X).

This statement is printed if an attempt is made to define more than 120 matrices for any one problem.
6) OVERLAP IN MATRIX DATA AND MAIRIX OPERAITION DATA.

This will be printed if the block of ll,000 words for matrix data and operations is exceeded.
7) IDENIIFICATION ERROR ON TAPE B XX. (MATRIX (XX).

This will be printed if the matrix requested, (named in the parentheses) is not found on tape during the execution of a BRING instruction. It is the tape analog of the sore error 3 .
8) DIMENSION ERROR IN (X X X X X X X X X X X X) will be printed, with the symbol in parentheses identifying the operation (and the first six characters following the operation) in which the matrices are nonconformable for some reason, or if the operation is storing a result in a previously defined matrix region which does not agree in size with the resuit; for instance in TRACE or INVRS if the argument is not a square matrix or in JUXIR if the number of columns in the two matrices are not equal.
9) ELEMENT TOO LARGE FOR PRINT FORMAT IN TRANSIENT,

The print format in transient has space for only 4 characters to the left of the decimal point. Therefore all numbers in TRNSI should be greater than -1000 and less than +1000 .
10) SPILL IN (X X X X X X X X X X X X). Index register 1, 2, 4, address of spill location and spill code follow.

This statement alone will indicate an underflow and the computation will be continued. The above statement along with the following will indicate overflow and the program will exit.
11) OVERFLOW ERROR IN -- ( $\mathrm{X} \times \mathrm{XXXXXXXXXX}$.
12) BLOT IS NOT AN ACCEPTABLE OPERATION IN AN IF LOOP.

For a complete sample output see Fig. 5.
13) EXCEEDED RESERVED BLOCK FOR HEADING VECTOR WITH X X X X X X . This statement is printed if there are more than 40 operations which have headings in Column 1-6. X X X X X X is the forty-first heading.




Fig. 4

# Matrix R 

| MATRIX |
| ---: |
|  |
| 0. |
| MATRIX |

0.09999999 E
H
7
$0.09999999 E$
01
$0.04949994 E E$
$0.09999999 E$
01
$0.09999999 E$
0.01
$0.0999799 E$
0.

| MATRIX |  |
| :--- | :--- |
|  | 4 |
| $0.20000000 E$ | 01 |

$0.20000000 \mathrm{E} 01 \quad 0.50000000 \mathrm{E}$ On $0 . \quad 0.34999999 \mathrm{E} 01$
$0.09999999 E 01$
0.
$\xrightarrow{0}$.

| $0.04999999 E$ | 01 | 0. |  | 0. | 0. |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| 0. लपप9प9994E | 01 | $0 \cdot$ |  | $\because$ | ? |  |
| 0. 0.0999999999 F | ${ }^{01}$ | 0. |  | 0. | . |  |
| 0.09999799 E | 01 | $0.09999999 E$ | 01 | 0. |  |  |
|  |  | 0.C9739999E | 0 | $\cdots$ |  | .09999999E | —__

0. 

0
0
0
0
0
$\dot{c} \dot{\circ} \dot{\circ} \dot{0} \dot{0}$

1
. 109799999 N 1
MATRI
TRANSITIUN MATRIX PH= EXP( $F *$ il ,
$\begin{array}{llllll}1.0000 & 0.0000 & 0.0000 & 0.0000 & 0.0600\end{array}$
c.0000
0.007 1.04a7 0.0000
$\begin{array}{lllllllllllllll}0.0000 & 0.0000 & 0.0000 & 0.0000 & 2.7183\end{array}$

DEC 31,1904
WVy90td SIS BHINAS JIIVWOINV
IN =INTEXPI F*TI)
$1112 * * K=0.50000$ on
number of columns 5
Integral expontential
$71=0.5000000 \mathrm{OC}$
number of rows 5
EXPINENT - -
5.00000 .0000 0.000n 0.00000 .0000
$0.00005 .68050 .0000 \quad 0.00000 .0100$ $0.0000 \quad 0.0000 \quad 6.4872 \quad 1.1564 \quad 0.0000$ $0.0000 \quad 0.0000 \quad 0.0000 \quad 6.4872 \quad 0.0000$



AUTOMATIC SYNTHESIS PROGRAM
PAGE 6
TRANSITION MATRIX FH= EXPI F*T2)
$0.0000 \quad 0.0000 \quad 0.0000 \quad 1.0000 \quad 0.0000$
$\begin{array}{llllll}0.0000 & 0.0002 & 0.0000 & 0.0000 & 0.0000\end{array}$
$\begin{array}{llllll}0.0000 & 0.0000 & 0.0040 & 0.0242 & 0.0000\end{array}$
$\begin{array}{llllll}0.0000 & 0.0000 & 0.0000 & 0.0040 & 0.0000\end{array}$
$0.0000 \quad 0.0000 \quad 0.0000 \quad 6.0000 \quad 1.6275$


FIG. 10
r
OEC 31.1964
EC 31.1964
$12=$ INT EXPI F*T? I
T2 $12 * * \mathrm{~K}=0.30$ OON गI
IUMBER JF COLUMINS 5
0.00060 .0000 n.n00n 0.00000 .0000
0.00000 .00380 .00000 .00000000
$\begin{array}{llllll}0.0000 & 0.0000 & 0.0000 & 0.0402 & 0.0000\end{array}$
-0.0000 .0 .0000 n. तnon 0.00008 .1317
END OF INSTRUCTION I

> FIG. 11
autumatic synthesis program
IKANSITION MATRIX PI $=$ EXPI $F * T 1$ )
T1 $=0.50000000$ on Ti $12 * * K=0$. NUMBER OF COLOMNS

[^0]
 --
_
DEC 31,1904
OEC 1.1504

$1=\cdots$
-

EXPISNFNT?
r.0100 0.0n00 ri. rest s.9nan 0.0000
0.0006 0.0448 a.0.0nc reme 0.0000

c.roon 0.0000 a.crid r.2004 n.ano

 $-$

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YNTHESIS DRGGAA DEC PI, 19G4

DEC 31.19 St
(1)




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(2)
TKANSITION MATKIX $\mathrm{PH}=\mathrm{EXPP} \quad F * \quad \mathrm{~F}$ )
$T=0.0999595 \mathrm{E} 1 \mathrm{~T} 10 \% \% \mathrm{~K}=0.1000 \mathrm{OE} 11 \mathrm{~K}=0$
NUMBER UF RWW 3 NUFEER DF CULUMINS 8
EXPGINFT 0
2.7183 c.000n 0.0000 0.0000 $0.0000 \quad 0.10000 .0000 \quad 0.0000$
0.00002 .7183 n.000n conom 0.2000 0.0030 0.0000 0.0090
$0.0000 \quad 0.0000 \quad 2.7182 \quad 0.0000 \quad 1.0000 \quad 0.0000 \quad 0.0000 \quad 0.0000$
$0.0000 \quad 0.0300$ 0.0000 2.7183 c.0n00 $0.0000 \quad 3.0000 \quad 0.0000$
$0000 \cdot 0 \quad 000003000^{\circ} 0$
$0.0000 \quad 0.0030$
$0.0000 \quad 0.3079 \quad 0.0300$
0.00000 .00000 .3679
.3679
2000

$0.0000 \quad 0.0000 \quad 0.0000-1.175 i$
0.00000 .0000 0.0000 1.00000
0.0000 0.0200 r.000n c.roou
-1.175? 0.0000 0.ron c.0000
PAUE 5
AUTIMATIC SYNTHESIS PRESRAM

ALPIIA $=0.03390574[01$
DEC $31,190^{\prime} 4$

C..._-_-_-_-_
automatic symthfisis pirggram

EXPUNF NT
0.00000 .00000 .00000 .000

$0.0000 \quad 0.00003 .3834 \quad$ c.000
0.0000 .0000 उ.000 0.0000
ALPHA $=0.13778113602$

## 

## PAGE 8

MATRIX KI

 --$\square-$ - _ -
 $\square$ $-$
 2 $-$ $\ldots$ $\ldots$
 ——— $\ldots$
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[^1]kivegnyd SISヨHINAS JIIVWr:IC:
PAGE 9
PUY 21

| MATRIX PU |
| :--- |
| TAU $=0$. ROO |
| NUMBER OF RO |
| EXPTNENT -3 |

$\begin{array}{llll}-0.0000 & 0.0000 & 0.000 \pi & 0.0000 \\ 0.0000 & 0.9158 & 0.1 .000 & 0.0000 \\ 0.0000 & 0.0000 & 4.5739 & 0.0000 \\ 0.0000 & 0.0000 & 0.0000 & 0.0000\end{array}$
$A L P H A=0.63890563 \mathrm{~F} 01$
DFG 31.1904
 $\square$


 -





DEC. 31,1964
AUTOMATIC SYNTHESIS PROGRAM.
-

OFC 31,1964

DEC 31.1904
autimatic synthesis program
Pact 15
PSEUUD-INVERSE UF MATKLX P

| 0.0000 | 0.0000 | 0.0000 | -0.0020 |
| :---: | :---: | :---: | :---: | :---: |
| 0.0000 | 4.01343 | 0.0000 | 0.0000 |
| 0.0000 | 0.0000 | 0.0059 | 0.0000 |

-0.0020 0.0900 o.ncon c.0000

DEC 31,1904
DEC 31,1904 Mutimatic shnthesis phigiram




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-

| Paje. | 1 |
| :---: | :---: |
| begin |  |
| [JAD | F.PT, I. R, H.PC. ${ }^{\text {a }}$ |
| tranf | H. HT, |
| TULT | H.fip, |
| WRTTE |  |
| Evo |  |

PAGE 3 AUTUMATIC SYNTHESIS PROKOAN

|  |
| :---: |
|  |
| MATRIX $\quad$ D |
|  |
| 0. |

0.09499999 E 01
2
$-$
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DEC 31,1904
ajtamitu spritheis prugent ___

ALPHA $=0.09999999 \mathrm{ED}$
DEC 31,1964
automatic shithesis priggrain
page 6

NUMBER UF CLLLUMNS
ALPHA $=0.47916000 \mathrm{E}-00$
DEC, 31,1964
AUTOMATIC SYNTHESIS PROGRAM
nutber of cidumiss 1

| MATRIX | KI | 21 |
| :--- | ---: | ---: |
|  |  |  |
| NUMBER OF ROWS | 4 |  |

EXPUNFNT -1
——_
0.1000
0.0000
6.0000
-
DEC 31,1964
()르…
ajtiomatic synthesis ordiza.


-0 = NnTuSd


| 0.1000 | 0.0000 | 0.0000 | 0.0000 |
| :--- | :--- | :--- | :--- | :--- |
| 0.0000 | 0.4500 | 0.0000 | 0.0000 |
| 0.0000 | 0.0000 | 1.0000 | 0.0000 |
| 0.0000 | 0.0000 | 2.0000 | 0.1615 |

$0.0000 \quad 0.0000 \quad 2.0000 \quad 0.1615$ $\square$

OEC 31,1964
$\square$
-
_


IE MB
BO B
ENO OF
NI,
END OF
TB,
END GF INSTRUCTION 13
TB.
R3,TB OF INSTRUCTION 14

## 1FI.KI.PRINT FI,R1,PRINT

FI, R1, PRINT

51
$2 \pi 1$
$\pi \cdot 1.02$ T3.11,LOOP

T3.P3

## T1.T2.T3 F.F.FT.FI


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PAGE 3 AUTMMATIC SYNTHFSIS PROSFAM






| 3 |
| :--- |
| $-\quad 0.2000$ mover 01 |
| $0.1399 .999 E$ |

- 



-





MATRIX P2
AUTUMATIC SYNTHESIS PRUGRAM

| NUABER OF ROWS ${ }^{3}$ | NUMBER DF COLUMNS | 3 |
| :--- | :--- | :--- |
| $0.12345678 E-C 1$ | -0. | -0. |
| -0. | $0.99999999 E-04$ | 0. |
| -0. | 0. | 0.09 |
| END NF INSTRUCTIOV |  |  |

NUMRER UF RONS 3 NUNBER OF COLUMNS 1
0.300 COOONF 01
$0.300 c 000 n \mathrm{~F}$ O1
$0.42857141 \mathrm{t}-00$
$0.83446503 E-05$
INGMEER UF CULU.ivS

$$
0.09998979 E 01
$$

DEC 31,1964

$$
\begin{gathered}
\text { MATRIX ER } \\
\hline 0.09999999 E \\
\hline 0 . \\
\hline 0 . \\
\hline 0 .
\end{gathered}
$$

$$
0 .
$$


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MATKIX EK
DEC 31,1964

DEC 31.1964
DEC 31,1904

autohatic synthesis pritgram


NUMBER OF ROWS 4 NUMBER OF COLUMNS 4
EXPONFT
-

| 0.3000 | 0.6000 | 1.2000 | 1.5000 |
| :--- | :--- | :--- | :--- |
| 0.6000 | 1.4000 | 2.5000 | 3.5000 |

$\begin{array}{llll}0.3000 & 0.6000 & 1.2000 & 1.5000 \\ 0.6000 & 1.4000 & 2.5000 & 3.5000\end{array}$
1.20002 .50006 .20006 .700

| 1.5000 | 3.5000 | 6.7000 | 8.9000 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| END OF INSTRUGTIONS 11 |  |  |  |

$\begin{array}{r}1.5000 \\ \text { END OF INSTRUCTIONS } 11 \text { AND } 12 \\ \hline\end{array}$
PAGE

| 0.3000 | 0.6000 | 1.2000 | 1.5000 |
| :--- | :--- | :--- | :--- |
| 0.6000 | 1.4000 | 2.5000 | 3.5000 |
| 1.2000 | 2.5000 | 6.2000 | 6.7000 |
| 1.5000 | 3.5000 | 6.7000 | 8.9000 |

MATRIX B
NUMBER OF RUWS 4 NUMBER OF COLUMNS 4
MB
MATRI
EXPONENT 1

EXPONFNT 1
$\qquad$
UFC 31,1954


$\frac{8.3447}{\text { EN! (1) INS IRUCTITN } 13}$

- Number df rows 1 Number of Columas 1
MATKIX TH
EXPONFNT 2
$-\frac{1.6800}{\text { ENO OF INSTRUCTITINS } 14}$

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DEC 31,1904
autgatide synthesis pruoram

$0.0000 \quad 0.0000 \quad 0.0000$
$0.0000 \quad 10.0000 \quad 0.0000$
0.0000 0.0000 c.0000
PAGE 1 ?

$\ldots$
 $\square$

[^2]DEC 31,1964
-

PAGF 16

DEC 31.1964 1
 -
 auturic synthesis prigrain
the folloning data has deen sturfd in the indicates matrix sturage.

| PAGE 17 |
| :--- |
|  |
| MATRTX PI |
| 0.20000000 OI |


| PAGE 17 |
| :--- |
|  |
| MATRTX PI |
| 0.20000000 OI |


| PAGE 17 |
| :--- |
|  |
| MATRTX PI |
| 0.20000000 OI |


| PAGE 17 |
| :--- |
|  |
| MATRTX PI |
| 0.20000000 OI |

aidmatic synthesis prigran
THE FOLLOWING DATA
-$\xrightarrow{-2}$




DEG 31,1964
AJTJMATIC SYINTHESIS PRJGRAM
PAGE 19
MATRIX FI 1 0.200nconot 211
MATRTX TIT T. TDMORCDE OI
Columivs 3
0.
$0.99999997 E-04$
END UF INSTRUCTIDNS 28. 29 AND 30.

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DEC 31.1964



## CHAPIER II

## THE EXPONENTIAL ROUTINES

1. Description of the Problem: We are interested in an efficient method to integrate linear differential equations, and therefore we want to compute $\exp (F t), \quad F=$ const. matrix.
2. Theory: Let us consider the linear dynamical system

$$
\begin{equation*}
\dot{x}=F(t) x+G(t) u(t) \tag{2.1}
\end{equation*}
$$

where x is an n -dimensional vector, the state and $\mathrm{u}($.$) is an m-dimensional$ vector function, the control function.

Under very mild restrictions on $F$ and $G$, this system will have unique solutions depending upon the time $t$, the initial time $t_{o}$, the initial state $x\left(t_{o}\right)$, and the control function $u($.$) . It is often convenient$ to exhibit this dependence explicitly; we shall therefore write a solution of (2.1) in the form

$$
\begin{equation*}
\varphi_{u}\left(t ; x\left(t_{o}\right), t_{o}\right) . \tag{2.2}
\end{equation*}
$$

The notation implies that

$$
\varphi_{u}\left(t_{o} ; x\left(t_{o}\right), t_{o}\right)=x\left(t_{o}\right)
$$

and that

$$
\frac{d}{d t} \varphi_{u}\left(t ; x\left(t_{o}\right), t_{o}\right)=F(t) \varphi_{u}\left(t ; x\left(t_{0}\right), t_{0}\right)+G(t) u(t) .
$$

It is well known [3] that the solutions of (2.1) can be expressed by means of the formula
(2.3) $x(t) \equiv \varphi_{u}\left(t ; x\left(t_{o}\right), t_{0}\right)=\Phi\left(t, t_{0}\right) x\left(t_{0}\right)+\int_{t_{0}}^{t} \Phi(t, \tau) G(\tau) u(\tau) d \tau$ which is valid for any $x_{0}=x\left(t_{0}\right)$, $t$ and $t_{0}$ (whether or not $t>t_{0}$ ). The matrix $\Phi\left(t, t_{0}\right)$ occurring in (2.3) is the transition matrix of (2.1) and is uniquely determined by the requirements [4]

$$
\begin{equation*}
\Phi(t, t)=I \quad \text { for all } t \tag{2.4}
\end{equation*}
$$

and

$$
\begin{equation*}
\frac{d}{d t} \Phi\left(t, t_{0}\right)=F(t) \Phi\left(t, t_{0}\right) \tag{2.5}
\end{equation*}
$$

From these properties and the uniqueness of solutions of (2.1) one can show at once that

$$
\begin{equation*}
\Phi^{-1}\left(t, t_{0}\right)=\Phi\left(t_{0}, t\right) \text { for all } t, t_{0} ; \tag{2.6}
\end{equation*}
$$

$$
\begin{equation*}
\Phi\left(t_{3}, t_{2}\right) \Phi\left(t_{2}, t_{1}\right)=\Phi\left(t_{3}, t_{1}\right) \text { for all } t_{1}, t_{2}, t_{3} \tag{2.7}
\end{equation*}
$$

As an example, consider

$$
\dot{x}=\left[\begin{array}{rr}
2 t-1 & t-1 \\
2-2 t & 2-t
\end{array}\right] x
$$

where

$$
\Phi(t, 0)=\left[\begin{array}{cc}
2 e^{\frac{t^{2}}{2}}-e^{t} & e^{\frac{t^{2}}{2}}-e^{t} \\
2 e^{t}-2 e^{\frac{t^{2}}{2}} & 2 e^{t}-e^{\frac{t^{2}}{2}}
\end{array}\right]
$$

For a one-dimensional system, the transition function for any linear system is given by

$$
\begin{equation*}
\int_{t_{0}}^{t} F(\tau) d \tau \tag{2.8}
\end{equation*}
$$

If $F$ is constant, the transition matrix is given by the matrix exponential $e^{t F}$, which can be defined by the everywhere convergent power series

$$
\begin{equation*}
e^{t F}=\sum_{i=0}^{\infty} \frac{(t F)^{i}}{i!} \tag{2.9}
\end{equation*}
$$

(To show the convergence of the series, observe that for $p>0$

$$
\left\|\sum_{i=p}^{p+q} \frac{(t F)^{i}}{i!}\right\| \leqq \sum_{i=p}^{p+q} \frac{\|t F\|^{i}}{i!}
$$

for any norm derived from a vector norm. This shows that the matrix series for $e^{t F}$ converges in norm whenever the scalar series for $e^{\|t F\|}$ converges; the latter however is well known to converge uniformly for $\|t \mathrm{t}\|$ in any bounded intcrval, and this is equivalent to uniform component convergence of $e^{t F}$.)

This matrix function is of interest in this report primarily because it is the fundamental matrix of the vector differential equation

$$
\begin{equation*}
\dot{x}=F x \quad(F \quad a \text { constant }) . \tag{2.10}
\end{equation*}
$$

That is [Coddington and Levinson, 1955],

$$
\begin{equation*}
x(t)=e^{\left(t-t_{0}\right) F} x\left(t_{0}\right) \tag{2.11}
\end{equation*}
$$

This may be proved very easily by termwise differentiation of the defining series, a valid procedure by its uniform convergence.

- Some other facts which can be proved about $e^{T F}$ are [Coddington and Levinson, 1955]
(2.12)

$$
e^{A+B}=e^{A} e^{B} \quad \text { if and only if } \quad A B=B A
$$

$$
\begin{equation*}
e^{T F T^{-1}}=T e^{F_{T}-1} \quad \text { for any nonsingular } T \tag{2.13}
\end{equation*}
$$ $\operatorname{det} e^{\boldsymbol{F}}=e^{\text {trace } F}$.

(2.14) shows that $e^{t F}$ is always nonsingular. We can now paraphrase (2.11) by saying that the columns of $e^{t F}$ are $n$ linearly independent solutions of (2.10) and thus any solution of (2.10) can be expressed as a linear combination of the columnvectors of $e^{t F}$.
$e^{t F}$ is computed in the ETPHI routine, using the series (2.9). We are often interested in the forced system

$$
\begin{equation*}
\dot{x}=F x+G u(t) \quad(F, G \quad \text { constant }) . \tag{2.15}
\end{equation*}
$$

The complete solution to (2.15) can be written as

$$
\begin{equation*}
x(t)=e^{t F_{x}(0)}+\int_{0}^{t} e^{(t-\tau) F_{G u}(\tau) d \tau} \tag{2.16}
\end{equation*}
$$

In sampled data systems $u($.$) is a piecewise constant and we have$

$$
\begin{equation*}
x(t)=e^{t F} x(0)+\int_{0}^{t} e^{(t-\tau) F_{G d \tau} u(0)} \tag{2.17}
\end{equation*}
$$

over any sampling interval.
Making the substitution $s=t-\tau$, the integral in (2.17) assumes the simpler form

$$
\left[\int_{0}^{t} e^{s F_{d s}}\right] G u(0)
$$

The integral $\int^{t} e^{s F} d s=\Gamma(t)$ is computed in the EAT routine. Its concrete definition can be obtained by term-by-term integration of the defining series for $e^{t F}$,
(2.20)

$$
\Gamma(t)=\sum_{i=0}^{\infty} \frac{F^{i} t^{i+1}}{(i+1)!}
$$

If $F^{-1}$ exists, this may be written as $F^{-1}\left(e^{t F}-I\right)$; however $\Gamma(t)$ exists even if $F$ is singular.
3. Computation: For computing $e^{t F}$, the sum of at most the first thirtyseven terms of its defining series (2.1) is used. Thus we compute

$$
\begin{equation*}
e^{t F}=\sum_{i=0}^{36} \frac{t^{i} F^{i}}{i!} \tag{3.1}
\end{equation*}
$$

The sum (3.1) is actually formed as follows. Iet $T_{i}$ be the $i^{\text {th }}$ term of the expansion: $T_{0}=I, T_{i}=F t$, etc. The sum is accumulated and $T_{i+1}$ is obtained as

$$
T_{i+1}=\frac{t F}{i+l} T_{i}
$$

The following motivates why thirty-seven terms are used in (2.1) and gives a condition necessary for the result to be accurate.

In the IBM 700-7000 computers a little more than eight significant decimal degits are carried when operating in the single-precision floating point mode. This imposes limitations on the accuracy of the program. Consider a scalar cosine series. We know that for any real value of the argument, the absolute value of the function is one or less. Yet if the argument
were 20, the term $\frac{20^{20}}{20!}$ is so large that the addition to it of any number less than one has no effect. That is, if any term of the series exceeds $10^{8}$, we know that no answer will have correct digits to the right of the decimal point. Thus if we want an answer that is correct to four decimal places, no term of the series may exceed $10^{4}$. The largest term of the $e^{t}$ series is $T_{j}$ where $i$ is the smallest integer such that $\frac{t}{j+1}<l$; therefore $T_{j}=\frac{t^{j}}{j!}$ where $. i=[t]$, the greatest integer less than $t$, For our purposes $\frac{t^{j}}{j!}$ should always be less than $10^{4}$, which implies that a conservative bound for $t$ is 10, since $\frac{10^{10}}{10!} \approx 2756<10^{4}$.

We can apply this analysis to the matrix case by using norms. Specifically let us define our norm as

$$
\|A\|=\operatorname{Min}\left\{\max _{i} \sum_{j}\left|a_{i j}\right|, \max _{j} \sum_{i}\left|a_{i j}\right|\right\}
$$

In this norm we have

$$
\begin{equation*}
\|\mathrm{AB}\| \leqq\|\mathrm{A}\|\|\mathrm{B}\| \quad \text { and } \tag{3.2}
\end{equation*}
$$

$$
\begin{equation*}
\left|a_{i j}\right| \leqq\|A\| \tag{3.3}
\end{equation*}
$$

We would like to say now that if $|t| \cdot\|A\| \leqq 10$ then we are assured of four decimal place accuracy. (3.2) and (3.3) guarantee that if the condition is satisfied, every element of every matrix in the sum will have absolute value less than $10^{4}$, which was a necessary condition for four-place accuracy. In addition it is necessary that we not terminate the result too soon. The last term taken will be $\frac{(t A)^{36}}{36!}$ each element of which is less than $.27 \cdot 10^{-5}$. The remainder can be majorized by a geometric series whose sum is $10^{-6}$. This begins to look as if $\|t A\|<10$ is sufficient for Tour-place accuracy. This however is incorrect. Clearly since $e^{10} \simeq 22000$

We can hope for no more than three place accuracy because we only . have three decimal places. But the situation is even worse than this. By the time the largest term is reached the partial sum is larger than $10^{4}$, from here on to the end of the summation, digits less than about .5 $10^{-3}$ will be dropped and digits of this size can occur out to the term $k=33$.

Thus for about 25 terms we are losing digits averaging $2.5 \cdot 10^{-4}$ for a total of about .006. Thus for positive eigenvalues the error is bounded by about .006. For negative eigenvalues the problem of large accumulations does not arise; here we only have the differences of numbers about 3000 which means that we should get four decimal place accuracy.

This analysis indicates that the restrictions we apply to $\|A t\|$ will suffice to give us four decimal place accuracy with (algebraically) small numbers and more than two decimal places (at least six significant figures), with large numbers.

The specified norm was chosen because, being sums of absolute values, it is simple and quick to compute and because the minimization gives a fairly small norm. This is of course desirable so as to maximize the allowable step size. We could not, however, use $\|A\|=\max \left|a_{i j}\right|$ because in this norm it is not necessarily true that $\|A B\| \leqq\|A\|\|B\|$.

EAT is computed in much the same way except that the initial term of the series is tI, not $I$.

The arguments concerning the maximum value of $t$ apply here also, with some modification. If $\frac{(F t)^{k}}{k!}$ is the largest term in the exponential, then $\frac{(F t)^{k-1}}{k!}$ will be the largest term in $\Gamma$. Again this must be less than $10^{4}$, so

$$
\begin{equation*}
t \leqq \frac{10^{4} \mathrm{k}!}{\|F t\|^{\mathrm{k}-1}} \tag{3.4}
\end{equation*}
$$

This is mechanized as follows: First $T$ is halved until
$\tau=\frac{\mathrm{T}}{2^{k}}<\frac{10.001}{\|F\|}$. Then if $\|F \tau\|$ is greater than 8 , we can check that
$\tau \leqq \frac{10^{4} 10}{(10.001)}$. If it is, we accept $\tau$ and proceed. If $\|F \tau\|$ is less than 8 and greater than 6 we check that $\tau \leqq \frac{10^{4} 7}{8^{6}}$. If it is, we accept $\tau$ and
proceed. This continues until, if $0<\|F \tau\|<2, \tau$ must be less than $10^{4}$, and is halved until it is less than $10^{4}$. (See Figure 2 where
$C_{1}=10^{4}, \quad c_{2}=\frac{10^{4} 3!}{4^{2}}, \quad C_{3}=\frac{10^{4} 5!}{6^{2}}, \quad c_{4}=\frac{10^{4} 7!}{8^{6}}, \quad$ and $\left.\quad C_{5}=\frac{10^{4} 10!}{\left(10.001^{9}\right.}.\right)$
In order to compute $\Phi=e^{T F}$, then for a $T$ which is too large, we select $\tau=\frac{T}{k^{2}}$ such that $\|F \tau\|<10.001$. To compute $\Phi$ and $\Gamma=\int^{T} e^{t F} d t$, we have additional restrictions as described above. In any case we arrive at a $\tau=\frac{T}{2^{k}}$ which will give us the accuracy described above. We then square $e^{\tau F} k$ times, obtaining $\left(e^{\tau F}\right)^{2^{k}}=e^{T F}$ by (2.12). The procedure with $\Gamma$ is similar. It follows from the fact that

$$
\int_{0}^{2 \tau} e^{t F} d t=\int_{0}^{\tau} e^{t F} d t+e^{\tau F} \int_{0}^{\tau} e^{t F} d t
$$

This process also is iterated $k$ times to produce

$$
\Gamma=\int_{0}^{T} e^{t F_{d t}}
$$

The procedures have their failings of course, the multiplications and additions required to bring $\tau$ up to $T$ introduce errors. No attempt is made to control this in the machine; however if a print is requested, the $\tau$ used is printed and will indicate how many squarings were required.

An option was found to be necessary. If we wish to compute the riccati solution over a given interval we must compute the fundamental matrix of the corresponding euler-lagrange equations over a submultiple of the interval ( $t-t_{0}$ ). This is signaled by putting an extra matrix in the calling sequence (only in ETPHI, not in EAT). When we exit from E T P H I the subinterval length $\tau=\frac{\mathrm{t}-\mathrm{t}_{0}}{2^{k}}$ where $\tau$ will be the maximum
value to satisfy the condition that $\tau \leqq \frac{10.001}{\|F\|}$ will be in the extra matrix and the exponential with that value of $\tau$ will be in PH. At first it seems that this could be handled by the ordinary process of reducing $\tau$ for the series computation and squaring up to the correct value. This is a poor procedure however, because the euler-lagrange equations have both stable and unstable roots. Althoush the riccati may converge, the fundamental matrix may overflow if $\tau$ is too large.

For illustrations of most of these processes, s e Chapter I, Fig. 5-18.

The summation process terminates at the $k^{\text {th }}$ term if every element of $T_{k}$, the $k^{\text {th }}$ term of the exponential sum is 0 . By virtue of the floating point spill routine a zero matrix can occur if every element is less than approximately $10^{-40}$.

Some experiments were made in this subroutine with what we have called pseudo double precision. This involved two changes: 1) All scalar products in matrix multiplication are accumulated in double precision, rounded and stored in single precision. For instance, $c_{i j}=\sum_{k=1}^{\ell} a_{i k} b_{k j}$ prociucts $a_{i j} b_{k j}$ would be computed as the single precision product of single precision numbers, the partial sums $\sum_{k=1} a_{i j} b_{k j}$, however, would be kept as the double precision sum of single $p$ prelision numbers. After the double precision $c_{i j}$ was obtained it was rounded to obtain the single precision value for storage. 2) These single precision terms are accumulated as above in double precision when the exponential is completed, the double precision matrix is rounded to single precision for storage. Theoret cally of course, this procedure is meaningless, for instance if we add $10^{9}$, $10^{-2}$, and $-10^{9}$, in that order, in single precision we get zero. Using pseudo double precision we get $10^{-2}$. But the immediate objection is that the errors in any single precision representation of $10^{9}$ are larger than $10^{-2}$.

- The results of a few experiments tend to corroborate these ideas. Most of the results achieved with the double precision code showed markedly greater significance, perhaps one more decimal place. However, in the most complicated check, the magnitude of one error actually increased. Tentatively one might say that when working with input numbers, this procedure is very helpful, but after a long sequence of computations, the mechanics of truncation create a situation where ordinary floating point is essentially the optimal computation procedure.

4. Checks. (A) The exponential and integral exponential were computed for the $7 \times 7$ matrix $\operatorname{diag}(-10,-4,-1,0,1,4,10)$, with $T=1$. The results appear in Fig. 3-A and 4-A, the correct answers in Fig. 3-B and $4-B$. Because the matrix is diagonal, the error analysis applied exactly and the answers show this very well. In the submatrix ( -10 ), where we are not only at the iimit of the acceptable range but are taking differences, we barely have four place accuracy and no correct significant figures. Where differences are not being taken as in (10) the answer is correct to seven significant figures.

One phenonemon that occurs repeatedly in series computation is that in the exponential of the positive eigenvalues, the computed value will be invariably less than the correct value because the error is caused by truncation of positive terms. With the negative eigenvalues the error does not display this characteristic.

The exponential of this matrix for $T=1$ was also computed using the pseudo double precision code. This gave the result

$$
\begin{gathered}
e^{F}=\operatorname{diag}[4.4255785 \mathrm{E}-5, \quad 1.8315656 \mathrm{E}-2, \quad 3.6787944 \mathrm{E}-1 \\
9.9999999 \mathrm{E}-1, \quad 2.7182817, \quad 5.4598150 \mathrm{E} 2 \\
2.025454 \mathrm{E} 4 .]
\end{gathered}
$$

(B) The exponential and integral exponential for a $15 \times 15$ Jordan block with eigenvalue zero were computed with $T=.1$, 1., and 10. The results were very good, probably because the series truncates. The answers were correct to more than seven decimal places. (See Fig. 5-10.)
(C) The exponential of the $7 \times 7$ skew-symmetric matrix.

| 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| -1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 0 | -1 | 0 | 1 | 0 | 0 | 0 |
| 0 | 0 | -1 | 0 | 1 | 0 | 0 |
| 0 | 0 | 0 | -1 | 0 | 1 | 0 |
| 0 | 0 | 0 | 0 | -1 | 0 | 1 |
| 0 | 0 | 0 | 0 | 0 | -1 | 0 |

was computed for $T=1$. This matrix should have been orthogonal. Multiplying by its transpose we obtained the identity matrix with errors of less than $2.10^{-7}$. (See Fig. 11.)

Using the double precision code we obtained an identity matrix with errors of $2.10^{-8}$.
(D) Using this orthogonal matrix we computed the exponential and integral exponential of $O A O^{-1}$ where $A$ was the matrix diag ( $-10,-4,-1,0,1,4,10$ ) used in Check (A) and 0 was the orthogonal matrix obtained in (C). The issue was confused slightly by the fact that $0^{\prime}$ was not quite equal to $0^{-1}$, but the accuracy was not greatly reduced. Except in the largest element, where the error was three in the seventh significant figure, the worst error was 2.5 in the fourth decimal place. (See Fig. 12.)

The exponential was computed using the double precision code and generally reduced the errors significantly, but one element, which should have been zero, actually increased in magnitude.

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Fig. 1


Fig. 2



$\circ \quad 0 \quad 0 \quad \stackrel{\underset{\sim}{\infty}}{\stackrel{\infty}{\infty}} \underset{\underset{\sim}{\sim}}{\underset{\sim}{\sim}}$
$000 \quad 0 \quad 0 \quad 0 \quad 0$

Fig. 3-B






MATRIX IINJT $0.09999999 E-001$
NUMBER UF COLUMNS 15
$\begin{array}{ll}\text { U. } 83333328 E-01 & 0.13888887 E-08 \\ 0.25052105 E-18 & 0.20870753 E-20\end{array}$
U. $41566664 \mathrm{E}-05 \quad 0.83333328 \mathrm{E}-07$
$\begin{array}{ll}0.16656666 E-03 & 0.41666664 E-05 \\ 0.27 \supset 57310 E-14 & 0.27557316 E-16\end{array}$
$0.49999990 E-02$
$0.24801584 E-12$ $0.0999 \overline{9} 99 \mathrm{E}-00$
$0.19841268 \mathrm{E}-10$
$0.16059041 E-22$
0. $13888887 E-00$ C. $20876753 E-20$
-
0. $23052105 E-18$
0.
$0.41606604 E-05$
$0.27551316 E-16$
0. $16066000 \mathrm{E}-03$
0. $27557310 \mathrm{E}-14$
0.
$0.24801584 \mathrm{E}-12$
0.04994.794E-00
U. $19841268 \mathrm{E}=10$
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$0.138888 \delta 7 E-08$
$.13888887 t-08$
$0.20876753 t-20$
$0.833333285-07$
$0.41000604 E-05$
$0.27557316 \mathrm{E}-16$
0.16000000E-03
$0.16000000 \mathrm{E}-03$
0.494ツ9999Eー02
$0.24801584 E-12$
$0.099994 У У E-00$
$0.19841268 \mathrm{E}-10$
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$0.83333323 E-07$
$0.83333328 E-07$
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$0.16656666 E-U 0$
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0.2755731 ロヒーン 5
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0.83333331 E－02
$0.416066666-01$
$0.10660600 \mathrm{E}-00$
0．
$\begin{array}{lllll}0 . & 0 . & 0.09999999 E 01 & 0.50000000 E 00 \\ 0 . & 0 . & 0.099990\end{array}$
$\begin{array}{lllll}0 . & 0 . & 0.09999999 E 01 & 0.50000000 E 00 \\ 0 . & 0 . & 0.099990\end{array}$
$0.166066665-00$
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FIG． 8
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0.160600000030 .41660600 E 03
$0.27557317 E 04$
0.166666601
$0.27551317 E 4$

$0.50000000 E 02$
$0.24801580 E \quad 04$





FIG. 9

 $\xrightarrow{2}$
$\square$



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| 0.1605904 jt 64 | U．11470744t 04 | U．764710\％0t J3 |  |  |  |
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$-0.79889878 E-00$
$0.41776511 E-05$
0.10000050 E OL
$-0.16149133 E-04$
$-0.15437603 E-04$
$-0.1068152 \mathrm{E}-03$
$+961.42 .10 N$

CHAPIER III

THE TRANSIENI PROGRAM

1. Statement of the Problem. This is a program to display solutions of a linear differential equation.
2. Theory. Having obtained a feedback control law for a system, we usually like to have some means of observing the output. We can do this most readily by computing the response of the system to unit initial conditions on the state variables.

If we have a differential system

$$
\dot{x}=F x+G u(t)
$$

$$
\begin{equation*}
y(t)=H x(t) \tag{2.1}
\end{equation*}
$$

with control law

$$
u(t)=-K x(t)
$$

then we can rewrite the system as

$$
\dot{\mathrm{x}}=(F-G K) \mathrm{x}
$$

$$
\begin{equation*}
y(t)=H x(t) \tag{2.2}
\end{equation*}
$$

with solution

$$
x(t+\tau)=e^{\tau(F-G K)} x(t)
$$

On the other hand, we may have a system which is monitored at intervals $\tau_{1}$, while the control is changed only at sampling intervals $\tau_{2}$ ( $\tau_{2}$ is some positive integral multiple of $\tau_{1}$.)

Furthermore the system may have a constant forcing term.
3. Computation. The Transient Routine mechanizes a set of equations which encompass these situations and provide, along with a time history of the solution, a rather detailed description of the process (see Chapter I, Fig. 16). For instance, the times when control is computed are marked with an asterisk. The equations used are:

$$
\begin{aligned}
& x\left(t+\tau_{1}\right)=\operatorname{Px}(t)+G u(t) \\
& u(t)=J r-K x\left(t_{0}+i \tau_{2}\right) \quad i \tau_{2} \leqq t-t_{0} \leqq(i+1) \tau_{2} .
\end{aligned}
$$

Thus $P$ is the transition matrix, $G$ is the integral of Green's function, $J \mathbb{R}$ represents a forcing function and $K x$ is the feedback term. The state vector is monitored at intervais $\tau_{I}$ and the control is constant during the sampling interval $\tau_{2}$ 。

In certain applications the state vectors are not the observables and in such cases it is desirable to monitor the actual system output. Furthermore at most seven state variables can be printed. So instead of printing the state variables we print

$$
y(t)=H x(t)
$$

wnere $H$ is a constant matrix having at most seven rows.
4. Checks. The Transient Routine is, mathematically, an extremely simple program; but the logic is somewhat complicated. Most of the complications of the routine are involved in setting up the printout with the correct number of state variables, control variables, etc. This makes it impossible to design a single run to check every possibility. Repeated use has given us considerable confidence in its freednm from error. For a sample run see Fig. 16, Chapter I.


Fig. 1

## CHAPIER IV

## THE GENERAIIZED INVERSE PROGRAM

1. Description of the Probiem. Many problems in optimization require computations in linear algebra which go beyond finding an inverse. For instance, determination of rank, least-squares solutions of linear equations, etc. These problems are readily handled via the concept of a pseudo-inverse (or generalized inverse) of a matrix.
2. Theory. In matrix calculus there is a frequently recurring difficulty due to the fact that the inverse of a matrix does not always exist. To prove the existence of the inverse of a given matrix is often cumbersome and difficult. Moreover, in many cases solutions of a set of linear equations exist even when the inverse of the matrix defining these equations does not.

To obviate some of these difficulties, it has been found convenient to make use of the notion of a so-called pseudo-inverse of a matrix. Roughly speaking, a pseudo-inverse must possess two properties to be useful: (i) it must always exist; (ii) when used in place of the inverse (which may not exist), it should give sensible answers to questions such as solutions of equations.

We shall present here a brief discussion of the properties of pseudoinverses, in particular the "generalized" inverse of Penrose. Further details may be found in Reference 1.

References.
[1] R. Penrose, (1955) "A generalized inverse for matrices", Proc. Cambridge Phil. Soc., 51 406-413.
[2] R. Penrose, (1956) "On best approximate solutions of linear matrix equations", Proc. Cambridge Phil. Soc., 52, 17-19.
[3] R. V. Andrée, (1951) Am. Math. Monthly, 58, 87-92.
[4] T. N. E. Greville, (1959) "The pseudo-inverse of a rectangular or singular matrix and its application to the solution of systems of linear equations", SIAM Review, 1, 38-43.

DEFINITION. Let $A$ denote the Moore-Penrose inverse of A. This a matrix that satisfies the following axioms:
(i) $\quad A A^{\#} A=A$,
(ii) $A^{\#} A A=A^{\#}$,
(iii) $\left(A^{\#} A\right)^{\prime}=A^{\#} A$,
(iv) $\left(A A^{\#}\right)^{\prime}=A A^{\#}$.

It can be shown that $A^{\#}$ always exists and is unique (see Theorems (2.5) and (2.8) below).

The axioms are readily seen to imply that
(2.1) $A^{\# \#}=A$,
(2.2) $A^{\#}=A^{-1}$ if $A^{-1}$ exists,
(2.3) $A^{\prime \#}=A^{\#^{\prime}}$.

It is not generally true that $(A B)^{\#}=B^{\#} A^{\#}$.
Furthermore $A^{\#}$ is a discontinuous function of $A$. For instance, let

$$
A=\left[\begin{array}{ll}
1 & a \\
1 & 1
\end{array}\right]
$$

then

$$
A^{\#}=A^{-1}=\left[\begin{array}{cc}
\frac{1}{1-a} & \frac{-a}{1-a} \\
\frac{-1}{1-a} & \frac{1}{1-a}
\end{array}\right]
$$

for $a \neq 1$, but

$$
A^{\#}=\left[\begin{array}{cc}
1 / 4 & 1 / 4 \\
1 / 4 & 1 / 4
\end{array}\right]
$$

for $a=1$. It is not true in any sense that $\lim A^{\#}(a)=A^{\#}(1)$.

$$
\mathrm{a} \rightarrow 1
$$

(2.4) LEMMA. $A(A \cdot Q A)^{\#} A^{\prime} Q A=A$ for any nonsingular symmetric
matrix $Q$.
Proof: Let $C=A\left(A^{\prime} Q A\right)^{H} A^{\prime} Q A-A$. Then $C^{\prime} Q C=0$, by use of axiom (i). This implies $C=0$.
(2.5) THEOREM. $A^{\#}$ exists.

Proof: (a) If $A=\operatorname{diag}\left(d_{1}, \ldots, d_{n}\right)$, then let

$$
\begin{array}{ll}
a_{i i}^{\#}=d_{i}^{-1} & \text { if } d_{i} \neq 0 \\
a_{i j}^{\#}=0 & \text { othe rwise. }
\end{array}
$$

(b) If $A=A^{\prime}$ is symmetric, we know that $A=U \wedge U^{\prime}, U$ orthogonal, $\Lambda$ diagonal. Then $A^{\#}=U^{\sharp} U^{\prime}$.
(c) If A is arbitrary, we let

$$
\begin{equation*}
A^{\#}=\left(A^{\prime} A\right)^{\#} A^{\prime} \tag{2.6}
\end{equation*}
$$

or

$$
\begin{equation*}
A^{\#}=A^{\prime}\left(A A^{\prime}\right)^{\#} . \tag{2.7}
\end{equation*}
$$

Either of these satisfy axiom (i) by use of Lemma (2.4) and axioms (ii), (iii) and (iv) by use of part (b) of this theorem.
(2.8) THEOREM. $A^{\#}$ is unique.

Proof: Let $X$ and $Y$ be Penrose inverses of $A$. Then:

$$
\begin{aligned}
X & =X A X=A^{\prime} X^{\prime} X=A^{\prime} Y^{\prime} A^{\prime} X ' X \\
& =A^{\prime} Y^{\prime} X A X=A^{\prime} Y^{\prime} X=Y A X=Y X^{\prime} A^{\prime} \\
& =Y A Y X^{\prime} A^{\prime}=Y Y^{\prime} A^{\prime} X^{\prime} A^{\prime}=Y Y^{\prime} A^{\prime}=Y A Y=Y . \quad Q: E \cdot D .
\end{aligned}
$$

In particular, equations (2.6) and (2.7) define the same matrix $A^{\#}$.
That hypotheses (i) - (iv) are independent (i.e., necessary for uniqueness), will be shown later.

The following theorem and its corollaries give, in increasingly general form, the main properties of the Penrose inverse. First, however, we need an elementary fact:
(2.9) ORTHOGONAL PROJECTION LEMMA. Given a normed vector space $V$, a constant vector $b \in V$, and a linear map $A: V \rightarrow V$. Then

$$
\left\|A x^{\circ}-b\right\|=\min _{x \in V}\|A x-b\|
$$

is equivalent to

$$
\left(A x, A x^{\circ}-b\right)=0 \quad \text { for } a l l \text { in } V
$$

Proof: Assume ( $\left.A x, A x^{\circ}-b\right)=0$ for all $x$ in $V$. We want to prove that $\left\|A x^{\circ}-\mathrm{b}\right\| \leqq\|A y-b\|$ for $y$ in $V$. Any $y$ in $V$ can be represented as

$$
\mathrm{y}=\mathrm{x}^{\circ}+\mathrm{z}, \quad \mathrm{z} \in \mathrm{~V}
$$

Therefore

$$
\|A y-b\|^{2}=\left\|A x^{\circ}-b+A z\right\|^{2}=\left\|A x^{0}-b\right\|^{2}+2\left(A z, A x^{\circ}-b\right)+\|A z\|^{2}
$$

Since $\left(A z, A x^{\circ}-b\right)$ is zero by hypothesis and $\|A z\|^{2} \geqq 0$, the desired conclusion follows.

Now assume that $\left\|A x^{\circ}-b\right\| \leqq\|A y-b\|$ for all $y$ in $V$ and show that $\left(A x, A x^{\circ}-b\right)=0$ for all $x$ in $V$. Suppose there is an $x$ such that $\left(A x, A x^{\circ}-b\right)=\alpha \neq 0$. Let

$$
v=\frac{-\alpha x}{\|A x\|^{2}}
$$

Then

$$
\begin{aligned}
& \left\|A v+A x^{0}-b\right\|^{2}-\left\|A x^{0}-b\right\|^{2} \\
= & \|A v\|^{2}+2\left(A v, A x^{0}-b\right)=\frac{\alpha^{2}}{\|A x\|^{2}}-\frac{2 \alpha^{2}}{\|A x\|^{2}}=\frac{-\alpha^{2}}{\|A x\|^{2}}<0
\end{aligned}
$$

This contradiction proves the lemma.
(2.10) THEOREM (Pentose): Consider the equation $A x=b$. Let $x^{\circ}=A^{\#} \mathrm{~b}$ and $\mathrm{x} \neq \mathrm{x}^{\circ}$. Then either
(a)

$$
\|A x-b\|>\left\|A x^{\circ}-b\right\| ; \quad \text { or }
$$

(b)

$$
\|A x-D\|=\left\|A x^{\circ}-b\right\| \quad \text { and }\|x\|>\left\|x^{\circ}\right\|
$$

Furthermore the minimum value of $\|A x-b\|$ is
(c)

$$
\left\|A x^{0}-b\right\|^{2}=\|b\|^{2}-\left\|A x^{0}\right\|^{2}=\|b\|_{I-A A^{\#}}^{2}
$$

In words, $\mathrm{x}^{\circ}$ is the smallest (in the usual norm) vector which gives the least square error.

Proof: (a) We must show first that ( $A x, A x^{\circ}-b$ ) $=0$. In fact,

$$
\left(A x, A x^{\circ}-b\right)=x^{\prime} A^{\prime} A A^{\#} b-x^{\prime} A^{\prime} b
$$

and by axiom (iv)

$$
\left(A x, A x^{\circ}-b\right)=x^{\prime} A^{\prime} A^{\#^{\prime}} A^{\prime} b-x^{\prime} A^{\prime} b,
$$

which is seen to be zero by equation (2.3) and axiom (i).
By Lemma (2.9) this proves

$$
\|A x-b\| \geqq\left\|A x^{\circ}-b\right\| .
$$

(b) Suppose $\|A x-b\|=\left\|A x^{\circ}-b\right\|$, and let us write $x=x^{\circ}+v$, where $v \neq 0$. Then $\|A x-b\|^{2}-\left\|A x^{0}-b\right\|^{2}=2\left(A x^{\circ}-b, A v\right)+\|A v\|^{2}=0$, but it has been shown above that $\left(\mathrm{Ax}^{\circ}-\mathrm{b}, \mathrm{Av}\right)=0$. Therefore $\mathrm{Av}=0$ so that $v$ is in the kernel of $A$,

$$
\begin{aligned}
\left\|x^{0}\right\|^{2} & =\left\|x-\left(x-x^{0}\right)\right\|^{2}=\|x\|^{2}+\left\|x-x^{0}\right\|^{2}-2\left(x, x-x^{o}\right) \\
& =\|x\|^{2}+\|v\|^{2}-2 v^{\prime} A^{\#} b-2 v^{\prime} v \\
& =\|x\|^{2}-\|v\|^{2}-2 b^{\prime} A^{\#^{\prime}} v .
\end{aligned}
$$

But, by axioms (ii) and (iii)

$$
A^{\#^{\prime}} \equiv A^{\#^{\prime}} A^{\prime} A^{\#^{\prime}} v=A^{\#^{\prime}} A^{\#} a v=0 .
$$

Thus

$$
\|x\|^{2}=\left\|x^{0}\right\|^{2} b\|v\|^{2}>\left\|x^{0}\right\|^{2}
$$

which proves part (b) of the theorem.
(c) By direct computation, we have

$$
\left\|A x^{\circ}-b\right\|^{2}=\left\|\left(I-A A^{\#}\right) b\right\|^{2}=\|b\|^{2}\left(I-A A^{\#}\right)^{\prime}\left(I-A A^{\#}\right)^{\cdot}
$$

But $\left(I-A A^{\#}\right)^{\prime}=I-\left(A A^{\#}\right)^{\prime}=I-A A^{\#}$ by axiom (iv). Moreover, (I $-A A^{\#}$ ) is idempotent by virtue of axiom (i). Hence

$$
\left\|A x^{0}-b\right\|^{2}=\|b\|_{I-A A^{\#}}^{2}=\|b\|^{2}-\left\|A x^{0}\right\|^{2}
$$

This theorem could have been stated as a problem in minimizing the quadratic form $\|A x-b\|^{2}$. Indeed, we can extend the theorem as follows:
(2.11) COROLLARY. Consider $\|A x-b\|_{P}^{2}$, where $P$ is symmetric, non-negative definite. Let $x^{0}=\left(A^{\prime} P A\right)^{\#} A^{\prime} P b$. Again we have aiternatives ( $a$ ) or ( $b$ ) of Theorem (1.10), while the minimum value of $\|A x-b\|_{P}^{2}$ is

$$
\left\|A x^{0}-b\right\|_{P}^{2}=\|b\|_{P-P A\left(A^{\prime} P A\right)^{2} A^{t} P}^{2}
$$

Proof: Since $P$ is non-negative definite symmetric there exists a symmetric matrix $Q=P^{1 / 2}$ such that $P=Q^{2}=\left(P^{1 / 2}\right)^{2}$. This allows us to write the quadratic form as $\left\|P^{1 / 2} A x-P^{1 / 2}\right\|^{2}$. Hence in view of the uniqueness theorem (2.9) all we have to show is that

$$
\left(A^{\prime} P\right)^{\#} A^{s} P^{1 / 2}=\left(P^{1 / 2} A\right)^{\#} .
$$

This is done by verifying directly that the left-hand side satisfies the axioms (i) = (iv). Q.E.D.

Theorem (2.10) and its corollary have the following simple geometric interpretation: $A X^{\circ}$ is the orthogonal projection (relative to $P$ ) of $b$ on the range of $A$. $x^{0}$ itself is the shortest vector whose image under $A$ is this projection.

It is worth noting also the following: If the minimization problem is solved formally by equating derivatives to zero, the resulting formulae are rigorously correct if inverses (which may not exist) are replaced by the Penrose inverses.

A further extension of these results can be made to sums of quadratic forms.

$$
\begin{aligned}
& \text { (2.12) COROLLARY. Consider } Q(x)=\sum_{i=1}^{m}\left\|A_{i} x-b_{i}\right\|_{P_{i}}^{2} \cdot \text { Let } \\
& x^{0}=\left(\sum_{i=1}^{m} A_{i}^{:} P_{i} A_{i}\right)^{\#}\left(\sum_{i=1}^{m} A_{i}^{\prime} P_{i} b_{i}\right) \text { and } x \neq x^{0} \cdot \text { Then either }
\end{aligned}
$$

(a) $Q\left(x^{\circ}\right)<Q(x) \quad$ or
(b) $\quad Q\left(x^{0}\right)=Q(x)$ and $\left\|x^{0}\right\|<\|x\|$.

Moreover,
(c) $\quad Q\left(x^{o}\right)=\sum_{i=1}^{m}\left\|b_{i}\right\|_{P_{i}}^{2}-\left\|A_{i} x^{o}\right\|_{P_{i}}^{2}$.

Through this proof we assume that the $A_{i}$ and $P_{i}$ are $n \times n$ matrices and the $b_{i}$ are $n$ vectors. There is no restriction since we may assume the addition of zero rows and columns where necessary.

Proof: This may be established directly by defining the mn dimensional vector $b$, the $m n \times n$ matrix $A$, and the $m n \times m n$ matrix $P_{i}$

$$
\mathrm{b}=\left[\begin{array}{c}
\mathrm{b}_{1} \\
\cdot \\
\cdot \\
\cdot \\
b_{m}
\end{array}\right], \quad \mathrm{A}=\left[\begin{array}{c}
A_{1} \\
\cdot \\
\cdot \\
\cdot \\
A_{m}
\end{array}\right], \quad \mathrm{P}=\left[\begin{array}{c}
\mathrm{P}_{1} \\
\cdot \\
\cdot \\
\\
0 \\
\\
\\
\\
\\
\\
\\
\\
\\
P_{m}
\end{array}\right]
$$

The the minimization of $Q(x)$ is the same as the minimization of $\|A x-b\|_{P}^{2}$, so that (2.12) follows from (2.11).
(2.13) COROLARY. Consider the quadratic form $\|\mathrm{Ax}-\mathrm{b}\|_{\mathrm{P}}^{2}$. Let

$$
-x^{\circ}=\left\{\left(I-A^{\#} A\right)\left[\left(I-A^{\#} A\right) R\left(I-A^{\#} A\right)\right]^{\#}\left(I-A^{\#} A\right) R-I\right\}\left(A^{\prime} P A\right)^{\#} A^{x} P b
$$

and $x \neq x^{\circ}$. Then either
(a)

$$
\begin{aligned}
& \|A x-b\|_{P}>\left\|A x^{\circ}-b\right\|_{P} \text { or } \\
& \|A x-b\|_{P}=\left\|A x^{\circ}-b\right\|_{P} \text { and }\|x\|_{R}>\left\|x^{o}\right\|_{R}
\end{aligned}
$$

(b)

The minimum value of the form is, of course, still
(c)

$$
\left\|A x^{\circ}-b\right\|_{P}^{2}-P A\left(A^{\prime} P A\right)^{\#} A^{\prime} P
$$

Proof: First we show that the most general vector which will give the minimum value of $\|A x-b\|_{p}$ is
(\#\#)

$$
\mathrm{x}^{I}=\left(\mathrm{A}^{3} \mathrm{PA}\right)^{\#} \mathrm{~A}^{1} \mathrm{~Pb}+\left(I-A^{\#} \mathrm{~A}\right) \mathrm{V}
$$

where $v$ is any vector. That $x^{1}$ gives the minimum value follows from Corollary (2.11) and the fact that (axiom (i)) $A\left(I-A^{\#} A\right)=0$. To show that the form (\#\#) encompasses all vectors which minimize $\|A x-b\|_{P}^{2}$ it is sufficient to note: (i) All vectors $y$ such that $x^{\circ}+y$ minimizes $\|A x-b\|_{D}$ are in the kernel of $A$; this was shown in the proof of Theorem 2.10. (ii) All vectors $x$ in the kernel of $A$ can be represented as (I - $\left.A^{\#} A\right) x$, fortiori as $\left(I-A^{\#} A\right) v$, where $v$ is an arbitrary vector. These observations simplify the original problem to minimization of $\left\|\left(A^{\prime} P A\right)^{\#} A^{\prime} P b+\left(I-A^{\#} A\right) V\right\|_{R}$ with respect to $v$, which can be done by Corollary (1.11) to give the desired result.
(2.14) LEMMA. (Generalization of Lemma (2.4)). Let $B(t)$ be an $m \times n$ matrix whose elements are continuous in $t$ in the interval [0, $T$ ]. Then

$$
B(t)-B(t)\left[\int_{0}^{T} B^{\prime}(\tau) B(\tau) d \tau\right]^{\#} \int_{0}^{T} B^{\prime}(\tau) B(\tau) d \tau=0
$$

for all $t$ in $[0, T]$.
Proof: Let $D(t)$ denote the matrix difference above. Using axiom (i), we find that

$$
\int_{0}^{T} D^{\prime}(t) D(t) d t=0
$$

Hence

$$
\int_{0}^{T}\|D(t) x\|^{2} d t=0
$$

for all fixed $x$, which (remembering that $D(t)$ is continuous in $t$ ) implies that $D(t)=0, \quad 0 \leqq t \leqq T$.
$B(t)$ may of course have piecewise constant elements and the lemma can be applied to finite sums. Note that the matrices in such a sequence need not have a constant number of rows.

An examination of (2.10) shows that in order to obtain the minimum error property only axioms (i) and (iv) are required. (ii) and (iii) then assure that the norm of $x^{\circ}$ is minimal; in control theory where the norm of $\mathrm{x}^{0}$ represents the required control energy, this is a desirable property. In general, if one of the axioms is dropped, the pseudo-inverse will not be unique. For instance, let

$$
A=\left[\begin{array}{ll}
0 & 1 \\
0 & 1
\end{array}\right]
$$

then

$$
A_{1}=\left[\begin{array}{ll}
0 & 0 \\
0 & 1
\end{array}\right]
$$

satisfies (i), (ii), and (iii), but not (iv).

$$
A_{2}=\left[\begin{array}{cc}
1 & 1 \\
1 / 2 & 1 / 2
\end{array}\right]
$$

satisfies (i), (ii), and (iv) but not (iii),

$$
A_{3}=\left[\begin{array}{cc}
1 & -1 \\
1 / 2 & 1 / 2
\end{array}\right]
$$

satisfies (i), (iii), and (iv) but not (ii), and

$$
Z=\left[\begin{array}{ll}
0 & 0 \\
0 & 0
\end{array}\right]
$$

satisfies (ii), (iii), and (iv) but not (i), whereas

$$
A^{\#}=\left[\begin{array}{cc}
0 & 0 \\
1 / 2 & 1 / 2
\end{array}\right]
$$

is the Pentose inverse.

The following corollary to Theorem (2.10) gives an alternative characterization of the Pentose inverse.
(2.15) Let $A^{\dagger} \neq A^{\#}$ be any matrix satisfying (i). Then $\left\|A^{\dagger}\right\|>\left\|A^{\#}\right\|$ where $\|M\|$ is defined as $\left(\text { trace } M^{\prime} M\right)^{\frac{1}{2}}=\left(\sum_{i, j} m_{i j}^{2}\right)^{\frac{1}{2}}$.

Proof: To prove this, it suffices to note that the matrix equation

$$
\mathrm{AXA}=\mathrm{A}
$$

may be interpreted as a vector equation in the elements of the matrix $X$. Since pseudo-inverses always exist, this equation always has a solution. By Theorem (2.10), $A^{\#}$ is the "smallest" solution in the sense of the norm defined above.

A further characterization is that given by Greville [4]. Here $A^{\#}$ is defined as the unique matrix satisfying (i) and having its row space and column space the same as $A^{\prime}$.

This characterization may be established by noting that $A^{\#}$ and $A^{\prime}$ have the same kernel.

If $A^{T} x=0$, then

$$
A^{\#} x=A^{\#} A A^{\#} x=A^{\#} A^{\#^{\prime}} A^{\prime} x=0,
$$

and if $A^{\#} X=0$, then

$$
A^{\prime} x=A^{\prime} A^{\#^{\prime}} A^{\prime} x=A^{\prime} A A^{\#}=0
$$

One of the most fruitful characterizations of the pseudo-inverse arises from a consideration of its mapping properties. Let $A$ map the space $V$ into the space $W$. Denote the range of $A$ by $R(A)$, the kernel of $A$ by $K(A)$, the orthogonal complement of $K(A)$ by $C K(A)$, and the orthogonal complement of $R(A)$ by $C R(A)$. Then the requirement that the
error $\left\|A A^{\#} \mathrm{~b}-\mathrm{b}\right\|$ is minimum is equivalent to saying that $A^{\#}$ is the inverse of $A$ on $R(A)$ and maps $C R(A)$ into $K(A)$. Clearly then if we want $A^{\#} \mathrm{~b}$ to be of minimum length, we must have that $A^{\#}$ maps $\mathrm{CR}(\mathrm{A})$ into zero.

We obtain the following two formulae which are equivalent to the four axioms:

$$
\begin{aligned}
\text { ia) } & A^{\#} A A^{\prime} & =A^{\prime} \\
\text { ii b) } & A A^{\#} A^{\#} & =A^{\# \prime} .
\end{aligned}
$$

Because we have concentrated so much on the lack of uniqueness of matrices which give the solution of the minimum error problem, we should point out that there is only one such matrix if either $A^{\prime} A$ or $A A^{\prime}$ is nonsingular.

We conclude with two formulae for the pseudo-inverse,
(2.16) PROPOSITION. Let $\mathrm{B}^{\dagger}$ be any matrix satisfying (i), then $A^{\#}=A^{r}\left(A A^{\prime}\right)^{\dagger} A\left(A^{\prime} A\right)^{\dagger} A^{\prime}$.

This is easily proved using ia) and ia).
The following is an iterative formula; we wish to find $[\mathrm{A} a]^{\#}$ where a is a vector. Unfortunately we must distinguish two cases. When a $\oint R(A)$, (rank $\left.[A a]>\operatorname{rank} A,\left(I-A A^{\#}\right) a \neq n\right)$.

$$
\left[\begin{array}{ll}
A & a
\end{array}\right]^{\#}=\left[\begin{array}{l}
A^{\#}\left(I-\frac{a a^{\prime}\left(I-A A^{\#}\right)}{a^{\prime}\left(I-A A^{\#}\right) a}\right.  \tag{2.17}\\
\frac{a^{\prime}\left(I-A A^{\#}\right)}{a^{\prime}\left(I-A A^{\#}\right) a}
\end{array}\right] .
$$

When $\left(I-A A^{\#}\right) a=0$

$$
\left[\begin{array}{ll}
A & a
\end{array}\right]=\left[\begin{array}{l}
A^{\#}\left(I-\frac{a a^{\prime} a^{\#^{\prime}} A^{\#}}{1+a^{\prime} A^{\dagger^{\prime}} A^{\dagger} a}\right. \\
\frac{a^{\prime} A^{\#^{\prime}} A^{\#}}{1+a^{\prime} A^{\#^{\prime}} A^{\#} a}
\end{array}\right]
$$

We must assume that $a$ is a vector only in the sense that the number of separate cases appears to be the number of possible ranks of (I - $A A^{\#}$ )a.

If minimum error is the only desideratum and minumum length of the fitting vector can be ignored, (2.17) can always be used with set equal to zero when the denominator is zero.

$$
\frac{1}{a^{\prime}\left(I-A A^{\#}\right) a}
$$

3. Computation: Several proposals for computing $A^{\#}$ have been made in the literature. These algorithms are often very inefficient from the point of view of numerical computation (though they might be useful in getting exact answers in simple cases). For instance, in establishing the existence of the Penrose inverse for a symmetric matrix $S$ we used the existence of a diagonalizing transformation, but this involved finding all the eigenvales of $S$ which is a more difficult problem mathematically then computation of $S^{\#}$. Moreover, the algorithms proposed so far do not simplify when $A^{-1}$ exists, where.as that given here does.

A description and proof of the algorithm follow.

Phase 1. Compute $A A^{\prime}$ or $A^{\prime} A$, whichever has smaller dimension. Call the resultant $n \times n$, symmetric, nonnegative definite matrix $B$. It will suffice to compute $B^{\#}$ because then one can write

$$
\begin{aligned}
& A^{\#}=\left(A^{\prime} A\right)^{\#} A^{\prime} \quad \text { or } \\
& A^{\#}=\left(A^{\prime}\left(A A^{\prime}\right)^{\#} .\right.
\end{aligned}
$$

Phase 2. Compute a nonsingular matrix $T_{1}$ such that $T_{1} B_{1}^{\prime}=E$ is a diagonal matrix with elements zero or one.

The matrix $T_{1}$ is computed iteratively in at most $n$ steps by a modification of the gaussian elimination procedure.

As a numerical example, we shall carry through the reduction of the matrix.

$$
B=\left[\begin{array}{rrrr}
2 & 1 & : & -2 \\
1 & 25 & -8 & 6 \\
-2 & -8 & 4 & 0 \\
-2 & 6 & 0 & 4
\end{array}\right]
$$

Let $T_{1}{ }^{(0)}=I$ and $B^{(0)}=B^{(1)}=B$.
Step 1. Select the largest diagonal element (IDE) of $B^{(1)}$ and divide by its square root the corresponding row and column of $B^{(1)}$ and $T_{1}{ }^{(0)}$.

In the example, the IDE of $\mathrm{B}^{(1)}$ is 25 and occurs in the 2nd row and column. Thus

$$
B^{(2)}=\left[\begin{array}{cccc}
2 & 1 / 5 & -2 & -2 \\
1 / 5 & 1 & -8 / 5 & 6 / 5 \\
-2 & -8 / 5 & 4 & 0 \\
-2 & 6 / 5 & 0 & 4
\end{array}\right] \mathrm{T}_{1}^{(1)}=\left[\begin{array}{cccc}
1 & 0 & 0 & 0 \\
0 & 1 / 5 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{array}\right]
$$

Having completed Step 1 , we obtain

$$
\begin{equation*}
\mathrm{T}_{1}^{(1)} \mathrm{BT}_{1}(1)^{\prime}=\mathrm{B}^{(2)} \tag{3.1}
\end{equation*}
$$

Step 2. Let $k_{1}$ be the row and column in which the IDE of $B^{(1)}$ occurred. Multiply the $k_{1}$-th row of $B^{(2)}$ resp. $T_{1}{ }^{(1)}$ by the $i k_{1}-t h$ element of $B^{(2)}$ and substract the resulting row vector from the i-th row of $B^{(2)}$ resp. $T_{1}{ }^{(1)}$. Do this for all $i \neq k_{1}$. Then set all the elements $b_{i_{1}}^{(2)} j$ equal to zero, except $b_{k_{1}}^{(2)} k_{1}=1$.

$$
B_{B}^{(3)}=\left[\begin{array}{cccc}
49 / 25 & 0 & -42 / 25 & -56 / 25 \\
0 & 1 & 0 & 0 \\
-42 / 25 & 0 & 36 / 25 & 48 / 25 \\
-56 / 25 & 0 & 48 / 25 & 64 / 25
\end{array}\right], \quad T_{I}^{(2)}=\left[\begin{array}{cccc}
1 & -1 / 25 & 0 & 1 \\
0 & 1 / 5 & 0 & 0 \\
0 & 8 / 25 & 1 & 0 \\
0 & -6 / 25 & 0 & 1
\end{array}\right] .
$$

We have now the identity

$$
\begin{equation*}
\mathrm{T}_{1}^{(2)} \mathrm{BT}_{1}(2)^{i}=\mathrm{B}^{(3)} \tag{3.2}
\end{equation*}
$$

Step 3. Apply Step 1 to $B_{B}^{(3)}$ disregarding in search for the largest diagonal element the row $k_{1}$ which occurred in steps l-2. Now $k_{2}=4$. The result is:

$$
B^{(4)}=\left[\begin{array}{cccc}
49 / 25 & 0 & -42 / 25 & -7 / 5 \\
0 & 1 & 0 & 0 \\
-42 / 25 & 0 & 36 / 35 & 6 / 5 \\
-7 / 5 & 0 & 6 / 5 & 1
\end{array}\right], \quad T_{1}^{(3)}=\left[\begin{array}{cccc}
1 & -1 / 25 & 0 & 0 \\
0 & 1 / 5 & 0 & 0 \\
0 & 8 / 25 & 1 & 0 \\
0 & -3 / 20 & 5 / 8
\end{array}\right] .
$$

Step 4. Apply Step 2 to $B^{(4)}$. Then

$$
B^{(5)}=\left[\begin{array}{cccc}
0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1
\end{array}\right], \quad T_{1}(4)=\left[\begin{array}{cccc}
1 & -1 / 4 & 0 & -7 / 8 \\
0 & 1 / 5 & 0 & 0 \\
0 & 1 / 2 & 1 & -3 / 4 \\
0 & -3 / 20 & 0 & 5 / 8
\end{array}\right]
$$

which completes the reduction in the example considered.
At each state of the iteration we have the identity

If the matrix

$$
\begin{equation*}
B^{(2 q+1)}=E \tag{3.4}
\end{equation*}
$$

for the first time, then
$\operatorname{rank} B=0$.

In the example, $q=2$.
This algoritnm is a slight modification of one given by Ref. [3].
Phase 3A. If $B^{(2 q+1)}=I=$ unit matrix, then $B$ is invertible and hence

$$
\begin{align*}
B & =\left[\mathrm{T}_{1}^{(2 q)}\right]^{-1}\left[\mathrm{~T}_{1}(2 q)^{)^{-1}}\right]^{-1} \\
B^{\dagger} & ={B^{-1}=T_{1}}_{(2 q)^{\prime}}^{T_{1}}(2 q) \tag{3.6}
\end{align*}
$$

Phase 3B. Suppose $B^{(2 q+I)}=E \neq I$. Then there exists a permutation (orthogonal) matrix $P$ such that

$$
\bar{E}=P T B T^{\prime} P^{\prime}=P E P^{\prime}=\left[\begin{array}{cc}
I_{q} & 0 \\
0 & 0
\end{array}\right]
$$

That is, the first $q$ elements on the diagonal are one and all other elements are zero. Note that $\mathrm{P}^{-1}=\mathrm{P}^{\mathrm{p}}$.

Further we have

$$
(3.7) \quad \bar{E}=P T P^{\mathbf{t}} P B P^{\mathbf{i}} P \mathrm{I}^{\mathbf{\prime}} \mathrm{P}^{\mathbf{y}}
$$

so that $\bar{T}=P I P$ : is the matrix given by the Andree algorithm for the matrix $\overline{\mathrm{B}}=\mathrm{PBP}{ }^{\mathbf{\prime}}$.

The method of construction of $T$ given above in the Andrée algorithm assures us that $\bar{T}$ has the form

$$
\overline{\mathrm{T}}=\left[\begin{array}{cc}
\overline{\mathrm{V}} & 0 \\
\overline{\mathrm{~W}} & I_{n-\mathrm{q}}
\end{array}\right],
$$

where $\overline{\mathrm{V}}$ is a nonsingular $\mathrm{q} \times \mathrm{q}$ matrix.
Partitioning $\vec{B}$ in the same manner we write

$$
\overline{\mathrm{B}}=\left[\begin{array}{ll}
\overline{\mathrm{B}}_{11} & \overline{\mathrm{~B}}_{12} \\
\overline{\mathrm{~B}}_{12} & \overline{\mathrm{~B}}_{22}
\end{array}\right]
$$

where $\overline{\mathrm{B}}_{\mathrm{Il}}$ is nonsingular.

Substituting (3.8-9) into the identity $\overline{\mathrm{TB}} \overline{\mathrm{T}}^{\prime}=\vec{E}$, we obtain the relations
(3.10)

$$
\overrightarrow{\mathrm{V}} \overrightarrow{\mathrm{~B}}_{11} \overline{\mathrm{~V}}^{\mathrm{v}}=\mathrm{I}_{\mathrm{q}},
$$

$$
\begin{gathered}
\overline{\mathrm{V}} \overline{\mathrm{~B}}_{11} \overline{\mathrm{~W}}^{\mathrm{r}}+\overrightarrow{\mathrm{V} \overline{\mathrm{~B}}_{12}=0} \\
\left(\overline{\mathrm{~W}}_{11}+\overline{\mathrm{B}}_{12}\right) \overline{\mathrm{W}}^{\%}+{\bar{W} \overline{\mathrm{~B}}_{12}+\overline{\mathrm{B}}_{22}=0}^{2}
\end{gathered}
$$

These equalities imply that

$$
\overline{\mathrm{B}}=\left[\begin{array}{cc}
\mathrm{I}_{\mathrm{q}} & 0 \\
-\overline{\mathrm{W}} & 0
\end{array}\right]\left[\begin{array}{cc}
\mathrm{B}_{11} & 0 \\
0 & 0
\end{array}\right]\left[\begin{array}{cc}
\mathrm{I}_{\mathrm{q}} & -\mathrm{W}^{\mathrm{t}} \\
0 & 0
\end{array}\right]
$$

and
(3.12) $\quad C=\left[\begin{array}{ll}D & 0 \\ 0 & 0\end{array}\right]=\left[\begin{array}{cc}I_{q} & -\bar{W}^{7} \\ 0 & 0\end{array}\right]\left[\begin{array}{cc}I_{q} & 0 \\ \bar{B}\left[\begin{array}{c} \\ -\bar{W}\end{array} 0\right.\end{array}\right]$
where $D=\left(I_{q}+\bar{W} \cdot \bar{W}\right) B_{11}\left(I_{q}+\bar{W}^{\prime} \cdot \bar{W}\right)$.
Because the rank of the sum of two nonnegative definite, symmetric matrices cannot be less than the greater of two ranks, ( $I q+\bar{W}^{\prime} \bar{W}$ ) and $D$ are of rank $q$, hence nonsingular.

Then
(3.13) $\quad B^{\#}=\left[\begin{array}{cc}I & 0 \\ -\bar{W} & 0\end{array}\right]\left[\begin{array}{cc}D^{-1} & 0 \\ 0 & 0\end{array}\right]\left[\begin{array}{cc}I & -\bar{W} \cdot \\ 0 & 0\end{array}\right]$
as can be verified by checking the four axioms of Penrose.
And the fact that
(3.14)

$$
\mathrm{B}^{\#}=\mathrm{P}^{s} \overline{\mathrm{~B}}^{\#} \mathrm{P}
$$

follows easily.
The steps followed in the machine are simplified in that the only matrices required are $\bar{W}$ and $\bar{D}$. Moreover the permutation matrix $P$ is not actually computed.

Step 1. Let $U$ be the following matrix

$$
\text { If } \begin{aligned}
i \neq j, \quad u_{i j} & =\left\{\begin{array}{ccc}
-t_{i j} & \text { if } & e_{i i} \\
=0 \\
0 & \text { if } & e_{i i}
\end{array}=1\right. \\
u_{i i} & =\left\{\begin{array}{cc}
0 & \text { if } \\
e_{i i} & =0 \\
1 & \text { if }
\end{array} e_{i i}=1\right.
\end{aligned}
$$

In the notation used previously $U$ can be written as

$$
U=P^{\prime} \bar{U}=P^{\prime}\left[\begin{array}{cc}
I_{q} & 0 \\
-\bar{W} & 0
\end{array}\right] P
$$

In the example

$$
U=\left[\begin{array}{cccc}
0 & 1 / 1 & 0 & -7 / 8 \\
0 & 1 & 0 & 0 \\
0 & -1 / 2 & 0 & 3 / 4 \\
0 & 0 & 0 & 1
\end{array}\right]
$$

Step 2. Compute

$$
U^{\prime} \mathrm{BU}=\mathrm{C} .
$$

## The result is

$$
\left[\begin{array}{cccc}
0 & 0 & 0 & 0 \\
0 & 35.125 & 0 & -4.5625 \\
0 & 0 & 0 & 0 \\
0 & -4.5625 & 0 & 13.90625
\end{array}\right]
$$

which can be written as $\mathrm{P}^{\mathbf{i}} \overline{\mathrm{C}} \mathrm{P}$.
After deleting the rows and columns corresponding to $e_{i i}=0$ we have the same nonsingular $q \times q$ matrix which we have previously called D.

Step 3. Compute $D^{-1}$ by means of the Andrée algorithm. As in Phase 3A, we have

$$
D^{-1}=T \cdot T_{2} T_{2}
$$

Step 4. Compute

$$
\bar{B}^{\#}=\bar{U}\left[\begin{array}{cc}
D^{-1} & 0 \\
0 & 0
\end{array}\right] \bar{U}^{\prime}
$$

This completes Phase 3B.
Phase 4. We now compute $A^{\#}$ using either $A^{\#}=B^{\#} A^{\prime}$ or $A^{\#}=A^{\prime} B^{\#}$.
A flow chart appears as Fig. I; if a plus sign is used in column 16 of the PSE U O instruction, implying that the argument matrix is already nonnegative definite, then the symmetrization process is not executed.

Remark: This algorithm has two very important features:
a) it takes much less time if $A$ is invertible.
b) $A^{\#}$ is a discontinuous function of $A$ because it depends critically on the rank of $A$. The Andrée algorithm and a norm error control newly developed allow to some extent control of the "apparent" rank of $A$. This is done as follows.

The algorithm reduction is carried out until the largest diagonal element of a non-reduced row is less than $\epsilon$, where $\epsilon$ is the product of the largest diagonal element and a number Pl of PIZER. (Pl is $10^{-2}$ unless the PIZER instruction is used.) Then

$$
\rho_{i}=\frac{\left\|B_{B}^{\#} B^{2}-B\right\|}{\|B\|}+\frac{\left\|B^{\#} B_{B}^{\#}-B^{\#}\right\|}{\left\|B^{\#}\right\|}\left(P_{2}^{r_{i}}\right)
$$

is computed and the test $\rho_{i} \leqq \rho_{i-1}$ is made where $P_{2}$ is the second number in the PIZER instruction and $i=r_{i}$ is the rank at the $i^{\text {th }}$ iteration. If $\rho_{i} \leqq \rho_{i-1}$ and $r_{i}<n$, the reduction is carried out on another unreduced row; this process continues until the above $\rho$ condition is met on $r=n$
'or a diagonal element is negative or zero. With sufficient knowledge of the matrix $B$ one can choose $P_{1}$ so that the $\rho$ computations are kept at a minimum and one can choose $P_{2}$ to control the rank.
4. Numerical Checks: The exact computation of the generalized inverse involves a very large amount of work.
A) The generulized inverse of the matrix of the numerical example of sect. 3 has been computed by hand, using the procedure described in Sect. 3. The result is as follows:

$$
10 B^{\#}=\left[\begin{array}{cccccccc}
0.5509 & 7061 & -0.0110 & 26088 & -0.4691 & 1021 & -0.6328 & 3101 \\
-0.0110 & 26088 & 0.2973 & 7046 & -0.0755 & 12056 & 0.0975 & 64232 \\
-0.4691 & 1021 & -0.0755 & 12056 & 0.4236 & 6934 & 0.5145 & 5108 \\
-0.6328 & 3101 & 0.0975 & 64232 & 0.5145 & 5108 & 0.7511 & 1093
\end{array}\right]
$$

The machine-computed value of the generalized inverse is:

$$
10 B^{\#}=\left[\begin{array}{cccccccc}
0.5509 & 7060 & -0.0110 & 26087 & -0.4691 & 1020 & -0.6328 & 3102 \\
-0.0110 & 26087 & 0.2973 & 7044 & -0.0755 & 12051 & 0.0975 & 64228 \\
-0.4691 & 1020 & -0.0755 & 12051 & 0.4236 & 6933 & 0.5145 & 5110 \\
-0.6328 & 3102 & 0.0975 & 64228 & 0.514 r & 5110 & 0.7511 & 1099
\end{array}\right] .
$$

This computation used iteration.
E. exact generalized inverse of the matrix

$$
A=\left[\begin{array}{cccc}
4 & -1 & -3 & 2 \\
-2 & 5 & -1 & -3 \\
2 & 13 & -9 & -5
\end{array}\right]
$$

was computed in [4]. His result is

$$
A^{\#}=\frac{1}{6,398}\left[\begin{array}{ccc}
608 & -362 & 130 \\
-197 & 212 & 242 \\
-431 & 204 & -250 \\
324 & -255 & -57
\end{array}\right] .
$$

To 10 decimal places, $A^{\#}$ is given by

$$
10^{2} A^{\#}=\left[\begin{array}{rrr}
9.502969678 & -5.658018131 & 2.031884964 \\
-3.079087215 & 3.313535480 & 3.782432010 \\
-6.736480150 & 3.188496405 & -3.907471085 \\
5.064085256 & -3.673022820 & -0.890903407
\end{array}\right]
$$

The rank of $A$ is 2 interated. The machine-computed result is (carrying 8 floating decimal digits):
$\left[\begin{array}{rrrr}9.5029695 & -5.6580181 & 2.0318849 \\ -3.0790870 & 3.3135353 & 3.7824319 \\ -6.7364801 & 3.1884964 & -3.9074711 \\ 5.0640824 & -3.6730227 & -0.89090338\end{array}\right]$.

The error amounts to only about 2-5 parts of the last deciman digit carried by the machine. This is of course exceptionally good. As a check, one finds that the machine result satisfies (i) to about 1 part in $10^{7}$ and (ii) to better than 5 part in $10^{8}$.
C) In addition to this we wanted a check that would show the differences between PSEUO, PSEUO+, and INV RS. This required a positive definite symmetric matrix. For this purpose we selected a matrix introduced by H. Rutishauer and appearing in Newman and Todd, "Evaluation of Matrix Inversion Program"s, SIAM JOURNAL December 1958. This is denoted by $A_{12}=B B^{\prime}$ in the reference, where

$$
b_{i j}=\left\{\begin{array}{cc}
(-1)^{j}\binom{i-1}{j-1} & i \geqq j \\
0 & i<j
\end{array}\right.
$$

$A_{12}^{-1}$ is $B^{\prime} B$ because $B^{2}=I$. The conditioning number $P\left(A_{12}\right)=\max _{i, j}\left|\frac{\lambda_{i}}{\lambda_{j}}\right|$ is asymptotic to $e^{2.77 n}$. Hence assuming the asymptotic formula to be correct for $n$ so small, we choose $n=7$ since this gave $P\left(A_{12}\right) \approx 10^{8}$, which is about the limit that we could expect to handle. We print out $A_{12}$ in Fig. 2, $A_{12}^{-1}=B \geqq B$ in Fig. 3, the difference between $A_{12}^{-1}$ and $A_{12}^{\#}$ as obtained by PSEU O+ in Fig. 4, and the difference between $A_{12}^{-1}$ and $A_{12}^{\#}$ as obtained by PSEUO in Fig. 5 .


Fig. 1


Fig. 1


| 0.70000000 El | -0.20999999E 02 | 0.34999999 E 02 | -0.34999999E 02 | 0.20999999 E 02 | -0.70000000E 01 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 0.09999999 E O1 |  |  |  |  |  |
| $-0.20999999 E \quad 02$ $-0.59999999 E \quad 01$ | 0.91000000 E O2 | -0.17500000E 03 | 0.18900000 E 03 | -0.11900000E 03 | $0.41000000 E 02$ |
| $0.34999999 E 02$ | -0.17500000E 03 | 0.37100000 E 03 | -0.42700000E 03 | 0.28100000 E 03 | -0.09999999E 03 |
| 0.15000000 O2 |  |  |  |  |  |
| $\begin{array}{ll}-0.34999999 E & 02 \\ -0.20000000 E & 02\end{array}$ | $0.18900000{ }^{\text {O }}$ | -0.42700000E 03 | $0.517000000^{03}$ | -0.35399999E 03 | $0.130000000^{\text {OS }}$ |
| 0.20999999 E 0 | -0.11900000E 03 | 0.28100000 E 03 | -0.35399999E 03 | 0.25099999603 | -0.95000000t 02 |
| 0.1500000002 |  |  |  |  |  |
| $\begin{aligned} & =0.70000000 \mathrm{E} \text { OI } \\ & -0.59999999 \mathrm{E} \end{aligned}$ | 0.41000000 E 02 | -0.09999999E O3 | $0.130000000^{03}$ | -0.95000000E O2 | 0.37000000 E O2 |
| 0.09999999 Ol | -0.59999999E 01 | 0.15000000 E 02 | -0.20000000E 02 | 0.15000000 E 02 | -0.59999999E 01 |
| 0.09999999 El |  |  |  |  |  |




## CHAPTER V

THE DECOMPOSITION ROUIINE

1. Statement of the Problem: It is frequently necessary to determine the rank of a matrix, factor it into two components, etc. This subroutine does such steps, without the necessity of writing a separate program around PSEUO.
2. Theory: In considering systems of the form

$$
\dot{\mathrm{x}}=\mathrm{Fx}+\mathrm{u}(\mathrm{t})
$$

where $u($.$) is a random process with a singular covariance matrix W$, it is desirable to transform to a representation

$$
\dot{\mathrm{x}}=\mathrm{Fx}+\mathrm{Gv}(\mathrm{t})
$$

where $\mathrm{v}($.$) has a nonsingular covariance matrix. If we obtain a factoriza-$ tion $W=G^{2} G$ where the number of columns of $G$ is the rank of $W$, then the new representation is obtained with $v$ having a covariance matrix equal to the identity matrix.

Another application occurs in the process of investigating the equations associated with a given transfer function. It becomes evident that one of the fundamental operations is that of decomposing a matrix of rank $r$ into the sum of $r$ Kronecker products of vectors. That is, if $A$ is an $m$ by $n$ matrix of rank $r$ we would like to find the column vectors $\left\{h_{i}\right\}$ and $\left\{g_{i}\right\}$ such that

$$
A=\sum_{i=1}^{r} h_{i} g_{i}^{\prime} \cdot
$$

This can also be written as $A=H G$ where the $i^{\text {th }}$ column of $H$ is $h_{i}$ and the $i^{\text {th }}$ row of $G$ is $g_{i}^{\prime}$. It is in this form that the decomposition is available in the machine.

As described in Chapter I, the decomposition program at present gives a decomposition only of nonnegative definite symmetric matrices. The output provides matrices $S$ and $E$ where $S$ is non-singular and $E$ has $r$ columns. Then if the input matrix is $B$, we have $B=S E E{ }^{\prime} S$ '.

But given this we can generate a decomposition for any matrix A. First form AA' or A'A, whichever is smaller. We shall assume here that we have $A A^{\prime}$. This being nonnegative definite and symmetric, we can use the D E C OM instruction to obtain $S$ and E. Further we can use the PSEUO instruction to obtain $A^{\#}$. Then $A\left(A^{\#} A\right)^{\prime}=A A^{\#} A$ by axiom (i). However, $A\left(A^{\#} A\right)^{\prime}=A A^{\prime} A^{\#^{\prime}}=$ SEE'S'A ${ }^{\#}$ '. Therefore if we take $H=S E$ and $G=\left(A^{\#} S E\right)^{\prime}$ we have the required factorization. If we had used $A^{\prime} A$ to enter DECOM, then the selection $H=A^{\# '} S E \quad G=E \cdot S$ ' would be used.

Notice that there can be no inconsistency about the rank of $A$ as determined by D EC O M provided that if $A^{\prime} A$ and $A A^{\prime}$ have the same dimension then $A A^{\prime}$ is used. The reason for this is that precisely the same operations are performed in both routines. This will be made clearer in Section 3.
3. Computation. Let $B=A A^{\prime}$ or $A^{\prime} A$. This program uses Phase 2 of the PSE U O computation. There a non-singular matrix $T$ is computed such that $T B I^{\prime}=F$ where $F$ is a diagonal matrix with elements 0 or 1 . As indicated in Chapter $V$, the diagonal elements of $B$ in phase 2 are compared with a number $\epsilon$ and the algorithm reduction ceases when $B_{i i}<\epsilon$ or rank $r$ of $B$ is maximal. If the code (column 18 is blank) in the D E C O M operation indicates that there is to be no iteration to compute the best decomposition ("best" as defined below), $\epsilon$ will be the product of $p_{1}$ of PIZER and the maximum diagonal element, and the program will exit with the resultant $T$ and $F$. If colum 18 is a 1 , $\in$ will be the product of the maximum $B_{i i}$ and $p_{1}$ (of the PIZER instruction). After $B$ has been reduced as described above

$$
\rho_{j}=\left\|\left(T_{j}{ }^{\left.-I_{F_{j}}\right)\left(T_{j}\right.}{ }^{-I_{F_{j}}}\right)^{\prime}-B\right\|_{p_{2}}^{r_{j}}
$$

is computed and if this is not the first iteration, is compared against $\rho_{j-I}$ •

If $\rho_{j} \geqq \rho_{j-l}$, computation ceases and the $(j-1) s t \quad T$ and $F$ are the result. If $\rho_{j}<\rho_{j-1}$ another row of $B$ is reduced and the comparison made. This process will continue until the pivotal element is nonpositive or rank is maximal. An explanation of $p_{1}$ and $p_{2}$ is in order at this point. $p_{1}$ and $p_{2}$ are stored as $10^{-2}$ and 1 , but both elements can be changed by the $P$ I ZER instruction. If $p_{1}$ is made smaller most of the reduction will be done the first time through the algorithm and there will be fewer $\rho$ computations thereby saving time. The obvious danger here is that the optimal rank as defined by $\rho$ will be bypassed. $p_{2}$ is a method of changing the rank.

Now to conform to the output notation as it appears in Chap. 1, Fig. 1 let $S=T^{-1}$. Then $B=$ SES'. But $E$ is idempotent and symmetric so $B=S E E^{2} S^{\prime}=S E(S E)^{2}$. But $S E$ does not conform to the requirement that the number of columns of $S E$ equal $r$, the rank of $B$, except trivially when $r$ is maximal and $E$ is the identity. If rank is not maximal, however, we can delete the zero columns of $E$ and call the resulting matrix $E_{r}$ without affecting the product

$$
B=S E_{r}\left(S E_{r}\right)^{\prime}
$$

It is also desirable sometimes to have a matrix $P$ such that

$$
\operatorname{PEP}^{\mathrm{t}}=\left[\begin{array}{ll}
I_{r} & 0 \\
0 & 0_{n}
\end{array}\right]
$$

This is the same as having the first $r$ rows of PEP being linearly independent and also the first $r$ columns.

The output to $D E C O M$ consists of the matrices $S, T, E_{X}, P$, $E$ and the rank $r$ of $B$ in that order.
4. Checks: To illustrate $D E C O M$ we have used the matrix $B$ appearing in Check A of Chapter 5. In Fig. 2 is SE. In Fig. 3 is SE (SE) and in Fig. 4 is TBT'. These results are quite good.

To illustrate the possibilities of the PIZER instruction we ran this same matrix with $p_{1}=1$ and $p_{2}=10^{8}$. This gave a rank of one; $p_{1}=1$ let it pivot only once before iteration began, $p_{2}=10^{8}$ guaranteed that $\rho$ would be larger for rank 2 than for rank one. SE, $\operatorname{SE}(S E)^{\prime}$ and $\mathrm{TBT}^{1}$ appear in Fig. 5, 6, and 7 .


Fig. 1
-

[^3]number uf culumins
paut 11
MATKIX MB $\qquad$
$\qquad$
$\qquad$
$\qquad$
$\qquad$ $-$

## Fig. 6

automatic synthésis prugraí
$-0.22399999 E \quad 01$
$0.29802322 E-07$
$0.19199999 E 01$
0.25000000101
DEC 8,1904 . $-\longrightarrow$

## CHAPIER VI

THE I NVRS PROGRAM

1. Theory. Elementary row operations may be represented as premultiplication by nonsingular matrices, elementary column operations as postmultiplication by nonsingular matrices. Furthermore, the proper matrix may be constructed by performing the desired operation on the identity matrix.

In the André algorithm (see Chapter IV) we can obtain a pseudo inverse of $M$ if we have matrices, $R, C$ such that $R M C=E$ where $E$ is a diagonal matrix containing either zeros or ones. The matrices $R$ and $C$ can be obtained by setting up the equation

## $I M I=M$

reducing the right hand $M$ to $E$ by elementary operations and performing the same row operations on the left hand identity and the same column operations on the right hand identity.

However if $M$ is nonsingular, then $M$ can be reduced to an identity by row (or column) operations alone.

It is precisely this procedure which the ASP INVRS routine (Share subroutine UA INV 1) uses. There is one interesting aspect, namely that the identity matrix and the matrix to be inverted are both kept in the same storage area, or rather that the matrix being inverted is systematically replaced by its inverse.
2. Computation. Column $I$ is searched to find the element $m_{p 1}$ which is largest in absolute value. The remaining elements of row $p$ are each divided by $m_{p l}$; the reciprocal of $p_{p l}$ and the resulting $n$ elements are stored. in eraseable storage in the following order:
1)

$$
\frac{m_{p 2}}{m_{p l}}, \ldots, \frac{m_{p n}}{m_{p l}}, \quad \frac{1}{m_{p l}}
$$

The first row of the matrix replaces row $p$ in the matrix, and a record is kept of this replacement.

At this point, the only elements of interest in the original matrix are those in rows and columns two through $n$. Row 1 (originally row $p$ ) has been kept in sotrage and column one, rows two through $n$ will be zero after reduction.

Remembering then that $i$ and $j$ range from two through $n$, each element $m_{i j}$ of the $(n-1) x(n-1)$ submatrix is replaced by

$$
m_{i j}-m_{i l} \frac{m_{p, j}}{m_{p l}}
$$

This reduced $m_{i j}$ is restored in location $m_{i-1, j-1}$. This process is carried on in row order and, at the end of each row, the quantity $-\frac{m_{i l}}{m_{p l}}$ is computed and stored in the cell that formerly held $m_{i-1, ~} n^{\circ}$

After this process has been completed for rows two through $n$, the $n$ elements l) from eraseable storage are stored in those cells which originally contained the last row.

Now to obtain an idea of what has been done, let us see what the last column of the matrix is now
2)

$$
\frac{-m_{21}}{m_{p l}}, \ldots, \quad \frac{-m_{11}}{m_{p 1}}, \quad \frac{-m_{p+1}}{m_{p l}}, \ldots, \frac{1}{m_{p l}}
$$

But this column is, except for order, the pth column of the identity matrix if we performed on it the row operations which reduced the first column of $M$ to all zeros except for a one in row $p$.

The foregoing process is repeated $n$ times, the only change being that during the initial search for the largest element, the law row is ignored during
the third reduction, etc. Notice that because of the one column shift, the first column contains successively the first, second, etc. columns of the reduced matrix.

Remembering that we worked first on the pth column of the identity matrix, it becomes evident that after all the reductions are completed, the row replacements that were made are examined and the corresponding columns are interchanged. The result is now the inverse of the original matrix.

Except for the destructive computation, this operation is very much like the Andrée algorithm used in PSEUO. There are two very significant differences. One is that PSEUO preserves and takes advantage of the symmetry of the input matrix, hence we might expect to do a little better on nonnegative definite matrices. Secondly, INVRS uses the largestelement in the first column to choose which now shall be used for reduction. In PSEUO, the choice is made from the largest element on the diagonal. Thus INVRS seems to have a slight advantage. This selection of the largest element to use in reduction is a purely numerical point and probably should be made even more sophisticated. For instance in the check problem, all elements in the first column are one, so I NVRS choose the last one it found. But unfortunately the last row was the worst one to choose as the $x_{1}$ equation.

It was actually rather surprising to find that PSEUO did a better job than INVRS. Probably more investigation should be done, but it appears that PSEUO, with PIZER equal to zero, should probably be used to invert nonnegative definite, symmetric matrices.

Care must be taken in using INVRS because the only control in the program is a test to insure that $m_{i j}$ the new pivot element (largest element in the $j^{\text {th }}$ row) is nonzero. If $m_{p j}=0$ INVRS will return with an error statement.
3. Checks. This being a Share subrouiine, we did not feel that a great amount of checking was necessary. However as a comparison we ran the $7 \times 7$ matrix used in check C) for PSEU O. The difference between $A_{12}^{-1}$ and the inverse as computed appears in Fig. 2. Notice that it is element by element, worse than PSEUO + and that the computed inverse was not symmetric.


Fig. 1
(1) 6.1964

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## CHAPIER VII

THE RICCATI EQUATION

1. Description of the Problem: Although ASP is useful for many purposes other than optimization calculations, the majority of the methods are derived from the calculus of variations. We are primarily interested in the so-called "theory of the second variation", which is implemented computationally with the help of the riccati equation. This chapter, much longer than the average, constitutes a short textbook of the second variation together with a detailed treatment of the riccati equation.
2. References: There does not exist at preseint a complete and modern treatment of the theory of the second variation written primarily from the computing point of view. True, the computing aspect is emphasized in the papers of Arthur Bryson (and also in the forthcoming book by Bryson and Y. C. Ho). But Bryson eschews rigor to such an extent that in his exposition the classical methods seem to be far more limited than they really are.

Almost all practical results of the calculus of variations are to be found in the pages which follow. The general theory (which we discuss only very briefly), is required to justify the passage from "linear" to "local" but plays no direct role in the computations.

Good treatments, showing full awareness of the history of the subject, may be found in
[1] J. Radon, "Zum Problem von Lagrange", Hamburger Matematische Einzelschriften, No. 6, 1928.
[2] C. Carathéodory, VARIATIONSRECHNUNG, Teubner, 1935.

Mathematical research concerning quadratic variational problems is by no means finished yet; in fact, this is a field of applied mathematics where functional analysis can provide new insight as well as practical benefits. See especially
[3] M. R. Hestenes, "Applications of the theory of quadratic forms in Hilbert space to the calculus of variations", Pacific J. Math., 1 (1951) 525-581.

Our treatment here is the continuation of our expository article
[4] R. E. Kalman, "The theory of optimal control and the calculus of variations", Chapter 16, MATHEMATICAL OPTIMIZATION TECHNIQUES, edited by R. Bellman, 1963, Univ. of California Press.

See also
[5] R. E. Kalman, "Contributions to the theory of optimal control", Boletin de la Sociedad Matematica Mexicana, 1960, pp. 102-119
which contains a detailed study of the riccati equation. The modern form of the necessary conditions of Euler and Lagrange, the so-called canonical differential equations of the calculus of variations, is given in the wellknown monograph
[6] I. S. Pontryagin, V. G. Boltyanskii, R. V. Gamkrelidze, and E. F. Mishchenko, THE MATHEMATICAL THEORY OF OPTIMAL PROCESSES, Interscience, 1962.
[7] I. M. Gel'fand and S. V. Fomin, CALCULUS OF VARIATIONS, PrenticeHall, 1963.
[8] M. Morse, CALCULUS OF VARIATIONS IN THE LARGE, Am. Math. Soc., 1934.
[9] S. Sternberg, IECTURES ON DIFFERENPIAL GEOMEIRY, Prentice-Hall, 1964.
[10] R. E. Kalman, Y. C. Ho, and K. S. Narendra, "Controllability of linear dynamical systems", Contr. to Differential Eqs., I (1963) 189-213.
[11] C. Carathéodory, "Über die Einteilung der Variations probleme von Lagrange nack Klassen", Comm. Helv. Mat., 2 (1933) l-19.
[12] Re E. Kalman, "When is a Linear Control System Optimal?" Journal of Basic Engineering, March 1964.
3. The General Optimization Problem: Consider the (differential or continuous time) dynamical system.

$$
\begin{equation*}
d x / d t=f(t, x, u(t)) \tag{3.1}
\end{equation*}
$$

where

$$
\begin{aligned}
t= & \text { time }=\text { real number; } \\
x= & \text { state }=\text { real } n \text {-vector } ;\{x\}=\chi \\
u(.)= & \text { input or control function }=\text { continuous } \\
& \text { function }: t \rightarrow u(t)=\text { real m-vector; }\{u(\cdot)\}=\Omega \\
f= & \text { continuous } n \text {-vector function of } t, x, u .
\end{aligned}
$$

The general solution of (3.1) is assumed to exist for all $t$ and is written as

$$
x(t) \equiv \varphi(t ; \tau, x, u(.))
$$

We wish to choose a control function $u($.$) for each initial state x$ in such a way that the functional

$$
\begin{align*}
V(\tau, & x, T ; u(.))=\lambda(T, \varphi(T ; \tau, x, u(.))) \\
& +\int_{t}^{T} L(t, \varphi(t ; \tau, x, u(\cdot)), u(t)) d t \tag{3.2}
\end{align*}
$$

is minimized over $\Omega$ subject to the condition

$$
x(\tau)=x
$$

(3.3)

$$
r_{i}(T, \varphi(T ; \tau, x, u(x))=0 \quad i=0, \ldots, q \leqq n
$$

[The second half of these conditions defines a boundary manifold $-\beta$, which is a subset of $\{(t, x)\}$. Hence ( $3.3 b$ ) can be written also as $(T, x(T)) \in-\mathcal{B}$. If $q=0$, there are no constraints on $x(T)$. Note that $T$ is implicitly determined by (3.3b).] We require also

$$
u(t) \in M, \quad t \in[\tau, T]
$$

We assume that $f, \lambda, L, \gamma_{i}$ are smooth functions. $M$ is often (but by no means always) a convex set and is sometimes aiso assumed to be compact (to express the fact that the control signals are limited in amplitude).
[It makes little difference theoretically but it greatly simplifies our exposition if $T=$ const. This we shall usually but not always assume. Then $r_{i}$ will be independent of $T$, and therefore $A$ will be a subset of X. 1
4. The Canonical Equations: It is well known that this problem is studied with the help of the hamiltonian

$$
\begin{equation*}
H(t, x, y, u(t))=\eta^{*} I(t, x, u(t))+\langle y, f(t, x, u(t))\rangle \tag{4.1}
\end{equation*}
$$

where $\eta^{*}=$ const., $y=$ real n-vector, called costate, and $\langle$,$\rangle denotes$ the scalar product.

According to the "minimum principle" of Pontryagin and his collaborators [6], which is none other but the modern version of the classical "multiplier rule", we have the following necessary condition for optimality:

THEOREM. A control function $u^{*}($.$) and the corresponding trajectory$ $x^{*}($.$) can be optimal only if there exists a costate function y^{*}\left({ }_{0}\right)$ and a constant $\eta^{*}$ such that the differential equations
(4.2)

$$
\left.\begin{array}{l}
d x / d t=H_{y}(t, x, y, u(t)) \\
d y / d t=-H_{x}(t, x, y, u(t))
\end{array}\right\}
$$

are satisfied by $x^{*}($.$) and y^{*}($.$) on t \in[\tau, T], \eta^{*}=0$ or 1 , and the "minimum condition"
(4.3) $H\left(t, x^{*}(t), y^{*}(t), u^{*}(t)\right) \leqq H\left(t, x^{*}(t), y^{*}(t), u\right), t \in[\tau, T]$ holds for any $u \in M$.

Moreover, the solutions $x^{*}($.$) and y^{*}($.$) of (4.3) must satisfy the$ boundary conditions
(4.4)

$$
x(\tau)=x
$$

$$
\langle y, z\rangle=\eta^{*}\left\langle\lambda_{x}, z\right\rangle \quad \text { if } \quad z \in \mathbb{T}_{\mathcal{h}^{\prime}}(T, x(T)),
$$

where $T_{\mathcal{R}}(t, x)=$ tangent manifold of $\left.K\right\}$ at $(t, x)$. Note that

$$
z \in T_{-12}(x) \text { iff } r_{x}^{i}(x(T)) z=0, \quad i=0, \ldots, q \leqq n
$$

Atriple of functions $\{x(),. y(),. u()$.$\} which satisfies Pontryagin's$ theorem quoted above is called a pseudo-extremal. We reserve the superscript * for minimizing curves. It is by no means true that every pseudo-extremal corresponds to a minimizing curve.

A pseudo-extremal is called regular if $\eta^{*}=1$ and if for each $t \in[\tau, t]$ the hamiltonian $H(t, x(t), y(t), u)$ has a unique (absolute)
(1) $H_{p}, H_{x}, \lambda_{x}$, etc. denote partial derivatives $\partial H / \partial p_{i}, \partial \lambda / \partial x_{i}$, etc.
minimum with respect to $u \in M$ (which then must be necessarily equal to $u(t))$. Thus a regular extremal is specified by the pair $\{x(),. y(\cdot)\}$; because $u($.$) is implicitly determined by x($.$) and y($.$) by (4.3) and$ the requirement of regularity.

A pseudo-extremal is called an extremal if it has the following property: If $t^{\prime}, t^{\prime \prime} \in[\tau, T]$ and $\left|t^{\prime \prime}-t^{\prime}\right|$ is sufficiently small there does not exist any input $\hat{u}(.) \neq \bar{u}($.$) such that$

$$
\begin{align*}
\hat{x}\left(t^{\prime \prime}\right)=\varphi\left(t^{\prime \prime} ; t^{\prime}, \bar{x}\left(t^{\prime}\right), \hat{u}(.)\right),  \tag{i}\\
\int_{t^{\prime}}^{t^{\prime \prime}} L(t, \hat{x}(t), \hat{u}(t)) d t<\int_{t^{\prime}}^{t^{\prime \prime}} L(t, \bar{x}(t), \bar{u}(t)) d t
\end{align*}
$$

Note that a pseudo-extremal merely satisfies a certain necessary condition (recall that Pontryagin's equations are the generalization of Euler's equations), while an extremal has the additional property that small pieces of it are actually minimizing curves.

The main theorem of the classical calculus of variations asserts: Every regular pseudo-extremal is an extremal.

By Pontryagin's theorem, the control function $u($.$) is optimal only$ if there is a pair $\{x(),. y()$.$\} which, together with u($.$) , is a pseudo-$ extremal. $x(=)$ is determined directly from $u($.$) using (3.1) (or the first$ canonical equation (4.2a)); $y($.$) then exists for abstract reasons and is$ generally not unique. Therefore having passed from $u($.$) to \{x(),. y(),. u()$.$\} ,$ it is not obvious whether "regularity" is an intrinsic property of the "independent variable" $u($.$) or whether it depends also on the choice of$ $\mathrm{y}($.$) . It can be shown, however, that regularity is well defined independently$ of the possible nonuniqueness of $y($.$) .$

It is not hard to prove [4] that regular pseudo-extremals satisfy the free canonical differential equations

$$
\left\{\begin{array}{l}
d x / d t=H_{y}^{0}(t, x, y)  \tag{4.5}\\
d y / d t=H_{x}^{0}(t, x, y)
\end{array}\right.
$$

together with the boundary conditions (4.4), where we have set

$$
\begin{align*}
H^{0}(t, x, y) & =\min _{u \in m} L(t, x, u)  \tag{4.6}\\
& =\min _{u \in M} L(t, x, u)+\langle y, f(t, x, u)\rangle .
\end{align*}
$$

This result is true if we make suitable smoothness assumptions concerning $H$ and the terminal set -13 . Note that by regularity we have set $\eta^{*}=1$.

Equations (4.5) allow us to determine each regular pseudo-extremal via the solution of a two-point boundary-value problem involving ordinary differential equations. Thus the problem is reduced to examining all solustion of (4.5) which satisfy the appropriate boundary conditions and then picking out those solutions (if there is one) which are actually optimal. Using the canonical equations, we can get only necessary conditions; suficiency can be proved by adducing additional arguments.
5. The hamilton-jacobi equation: Under suitable smoothness assumptions, the family of all optimal trajectories can be determined at the same time by solving the hamilton-jacobi partial differential equation
(5.1)

$$
V_{t}^{O}+H^{O}\left(t, x, V_{x}^{O}\right)=0
$$

subject to the initial condition

$$
\begin{equation*}
v^{o}(t, x)=\lambda(t, x) \text { for }(t, x) \in \mathcal{K}^{3} \tag{5.2}
\end{equation*}
$$

Note the substitution of $V_{x}^{\circ}$ for $y$ in $H^{\circ}$. It follows that

$$
\begin{gather*}
v^{0}(\tau, x)=\min _{u \in \Omega}\left[\lambda(x(T))+\int_{\tau}^{T} L(t, x(t), u(t)) d t\right],  \tag{5.3}\\
(T, x(T)) \in G^{\top}
\end{gather*}
$$

The existence of a function satisfying (5.1-5.2) is a sufficient (but in general not necessary) condition for the existence of optimal trajectories. Moreover, our notations imply that $H$ has a unique minimum with respect to $u$, from which it follows that if $v^{\circ}$ given by (5.3) satisfies (5.2), trajectory $x($.$) starting at x(\tau)=x$ is unique.

By slight abuse of language, let us henceforth call a regular pseudoextremal simply an extremal. (We shall be concerned solely with regular problems, that is, the case where all pseudo-extremals are not regular and hence, by the main theorem of the classical calculus of variations, extremals.)
6. The Accessory Variational Problem. Let $\{\bar{x}(),. y()$.$\} be an extremal, i.e.$ a pair of functions satisfying the canonical differential equations (4.5) with arbritary initial values $\bar{x}_{0}, \bar{y}_{0}$. One can show by standard arguments in the theory of differential equations see, e.g., [2]) that

$$
x(t)-\bar{x}(t)=\xi(t)+o\left(\left\|x_{0}-\bar{x}_{0}\right\|+\left\|y_{0}-\bar{y}_{0}\right\|\right)
$$

and

$$
y(t)-\bar{y}(t)=\eta(t)+o\left(\left\|x_{0}-\bar{x}_{0}\right\|+\left\|y_{0}-\bar{y}_{0}\right\|\right)
$$

where the functions $\boldsymbol{\xi}($.$) and \eta($.$) are determined by$

$$
\left\{\begin{array}{l}
d \xi / d t=\bar{H}_{y x}^{o}(t) \xi+\bar{H}_{y y}^{o}(t) \eta  \tag{6.1}\\
d \eta d t=\bar{H}_{x x}^{o}(t) \xi-\bar{H}_{x y}^{o}(t) \eta
\end{array}\right.
$$

with initial conditions

$$
\xi_{0}=x_{0}-\bar{x}_{0}, \quad \eta_{0}=y_{0}-\bar{y}_{0}
$$

The $\quad \therefore n$ matrix functions $\overrightarrow{\mathrm{H}}_{\mathrm{yx}}^{\circ}(),. \ldots$ are second partial derivatives evalu along the fixed extremal $\{\bar{x}(),. \vec{y}()$.$\} . We assume of course that$ F, L, $\quad \lambda$ are so smooth that $H^{\circ}$ is at least twice continuously differertinl.e.

Let us introduce the abbreviations:
(6.2)

$$
\begin{aligned}
\bar{F}(t) & \left.=\bar{H}_{y x}^{o}(t) \quad \text { (implies } \quad \bar{H}_{x y}^{o}(t)=\bar{F}^{r}(t)\right) \\
\bar{Q}(t) & =\bar{H}_{x x}^{o}(t) \\
\bar{S}(t) & =\lambda_{x x}(t) \\
\bar{G}(t) \bar{G}^{r}(t) & =\bar{H}_{y y}^{o}(t) .
\end{aligned}
$$

The last step is legitimate only if we can show that $\bar{H}_{\mathrm{yy}}^{\mathrm{O}}(\mathrm{t})$ is nonpositive definite. This follows from minimality. (Note that $G$ is not determined uniquely by (6.2), but this fact will be of no interest for us.) The proof is as follows:

Let $c(t, x, y)$ be the argument at the absolute minimum of $H$ with respect to $u \in M$ for given $t, x, y$. Then

$$
H^{0}(t, x, y)=H(t, x, y, c(t, x, y))
$$

We fix $t$ and write $H^{\circ}$ for $H^{0}(t, \bar{x}(t), \bar{y}(t))$, $\bar{x}$ for $\bar{x}(t), \bar{c}$ for $c(t, \bar{x}(t), \bar{y}(t))$, etc.; $y$ will be a free variable. We regard $H^{0}(t, \bar{x}, y)$ as a function of $y$ and expand it by Taylor's theorem around $y=\bar{y}$. Thus for any $y$ we have the identity

$$
H^{o}(t, \bar{x}, y)=\stackrel{H}{H}^{0}+\left\langle\widehat{\bar{H}}_{y}^{o}, y-\bar{y}\right\rangle+\theta\|y-\bar{y}\|_{\bar{H}_{y y}^{o}}^{2} *
$$

where $0 \leqq \theta \leqq 1$ is a scalar dependent on $y$. Since

$$
\bar{H}_{y}^{o}=f(t, \bar{x}, \bar{c}),
$$

it follows that

$$
\begin{aligned}
& \theta(y)\|y-\bar{y}\|_{\overline{H_{y y}^{0}}}^{2}=H^{0}(t, \bar{x}, y)-H(t, \bar{x}, y, \bar{c}) \\
& \leqq 0
\end{aligned}
$$

* The notation $\|x\|_{A}^{2}$ means: quadratic form with respect to the waws tric
matrix A.
by the definition of $H^{\circ}$. Hence $\overline{\mathrm{H}}_{\mathrm{yy}}^{\mathrm{o}}$ is nonpositive definite. (If $\theta(\mathrm{y})=0$, then $\mathrm{H}^{\mathrm{O}}(\mathrm{t}, \overline{\mathrm{x}}, \cdot)$ is linear and so $\|\mathrm{y}-\overline{\mathrm{y}}\|_{\overline{\mathrm{H}}^{\mathrm{o}}}^{2}=0$.) Note the similarity of our proof to the classical arguments assoclated with the weierstrass "E-function".

Equations (6.1) characterize the situation near an extremal. We shall now show that these linearized equations may be regarded also as the canonical equations of a certain variational problem related to the original one. Thus each extremal $\{\bar{x}(),. \bar{y}())$.$\} will give rise to a so-called$ accessory variational problem. To define this accessory problem, we must say what $f, L, \lambda$ are and then we must specify appropriate boundary conditions.

We will use the hat to denote the functions defining the accessory problem, while the Greek letters $\xi, \eta$, $\mu$ will correspond to $x, y$, and $u$ in the original variational problem. We introduce the following definitions

$$
\left\{\begin{array}{l}
\hat{\mathrm{f}}(t, \xi, \mu(t))=\bar{F}(t) \xi+\bar{G}(t) \mu(t)  \tag{6.3}\\
2 \hat{L}(t, \xi, \mu)=\|\xi\|_{\bar{Q}(t)}^{2}+\|\mu\|^{2} \\
2 \lambda(t, \xi)=\|\xi\|_{\bar{S}(t)}^{2} .
\end{array}\right.
$$

Then we find that

$$
\begin{equation*}
2 \hat{H}(t, \xi, \eta, \mu)=\|\xi\|_{\bar{Q}(t)}^{2}+2\langle\eta, \bar{F}(t) \xi+\bar{G}(t) \mu\rangle+\|\mu\|^{2} \tag{6.4}
\end{equation*}
$$

and

$$
\begin{equation*}
\hat{2 \hat{H}^{\circ}}(t, \xi, \eta)=\|\xi\|_{\bar{Q}(t)}^{2}+2\langle\eta, \bar{F}(t) \xi\rangle-\left\|\bar{G}^{\prime}(t) \eta\right\|^{2} . \tag{6.5}
\end{equation*}
$$

It is clear that the accessory variational problem is always regular. (In other words, pseudo-extremals of the original variational problem which are near a regular pseudo-extremal are regular in the first approximation.

Of course, when the given pseudo-extremal of the original variational problem is not regular, we cannot define an accessory problem in the manner indicated because then equations (6.1) have no meaning.)

Using (4.5) we can write down the canonical equations of the accessory extremals:

$$
\begin{equation*}
\mathrm{d} \xi / \mathrm{d} t=\hat{\mathrm{H}}_{\eta}^{0}=\overline{\mathrm{F}}(\mathrm{t}) \xi-\overline{\mathrm{G}}(\mathrm{t}) \overline{\mathrm{G}}^{\prime}(\mathrm{t}) \eta \tag{6.6}
\end{equation*}
$$

$$
\mathrm{d} \eta / \mathrm{d} t=\hat{H}_{\xi}^{\circ}=-\bar{Q}(t) \xi-\overline{\mathrm{F}}^{\mathbf{t}}(\mathrm{t}) \eta
$$

Recalling our abbreviations (6.2), we see that these equations are the same as (6.1). Hence we have a fundamental result which is the basis of the entire theory of the so-called second variation:

THEOREM. The extremals near a (regular) extremal are obtained in the first approximation by solving the accessory variational problem defined by (6.1), (6.2), and (6.3).

Let us now specify the boundary conditions for the accessory problem in the case when $T=f i x e d$. The terminal point must belong to the tangent manifold of 13 , hence

$$
\begin{equation*}
\bar{A}(T) \xi(T)=0 \tag{6.7}
\end{equation*}
$$

where

$$
\bar{A}(T)=\Gamma(\bar{x}(T)), \quad \Gamma=\left(\begin{array}{c}
r_{x}^{I}  \tag{6.8}\\
\cdot \\
\cdot \\
\cdot \\
r_{x}^{2}
\end{array}\right)
$$

(By convention, $\bar{A}(\mathbb{T})=0$ if $q=0$, i.e., there is no constraint on $x(T)$.) On the other hand, (4.4) gives the constraint

$$
\langle\eta(\mathbb{T}), z\rangle=\langle\overline{\mathrm{S}}(\mathbb{T}) \xi(\mathbb{T}), z\rangle
$$

whenever $\bar{A}(T) z=0$; otherwise $\eta(T)$ is a free variable.
7. Digression on the Second Variation: Let us give now a derivation of the accessory variational problem, reminiscent of the way it was done in the nineteenth century. The idea is to expand the functional $V(T, x, T ; \cdot)$ defined by (3.2) into a generalized Taylor series near a given fixed value $\bar{u}($.$) of the function u($.$) . Thus one introduces the$ "first variation"

$$
\delta u(\cdot)=u(\cdot)-\bar{u}(\cdot),
$$

and second variation $\delta^{2} u($.$) , etc. The term the "second variation" asso-$ ciated with $\delta^{2} u($.$) , turn out to be essentially the same as the V$ function associated with (6.3).

Although these imprecise ideas can be given meaning using functional analysis (see particularly [7], where a clear discussion of "strong" and "weak" first variation may be found), this is not especially fruitful from a practical point of view because it requires the apparatus of infinite-dimensional analysis, whereas the main advantage of the classical theory lies in its ability to treat finite-dimensional problems by fairly well-known methods. Since there is monstrous confusion in the engineering literature concerning the use of the purely symbolic first variation $\delta u($.$) (see Bryson, loc. cit. in Sec. 2$ for a careful treatment), it is of some interest to give here a rigorous derivation of the "second variation" using only finite-dimensional analysis. It is emphasized that this derivation is included mainly for cultural reasons, since the analysis of the previous section has already shown why the arcessory variational problem is important in the study of local properties of extremals

We follow Carathéodory's treatment [2, §315-316].
In order to calculate rigorously the derivative of $V$ with respect to $u($.$) , we assume that instead of infinitely many independent variables,$ namely $u(),$.$V depends only on the n$-vector $\rho$. In other words, the family of control functions $\{u()\}=.\Omega$ admitted into competition for the minimum of $V$ will be an $n$-parameter family, indexed by the $n$-vector $\rho$.

This is a very great simplification of the original variational problem; it is justified as follows. By regularity, our extremals \{x(.), $y()$.$\} are at most of a 2 n$-dimensional family since they must satisfy the canonical equations (4.5) and are therefore uniquely determined by $2 n$ initial (or end) conditions in (4.5). But the transversality conditions (4.4) impose precisely $n$ constraints, so that the extremals may be indexed by precisely $\infty^{n}$ numbers, hence by the $n$-vector $\rho$.

To show how $\rho$ is actually determined, suppose the terminal surface has $r \leqq n$ dimensions ( $\mathcal{A}$ is embedded in the $(n+1)$-dimensional space $X \times$ time). Since $-\beta$ is smooth, it can be parametrized by an r-vector

- $\mu$. The tangent space $T \mathcal{S}^{\beta}$ at $(T, x(T))$ is a linear space of dimension $r$; it follows from the transversality conditions that the vector $y(T)$ is the sum of $\lambda_{x}(\mu)$ and a vector $y_{f r e e}$, which lies on a linear manifold of dimension $n-r$. We write $y_{\text {free }}=y(v)$, where $v$ is an $(n-r)$-vector. Then

$$
\begin{equation*}
\rho=(\mu, v) \tag{7.1}
\end{equation*}
$$

(Consult [8, Chapter 2] or [9, Chapter 6] for a rigorous description of the transversality conditions for parametrized terminal surfaces. Unfortunately both authors restrict themselves to the ordinary $(\dot{x}=u(t))$ variational problem.)

$$
\varphi(\cdot ; T, x(T), y(T))
$$

and

$$
\psi(\cdot ; T, x(T), y(T))
$$

are the solution functions of (4.5), we may consider both $\varphi$ and $\psi$ to depend on the $n$-vector parameter $\rho$ by setting

$$
T=T(\mu), \quad x(T)=x(\mu), \quad y(T)=\lambda_{x}(\mu)+y(\nu)
$$

We consider $x(t)=\varphi(t ; \rho), \quad y(t)=\psi(t ; \rho) u(t)=c(t, \varphi(t ; \rho)$, $\psi(t ; \rho))=\omega(t, \rho) ;$ after substitution into $I, H, \lambda, F$, etc., everything becomes a function of $t$ and $\rho$ only. Thus, with a slight abuse of notation

$$
\begin{equation*}
L(t, \rho)=H^{\circ}(t, \varphi, \psi)-\langle\psi, f(t, \varphi, \omega)\rangle \tag{7.2}
\end{equation*}
$$

Differentiating with respect to $\rho$ we get
(7.3)

$$
\left\{\begin{aligned}
L_{\rho} & =H_{x}^{0} \varphi_{\rho}+H_{y}^{0} \psi_{\rho}-\left\langle\psi, f_{x} \varphi_{\rho}+f_{u} \psi_{\rho}\right\rangle-\left\langle\psi_{\rho}, f\right\rangle \\
& =\left(H_{x}^{\circ}+\dot{\psi}\right) \varphi_{\rho}+\left(H_{y}^{O}-f\right) \psi_{\rho}-\left\langle\psi, \varphi_{\rho}\right\rangle_{t} \\
& =-\left\langle\psi, \varphi_{\rho}\right\rangle_{t} .
\end{aligned}\right.
$$

We have used the following substitutions:

$$
\begin{aligned}
& f_{x} \varphi_{\rho}+f_{u} \omega_{\rho}=\dot{\varphi}_{\rho}=\varphi_{\rho t} \\
& f=H_{y}^{o} \\
& \dot{\psi}=-H_{x}^{O}
\end{aligned}
$$

they are true because $\varphi$ and $\psi$ satisfy the canonical equations (4.5).
Along our n-parameter family of extremals the derivative of $V$ is given by

$$
V_{\rho}(\tau, x, T ; \rho)=\frac{\partial}{\partial \rho}\left[\lambda(T(\rho), \varphi(T, \rho))+\int_{\tau}^{T(\rho)} I(t, \rho) d t\right]
$$

Using (7.3) we obtain

$$
V_{\rho}=\lambda_{t}(T) T_{\rho}+\lambda_{x}(T) \varphi_{\rho}(T)+L(T) T_{\rho}+\left.\left\langle\psi(t), \varphi_{\rho}(t)\right\rangle\right|_{T(\rho)} ^{\tau}
$$

Using the transversality condition (4.5) this simplifies to

$$
\begin{equation*}
V_{\rho}=\left[\lambda_{t}(T)+L(T)\right] T_{\rho}+\left\langle\psi(\tau), \varphi_{\rho}(\tau)\right\rangle \tag{7.4}
\end{equation*}
$$

If $T=$ const., this formula shows that the initial value of $y$ must be chosen in such a way that

$$
\begin{aligned}
V_{\rho}(\tau, x, T ; \rho) & =\frac{\partial}{\partial} V_{\rho}^{O}\left(\tau, \varphi_{\rho}(\tau), T\right) \\
& =\left\langle V_{x}^{O}(\tau), \varphi_{\rho}(\tau)\right\rangle ;
\end{aligned}
$$

in other words

$$
\mathrm{y}(\tau) \approx \mathrm{v}_{\mathrm{x}}^{\mathrm{O}}(\tau)
$$

This is a well-known result; the substitution $y \rightarrow V_{x}^{\circ}$ was already encountered in connection with the hamilton-jacobi equation.

The second variation of $V$ is now easily calculated. From (7.3) we have

$$
\begin{aligned}
-I_{\rho \rho} & =\frac{\partial^{2}}{\partial \rho \partial t}\left\langle\psi, \varphi_{\rho}\right\rangle \\
& =\frac{\partial^{2}}{\partial t \partial \rho}\left\langle\psi, \varphi_{\rho}\right\rangle \\
& =\left\langle\dot{\psi}_{\rho}, \varphi_{\rho}\right\rangle+\left\langle\psi_{\rho}, \dot{\varphi}_{\rho}\right\rangle+\left\langle\psi, \varphi_{\rho \rho}\right\rangle_{t}
\end{aligned}
$$

or
(7.5)

$$
I_{\rho \rho}=\left\|\varphi_{\rho}\right\|_{\mathrm{H}_{\mathrm{xx}}^{\circ}}^{2}-\left\|\psi_{\rho}\right\|_{\mathrm{H}_{\mathrm{yy}}^{\circ}}^{2}-\left\langle\psi, \varphi_{\rho \rho}\right\rangle_{t}
$$

The -last step follows by differentiating the canonical equations (4.5) with respect to $\rho$.

Using (7.5), we obtain the following expression for the second variation of $V$ :

$$
\begin{align*}
V_{\rho \rho} & =\left[\lambda_{t}(T)+L(T)\right] T_{\rho \rho}+2\left\langle\tau_{\rho}(T), T_{\rho}\right\rangle+\left\|T_{\rho}\right\|_{\lambda_{t t}}^{2}(T) \\
& +\left\langle\psi(\tau), \varphi_{\rho \rho}(\tau)\right\rangle \\
& \left.\left.+\left\|\varphi_{\rho}(T)\right\|_{\lambda_{x x}}^{2}(T)+\int_{\tau}^{T(\rho)}\left[\| \varphi_{\rho}\right) t\right)\left\|_{H_{x x}^{0}(t)}^{2}-\right\| \Psi_{\rho}(t) \|_{H_{y y}^{o}(t)}^{2}\right] d t .
\end{align*}
$$

The first two lines depend on quantities associated with the endpoints $\tau$ and $T(p)$. The third line has the same general appearance as the accessory variational problem. We shall make this relationship precise in the next section; we summarize the discussion so far as follows:

THEOREM. If the variational problem is regular, we may confine the search for an optimal trajectory to the solutions of the "reduced" canonical equations (4.5). Taking account of the boundary conditions, we are led to consider an n-parameter family of solutions of these equations. It suffices to calculate the first and second variation of $V$ along this family, since no other trajectories are admitted into competition for the minimum of $V$.

This being so, the first and second variation of $V$ may be computed rigorously via ordinary calculus; the formulas for the derivatives of V are given by (7.4) and (7.6) These formulas show that the derivatives consist of two parts: (i) a part dependent only on the derivatives of various functions at the endpoints $\tau$ and $T$ of a given extremal; (ii) a part (occurring in $\mathrm{V}_{\rho \rho}$ only) which is the V function of the accessory variational problem.

Note that for the accessory variational problem (part (ii) in (7.6)) we may assume that $T=$ const.

The formulas we have obtained must be interpreted with some care. For instance, in the engineering literature the term $\varphi_{\rho \rho}(\tau)$ is sometimes neglected as "small". This is legitimate in certain cases, but for different reasons: Usually we wish to solve the problem for arbitrary initial $x(\tau)$, so that the initial boundary surface may be regarded as free. If we parametrize this boundary surface instead of the one at $t=T$, then we may take $\rho=x(\tau)$, so that $\varphi_{\rho}(\tau)=$ unit matrix and $\varphi_{\rho \rho}(\tau)=0$ (a threetensor). But this parametrization may be inconvenient because we have no natural transversality conditions given at $t=\tau$ (we would have to know what $V_{x}^{O}(\tau)$ is) and therefore the boundary conditions at $t=T$ may be difficult to meet. For such reasons, it is usually more convenient to parametrize the boundary surface at which there are nontrivial boundary conditions, and in that case it is not true that $\varphi_{\rho \rho}(\tau)$ can be neglected.

The particular choice of parameters adopted here will be useful in our later studies. The reader should be ciear, however, that the same technique can be used to investigate $V$ as a function of families of curves which are not necessary extremals. In that case, we consider instead of (7.2) the expression

$$
L(t, \rho)=H(t, \varphi, \psi, u)-\langle\psi, f(t, \varphi, u)\rangle
$$

where $\varphi$ is a solution of $\dot{x}=f$ depending parametrically on $\rho$ since $\{u()$.$\} is a family parametrized by \rho$. In order for (7.3) to remain true, we must assume that $\psi$ satisfies

$$
\dot{\mathrm{y}}=-\mathrm{H}_{\mathrm{x}}(\mathrm{t}, \varphi, \mathrm{y}, \rho) ;
$$

then the previous considerations remain valid. If we take the family $\{u(\cdot)\}$ such that

$$
x=\varphi(\tau ; \rho)
$$

for all $\rho$, then we obtain a necessary condition for minimizing curve as $V_{\rho}=0$. This is the old-fashioned way of deriving necessary conditions.

We must emphasize that formulas (7.4) and (7.6) remain valid only as long as $\psi$ satisfies (7.7); each parametrization will in general provide a different $\psi$.
8. The General Quadratic Variational Problem: Most of our succeeding work will be concerned with the solution of the accessory variational problem, which is also called a quadratic variational problem. We wish to standardize the notation as much as possible, and therefore we now repeat the definition of this problem in a notation that will remain in use throughout the report.

A (continuous-time) quadratic variational problem consists of the following:
(i) Dynamics. This is a linear differential system given by

$$
d x / d t=F(t) x+G(t) u(t)
$$

(ii) Performance index. This is the functional

$$
V(\tau, x, T)=\|x(t)\|_{S(T)}^{2}+\int_{\tau}^{T}\left[\|x(t)\|_{Q(t)}^{2}+\|u(t)\|_{R(t)}^{2}\right] d t
$$

(iii) Boundary conditions.

$$
\begin{array}{llll}
\text { At } & t=\tau, & x(\tau)=x & (\tau=\text { const. }) \\
& t=T, & A(T) x(T)=0 & (T=\text { const. }) .
\end{array}
$$

(iv) Assumptions. The matrix $R$ will always be symmetric and positive definite (for regularity) and usually $R=I . Q$ and, $S$ will always be symmetric.
(v) Hamiltonian.

$$
2 H^{0}(t, x, y)=\|x\|_{Q(t)}^{2}+2\langle y, F(t) x\rangle-\left\|G^{\prime}(t) y\right\|_{R^{-1}(t)}^{2}
$$

(vi) Canonical equations.

$$
\begin{aligned}
& d x / d t=F(t) x-G(t) R^{-1}(t) G^{\prime}(t) y \\
& d x / d t=-Q(t) x-F^{\prime}(t) y
\end{aligned}
$$

(vii) Optimal control law.

$$
u(t)=-R^{-1}(t) G(t) y(t)
$$

Remark. "Quadratic" means that $L$ must be a quadratic function of $x$ and $u$ (the t-dependence may be more or less arbitrary). It may be useful occasionally to consider cases where $L$ contains a term of the type u'Wx. Such problems can be reduced to our present problem by a simple change of variables. See [I2]. For most of our work we prefer not to carry along this extra notation in the definition of I . In particular, the riccati equation program is written under the assumption that the term $W$ in $L$ is zero.

It is easy to show now that the last part of (7.6) corresponds to a quadratic variational problem.

Let $\rho_{0}=0$ be the parameter corresponding to the extremal $\{\bar{x}(),. \bar{y}()$.$\} considered in Sect. 6. Write$

$$
\begin{aligned}
& \xi(t)=\delta \varphi(t)=\varphi(t, \rho)-\bar{x}(t) \cong \varphi_{\rho}(t, 0) \rho \\
& \eta(t)=\delta \psi(t)=\psi(t, \rho)-\bar{y}(t) \cong \psi_{\rho}(t, 0) \rho \\
& \mu(t)=\delta u(t)=u(t, \rho)-\bar{u}(t) \cong-\omega_{\rho}(t, 0) \rho
\end{aligned}
$$

where $\cong$ means correct "to the first approximation".
Diffen ntiating (4.5) and making use of the abbreviations (6.2) (but dropping superscripts, etc.) we obtain

$$
\begin{align*}
& \dot{\varphi}_{\rho}=F(t) \varphi_{\rho}-G(t) G^{2}(t) \psi_{\rho}  \tag{8.1}\\
& \dot{\psi}_{\rho}=-Q(t) \varphi_{\rho}-F^{\prime}(t) \psi_{\rho}
\end{align*}
$$

In.other words, $\varphi_{\rho}$ and $\psi_{\rho}$ are a pair of matrix solutions of the canonical differential equations of the generic quadratic variational problem. (To agree with the equations given under (vi) above we must set $R=$ I.) In view of this observation we introduce a special notation which is to remain in effect throughout the report:

$$
\begin{equation*}
X(t)=\varphi_{\rho}(t), \quad Y(t)=\psi_{\rho}(t) \tag{8.2}
\end{equation*}
$$

Then we have

$$
\xi(t)=X(t) \rho, \quad \eta(t)=Y(t) \rho, \quad \mu(t)=-G^{\prime}(t) Y(t) \rho
$$

for each fixed $\rho$. Of course, $\omega_{\rho}=G^{\prime} Y$.
Then, if $\rho=\xi(\tau), \quad(7 \cdot 6)$ shows that

$$
\begin{align*}
\|\xi(\tau)\|_{V_{\rho \rho}}^{2} & =\|\xi(T)\|_{S(T)}^{2}+\int_{\tau}^{T}\left(\|\xi(t)\|_{Q(t)}^{2}+\|\mu(t)\|^{2}\right) d t  \tag{8.3}\\
& + \text { terms depending directly on } \tau, T .
\end{align*}
$$

Thus the critical part of the second variation corresponds to the evaluation of the performance index of a quadratic variational problem along its extremals.

We will see that the study of the accessory extremals provides considerable information about the solution of the two-point boundary-value problem; in fact, this aspect of our theory will turn out to be more important than the somewhat pedantic emphasis on the second variation.
9. Solution of the General Quadratic Variational Problem: Quadratic variational problems can be solved explicitly with the help of the hamilton-jacobi partial differential equation. In our case this equation is

$$
\begin{equation*}
v_{\tau}+\left\langle v_{x}, F(t) x\right\rangle-\frac{1}{2}\left\|G^{\prime}(t) v_{x}\right\|_{R^{-1}(t)}^{2}+\frac{1}{2}\|x\|_{Q(t)}^{2}=0 \tag{9.1}
\end{equation*}
$$

subject to

$$
\begin{equation*}
2 V(T, x)=\|x\|_{S(T)}^{2} \text { for } x \in-\mathcal{K} \tag{9.2}
\end{equation*}
$$

The hamilton-jacobi equation is easily solved in the special case when

$$
\begin{equation*}
\mathcal{R} .=\left\{(t, x)_{s}+=T=\text { fixed, } \quad x=\text { arbitrary }\right\} \tag{9.3}
\end{equation*}
$$

In the remaining cases an indirect procedure must be used. One of our objectives is a detailed explanation of the theory and computing procedure in the general case when $\mathcal{1}$ may be a linear manifold of any dimension. For the moment we shall consider only the special case when $\operatorname{dim}-h\}=n$.

It can be easily proved that when $T=$ fixed, $\mathcal{A}=\mathcal{K}$ the hamiltonjacobi equation, as well as any first-order partial differential equation, has a unique $C^{2}$ solution (as long as $\lambda$ is $C^{2}$ and various other natural smoothness hypotheses hold.) see, e.g., [2, §22].

We will now exhibit this solution.
We assume that

$$
\begin{equation*}
2 V(t, x)=\|x\|_{P(t)}^{2} \tag{9.4}
\end{equation*}
$$

where $P$ is a symmetric matrix.
In order that $V$ given by (9.4) constitute the desired solution of the hamilton-jacobi equation, it is necessary that

$$
\text { (9.1 } 1^{\text {P }}-\mathrm{dP} / \mathrm{dt}=F^{\prime}(t) P(t)+P(t) F(t)-P(t) G(t) R^{-1}(t) G^{\prime}(t) P(t)+Q(t)
$$

and that

$$
P(T)=S(T)=\text { const }
$$

The first equation corresponds to the hamilton-jacobi equation and the second corresponds to the initial condition of that equation.

Conditions ( $9 . I^{\prime}-9.2^{\text {i }}$ ) are also sufficient, by the uniqueness of solutions of the hamilton-jacobi equation. (Substitute (9.4) into (9.1) and note that $V$ satisfies (9.1) iff $P($.$) satisfies (9.1'). It is vitally$ important for the understanding of this report that the reader be familiar with all details of this particular substitution. No tricks are involved, just matrix notation and a large amount of manipulation.).

We have then the

THEOREM. The special quadratic variational problem is solved if and only if the riccati equation (9.1') has a solution $\Pi(. ; T, S(T), Q()$. defined for $t=\tau$.

Note that since (9.1') is a nonlinear differential equation (the quadratic term is essentiai.) it may be subject to the phenomenon of finite escape time, namely a solution may be defined on an interval ( $\left.t^{\prime}, T\right]$ and as $t \rightarrow t^{\prime} P(t)=\prod(+: T, S(T), Q().) \rightarrow \infty$ (at least one element of $P \rightarrow \infty$ ). Then $t=t^{\prime}$ is called the (left) conjugate point associated with T. If $\tau$ Et', then the solution of our problem does not exist, because (proof later) then $V(\tau, x)$ can be made arbitrarily negative by suitable choice of $u($.$) . This obviously cannot happen if both S$ and $Q($.$) are$ nonnegative definite.

The main objective of the theory of the second variation is to investigate the existence and nonexistence of conjugate points, as a function of $Q(),$.$S , the boundary conditions, etc. In the course of this theoretical$ investigation, we will obtain explicit formulas for the solution of the riccati equation (9.1'). We will also see the role played by controllability in the investigation of conjugate points.

Our considerations are motivated by the roughly correct fact that when no conjugate point exists, the necessary conditions leading to the canonical equations are also sufficient for optimality. In other words,

$$
\text { \{extremal }+ \text { no conjugate point\} }=\text { \{optimal trajectory\}. }
$$

We will give a precise discussion of this result, the most important theorem of the classical calculus of variations. The theory surrounding this result also motivates all methods of numerical computation of extremals.
10. Theory of the Riccati Equation Associated with a Quadratic Variational Problem: The general form of the matrix riccati equation is

$$
d X / d t=A X+X B+X C X+D
$$

We will not be concerned with such complete generality (whose theory is similar to the case we shall treat) but will deal exclusively with (9.1'). The theory of this equation is very closely related to the theory of the canonical equations.

The solution of the canonical equations is equivalent to the solution of the riccati equation, provided no conjugate point exists.

We consider first the special problem.
As before let the pair $\{\mathrm{X}(),. \mathrm{Y}()$.$\} be a matrix solution of the$ canonical equations, that is.

$$
\left\{\begin{array}{l}
d X(t) / d t=F(t) X(t)-G(t) R^{-1}(t) G^{\prime}(t) Y(t)  \tag{10.1}\\
d Y(t) / d t=-Q(t) X(t)-F^{\prime}(t) Y(t)
\end{array}\right.
$$

and specify the initial conditions as

$$
\left\{\begin{array}{l}
X(\mathbb{T})=I \\
Y(\mathbb{T})=S
\end{array}\right.
$$

We say that $T$ has no conjugate point (in the special problem) if $\operatorname{det} X(t) \neq 0, \quad t<T$. Then we claim

THEOREM. If $T$ has no conjugate point, the solution of the special problem is given by

$$
\begin{equation*}
2 V(t, x)=\|x\|_{P(t)}^{2}=\|x\|_{Y(t) X^{-1}(t)}^{2}, \quad t \leq T . \tag{10.3}
\end{equation*}
$$

Proof. We must show: If the pair $X(),. Y($.$) satisfies (10.1)$ with initial conditions (10.2), then $P()=.Y(.) X^{-1}($.$) is a solution of$ the riccati equation (9.1'), with initial conditions $P(T)=H(T) X^{-1}(T)=S I^{-1}=S$.

This is proven by straightforward but tedious substitions, which the reader is again strongly urged to carry out for himself. Similar manipulations occur frequently in deriving the riccati equation for various problems.

Note that our definition of the "nonexistence of a conjugate point" is precisely that necessary and sufficient for the important formula $P=Y X^{-1}$ to make sense.

Our theorem admits the following converse:
THEOREM. If the riccati equation (9.1') has a solution defined on $[\tau, \mathbb{T}]$, then there is no conjugate point in this interval, that is, $\operatorname{det} X(t) \neq 0$ for $t \in[\tau, T]$. (Of course $X($.$) is defined via the initial$ conditions (10.2).)

Proof. If the riccati equation has a solution, then (recall $Y=V_{x}$ ) the optimal control law is given by

$$
u(t)=-R^{-1}(t) G^{\prime}(t) Y(t)=-R^{-1}(t) G^{\prime}(t) P(t) x(t) .
$$

Therefore the optimal motion $x($.$) satisfies$

$$
\begin{equation*}
d x / d t=H_{P}^{o}=\left[F(t)-R^{-1}(t) G^{\prime}(t) P(t)\right] x \tag{10.4}
\end{equation*}
$$

We want to show that $X($.$) , which satisfies (10.1-2), is equal to \Phi(., T)$, the transition matrix of (10.4), that is, of the optimal closed-loop system. Then the theorem follows, because transition matrices are never singular. We define

$$
\left\{\begin{array}{l}
X(\cdot)=\Phi(., T), \\
Y(\cdot)=P(\cdot) X(\cdot)
\end{array}\right.
$$

Then $X(T)=I$ and $Y(T)=S$ moreover, the pair $\{X(\cdot), Y(\cdot)\}$ satisfies (10.1). The latter fact is shown by direct substitution into (9.1') and (10.4). This is the third type of substitution which the reader is urged to carry out.

In the general problem the procedure we have used here to relate the riccati equation to the canonical equations (and to relate both to questions concerning the existence of a conjugate point) requires much more delicate arguments. These will be discussed in the remaining parts of this chapter. Before doing so we wish to establish two important properties of the riccati equation:
A. Exact interpolation formula. Although the digital computer cannot compute $P(t)$ continuously in $t$, we can give a formula which expresses $P(t)$ exactly for any fixed $t$ in terms of the initial values $X(\mathbb{T}), Y(\mathbb{T})$ of the canonical equations.

Let $\Theta$ be the transition matrix of the canonical equations; i.e., $\Theta$ satisfies

$$
d \Theta / d t=\left[\begin{array}{cc}
F(t) & -G(t) R^{-1}(t) G^{\prime}(t) \\
-Q(t) & -F^{\prime}(t)
\end{array}\right]\left[\begin{array}{ll}
\Theta_{11} & \Theta_{12} \\
\Theta_{21} & \Theta_{22}
\end{array}\right] .
$$

Then

$$
\begin{align*}
P(t) & =\left[\Theta_{21}(t, T) X(T)+\Theta_{22}(t, T) Y(T)\right] \times \\
& \times\left[\Theta_{11}(t, T) X(T)+\Theta_{12}(t, T) Y(T)\right]^{-1} . \tag{10.5}
\end{align*}
$$

In other words, to find explicit solutions of the riccati equation we require no more and no less than an explicit transition matrix of the canonical equations. This observation is the most important principle in the entire $A S P$ computing procedure.

Although the right-hand side of (10.5) does not appear to be symmetric, it is known abstractly to be so if $P(T)$ is symmetric. For if $P(T)=S$ is symmetric (which is always assumed, then by (9.1') $P(T)=$ symmetric.

This is very important practically; for if $P$ become unsymmetric due to numerical errors, the errors may propagate and lead to difficulties of various sorts. The user of ASP should always check whether the assumption of symmetry is needed in the derivation of equations to be computed. (The riccati program contains an extra operation which assures that the output is always symmetrical. This is desirable to impede error propagation due to asymmetry.)

One can also show by direct algebraic arguments that the matrix (10.5) is symmetric whenever

$$
Y(T) X^{-1}(T)=\text { symmetric. }
$$

Condition (10.6) plays an important role in the general problem.
B. Symplectic character of $\Theta$. Let
(10.7)

$$
z=\left[\begin{array}{c}
x \\
y
\end{array}\right] \text { and } J=\left[\begin{array}{cc}
0_{n} & I_{n} \\
-I_{n} & 0_{n}
\end{array}\right] \quad\left(J^{-1}=J^{\prime}=-J\right)
$$

A system of differential equations

$$
\begin{equation*}
\mathrm{dz} / \mathrm{dt}=\mathrm{A}(\mathrm{t}) \mathrm{z} \tag{10.8}
\end{equation*}
$$

is said to be hamiltonian iff it can be written as

$$
d x / d t=H_{y}, \quad d y / d t=-H_{x}
$$

where

$$
H=z^{\prime} M(t) z
$$

and $M(t)$ is a symmetric matrix. It is easy to show that (10.8) is hamiltonian iff $J A(t)=M(t)=$ symmetric matrix. Our canonical equations (8-(vi)) are of course the principal example of a hamiltonian system.

A matrix $X(t)$ is called symplectic iff $X^{-1}(t)=J^{\prime} X^{\prime}(t) J . \quad A$ symplectic matrix cannot be singular; in fact det $X(t) \equiv$. If $X$ is symplectic, so is its inverse; if $A, B$ are symplectic, then $A B$ is also symplectic. So symplectic matrices form a multiplicative group. "Symplectic" is similar to "orthogonal" and has interesting geometric interpretations (for which see Mal'cev, IINEAR ALGEBRA).

We are interested in symplectic matrices because of the following well-known result:

THEOREM. The transition matrix of a hamiltonian system is symplectic.
Proof. If $\Theta(t, \tau)$ is the transition matrix of a hamiltonian system, then

$$
d \Theta / d t=-J M(t) \Theta, \quad M(t)=\text { symmetric. }
$$

Let $\Gamma(t, \tau)=\Theta^{q}(\tau, t)$ be the adjoint of $\Theta$. Then $\Gamma$ satisfies

$$
d \Gamma / d t=M(t) J^{\prime} \Gamma
$$

or

$$
\mathrm{d}\left[\mathrm{~J}^{t} \Gamma J\right] / \mathrm{d} t=-\mathrm{JM}(\mathrm{t})\left[J^{\imath} \Gamma J\right]
$$

Since $J^{2} \Gamma(t, t) J=J^{\prime} J=I, J^{2} \Gamma J$ is a transition matrix; and since it satisfies the same differential equation as $\Theta$, we have

$$
J^{\prime} \Theta^{\prime}(\tau, t) J=\Theta(t, \tau)=\Theta^{-1}(\tau, t)
$$

So $\Theta(\tau, t)$ is symplectic and therefore also $\Theta^{-1}(\tau, t)=\Theta(t, \tau)$. Q.E.D. Using the fact that $\Theta$ is symplectic we obtain the identity

$$
\Theta(t, \tau)=\left[\begin{array}{ll}
\Theta_{11}(t, \tau) & \Theta_{12}(t, \tau) \\
\Theta_{21}(t, \tau) & \Theta_{22}(t, \tau)
\end{array}\right]=\left[\begin{array}{cc}
\Theta_{22}^{\prime}(\tau, t) & -\Theta_{12}^{1}(\tau, t) \\
-\Theta_{21}^{\prime}(\tau, t) & \Theta_{11}^{\prime}(\tau, t)
\end{array}\right] .
$$

Later it will be useful to know:

PROPOSITION. Let $\{X(),. Y()$.$\} be matrix solutions of the linear$ equations (10.1). If

$$
X^{\prime}(t) Y(t)=Y^{\prime}(t) X(t)
$$

for some $t=\tau$, then the same relation holds for all $t$.
Proof. Write

$$
\begin{aligned}
& X(t)=\Theta_{11}(t, \tau) X(\tau)+\Theta_{12}(t, \tau) Y(\tau) \\
& Y(t)=\Theta_{21}(t, \tau) X(\tau)+\Theta_{22}(t, \tau) Y(\tau) .
\end{aligned}
$$

Then,

$$
\begin{aligned}
X^{\prime}(t) Y(t) & =X^{\prime}(\tau) \Theta_{11}^{\prime}(t, \tau) \Theta_{21}(t, \tau) X(\tau) \\
& +Y^{\prime}(\tau) \Theta_{12}^{\prime}(t, \tau) \Theta_{21}(t, \tau) X(\tau) \\
& +X^{\prime}(\tau) \Theta_{11}^{\prime}(t, \tau) \Theta_{22}(t, \tau) Y(\tau) \\
& +Y^{\prime}(\tau) \Theta_{12}^{\prime}(t, \tau) \Theta_{22}(t, \tau) Y(\tau) .
\end{aligned}
$$

Now

$$
\begin{array}{rlrl}
\Theta_{11}^{\prime}(t, \tau) \Theta_{21}(t, \tau) & =\Theta_{22}(\tau, t) \Theta_{21}(t, \tau) & & \text { (by symplectic) } \\
& =\Theta_{21}(\tau, t) \Theta_{11}(t, \tau) \quad \text { (composition property } \\
& =\Theta_{21}^{\prime}(t, \tau) \Theta_{11}(t, \tau) & \text { (by symplectic). }
\end{array}
$$

The other terms may be rearranged similarly. Thus a term-by-term comparison shows that the proposition is true.

Similarly, we can prove that $P(t)$ given by (10.5) is a symmetric matrix iff $P(t)=N(T) X^{-1}(T)$ is symmetric.
11. n-Parameter Families of Extremals: Let $\rho$ be a constant $n$-vector. Given any matrix pair $\{X(),. Y()$.$\} satisfying (10.1), we define an$ n -parameter family of vector solutions of (10.1) by setting
(11.1)

$$
\left\{\begin{array}{l}
\xi(t)=X(t) \rho \\
\eta(t)=Y(t) \rho
\end{array}\right.
$$

(We are applying the considerations of Sec. 7 to the general quadratic variational problem. According to the preceding theory every extremal of a quadratic variational problem must be of the form (11.1).

Conversely, we may ask the question: Is every pair $\{\xi(),. \eta()$.$\} of$ solutions of (8-(vi)) a (regular pseudo-) extremal of the associated quadratic variational problem?

The answer is well known to be NO. There is no difficulty in satisfying the minimum requirement (4.3) (since $u_{o p t}$ is a function only of $y$ and since the relation $u_{o p t}(t)=-R^{-1}(t) G^{\prime}(t) y(t)$ has been built into (10.1)). However, there is an additional constraint imposed by the transversality conditions (4.4).

PROPOSITION. An $n$-parameter iamily of solutions of (8-(vii)) defined by (11.1) is a family of extremals of a quadratic variational problem if and only if

$$
\begin{equation*}
X^{\prime}(T) Y(T)=Y^{\prime}(T) X(T) \tag{11.2}
\end{equation*}
$$

In view of the fact shat $(3-(v i))$ is a hamiltonian system, relation (11.2) guarantees that $X^{\prime}(t) Y(t)=Y^{\prime}(t) X(t)$ for all $t$.

Proof. The transversality condition imposes on $X(T)$ and $Y(T)$ the requirements
(11.3)

$$
A(T) X(T) \rho=0 \text { for all } \rho,
$$

(11.4) $\langle Y(T) \rho, z\rangle=\langle S(T) X(T) \rho, z\rangle$ for all $\rho$ and all $z$ satisfying $A(T) z=$

Therefore any row vector of the type

$$
z^{\prime}[Y(T)-S(\mathbb{T}) X(\mathbb{T})]
$$

is zero; since by (11.3) $X(t) \rho=z$ satisfies $A(T) z=0$,

$$
\rho^{\prime}\left[X^{\prime}(T) Y(T)+X^{\prime}(T) S(T) X(T)\right]=0
$$

for all $\rho$, which proves (11.2).
We will now derive a canonical set uf coordinates which will enable us to state the constraints (11.3-4) in a particularly simple form. In other words, we translate the transversality conditions into a specification of the pair $X(T), Y(T)$.

Let $n-r$ be the rank of $A(T)$ (hence $r=$ dim -13 ). By changing coordinates we can exhibit $A(T)$ in the canonical form

$$
A(T)=\left[\begin{array}{ll}
0 & I_{n-r} \tag{11.5}
\end{array}\right]
$$

I.E., we rotate the terminal manifold -13 so that it is given by

$$
r^{i}(x)=x^{i}=0, \quad i=1, \ldots, r
$$

Then $x$ can be written as $\left(x^{1}, x^{2}\right)$, where $x^{I}$ is an r-vector and $x^{2}$ is an $(n-r)$-vector; $x$ belongs to the terminal manifold iff $x^{2}=0$. As in Sect. 7, we parametrize the terminal manifold by the $r$-vector $\mu$. Then
$x \cdot$ belongs to the terminal manifold iff $x=(\mu, 0) . \mu$ must be part of the parameter $\rho$ which determines our n-parameter family of extremals. Hence we set (cf. Sect. 7)

$$
\rho=(\mu, v)
$$

Let us determine the special form of the matrices $X(T)$ and $Y(T)$ in the coordinate system introduced above, writing them in such a way that the condition (11.2) is automatically satisfied.

Since $-\alpha$ is to be parametrized by $\mu$ and since every $x(T)=X(T) \rho$ must belong to $-A^{2}$, i.e., $x(T)=(\mu, 0)$, it is clear that

$$
X(T)=\left[\begin{array}{ll}
I_{r} & 0 \\
0 & 0
\end{array}\right]
$$

Condition (11.4) shows that

$$
Y(T)=\left(\begin{array}{ll}
S_{\mu \mu} & 0 \\
B & C
\end{array}\right)
$$

where $B, C$ are arbitrary matrices. We set $\Sigma=S_{\mu \mu}$ for the sake of a simpler notation. Then

$$
y(T)=Y(T) \rho=\left(S_{\mu \mu} \mu, B \mu+C v\right)
$$

The second term is an arbitrary ( $n-r$ )-dimensional parameter. We lose no generality if we set $B=0, C=I$. Thus

$$
Y(T)=\left[\begin{array}{cc}
\Sigma & 0 \\
0 & I
\end{array}\right]
$$

It is clear that (11.6) and (11.7) define the most general n-parameter family of solutions of (8-(vii)), which are extremals.
12. Two Important Formulas: To complete our discussion of the parametric representation of extremals, let us calculate the optimal performance index. The first formula is

$$
\begin{equation*}
\int_{t}^{T} L\left(t, \xi(t), u_{o p t}(t)\right) d t=\left.\langle\xi(t), \eta(t)\rangle\right|_{T} ^{\tau} \tag{12.1}
\end{equation*}
$$

To prove it, write

$$
L\left(t, x, u_{o p t}\right)=2 H^{o}(t, x, y)+\left\|G^{\prime} y\right\|_{R^{-1}}^{2}-2 y^{\prime} F x
$$

By homogeneity of $\mathrm{H}^{\circ}$,

$$
L\left(t, x, u_{o p t}\right)=H_{x} x+H_{y} y+\left\|G^{\prime} y\right\|_{R^{-1}}^{2}-2 y^{\prime} F x
$$

Using the canonical equations we get

$$
\begin{aligned}
L\left(t, x, u_{o p t}\right)= & -x^{\prime} \dot{y}+y^{\prime} \dot{x}-2 y^{\prime}\left(F x-G^{\prime} R^{-1} G_{y}\right) \\
& \left.=-y^{\prime} x\right)
\end{aligned}
$$

which proves (12.1).
Now suppose that $\operatorname{det} X(\tau) \neq 0$. Then we can write the right-hand side of (12.1) as a function of $p$, as follows:

$$
\begin{aligned}
\xi(\tau) & =X(\tau) \rho \\
\rho & =X^{-1}(\tau)(\tau)
\end{aligned}
$$

On the other hand,

$$
\begin{aligned}
\langle\xi(T), \quad \eta(t)\rangle & =\rho^{\prime} X^{\prime}(T) Y(T) \rho \\
& =\|\mu\|_{\Sigma}^{2}
\end{aligned}
$$

by (11.7). Thus (12.1) becomes

$$
\begin{equation*}
\|\mu\|_{\Sigma}^{2}+\int_{\tau}^{T} L\left(t, \xi(t), u_{o p t}(t)\right) \mathrm{d} t=\|\xi(\tau)\|_{Y(\tau) X^{-1}(\tau)}^{2} \tag{12.2}
\end{equation*}
$$

which is our second important formula.
Suppose now that we have not merely $\operatorname{det} X(\tau) \neq 0$, but
(12.3) $\operatorname{det} X(t) \neq 0$ for all [ $T, T)$.

Then according to Sect. 10 we know that $Y(t) X^{-1}(t)$ satisfies the hamiltonjacobi partial differential equation on the interval [ $\tau, \mathbb{T}$ ). (Note that the right endpoint $T=t$ is not included in this statement since $X(T)$ is singular when $r<n$. ) But the existence of solutions of the hamilton-jacobi equation is a sufficient condition for optimality. Hence we have our

FIRST MAIN THEOREM: If an n-parameter family of extremals satisfies (12.3), then $X(.) \rho$ is an optimal trajectory for each $\rho$.

We now embark on a detailed investigation of the conjugate point condition (12.3). It should be remarked right away that (12.3) is not a necessary condition for optimality; the degree to which it fails to be optimal is related to the controllability properties of the family of extremals.
13. The Boundary-Value Problem: Let us return now for a moment to the original (not accessory) variational problem. If this problem has a solution in terms of a (regular pseudo-) extremal, then this extremal must be determined using the free canonical equations (4.5). This means that we must know either the two initial conditions, $x(\tau)$ and $y(\tau)$ or the two final conditions, $x(T)$ and $y(T) \cdot x(\tau)$ is given as part of the specification of the problem, while $y(\tau)$ must be determined by solving a so-called "two-point boundary-value problem". Usually neither $x(T)$ nor $y(T)$ is given.

Let us consider some typi, . examples. Recall that $\varphi(t ; \tau, x(\tau)$, $y(\tau))$ and $\psi(t ; \tau x(\tau), y(\tau))$ is the solution pair of (4.5) corresponding to the initial values $x(\tau), y(\tau)$.
(1) The endpoint is free, i.e., $-A^{\prime}=\mathcal{X}$. Then we must satisfy the condition (obtained from the transversality condition)

$$
\begin{align*}
y(T ; \tau, x(\tau), y(\tau)) & =y(T)  \tag{19.1}\\
& =\lambda_{x}(T, x(T)) \\
& =\lambda_{x}(T, \phi(T ; \tau, x(\tau), y(\tau)))
\end{align*}
$$

This is an implicit relationship which determines $y(\tau)$ as a function of $x(\tau)$. Once $y(\tau)$ is determined, the extremals can be computed by (4.5). If (13.1) has a solution, $x^{\circ}(\tau)$ and $p^{\circ}(\tau)$, i.e., i! we bave determined a particular extremal*, then using the implicit function theorem we car. Slve (13,I) provided the relevant jacobian is $\neq 0$. This jacobian can
 as unknowns. In our presert case, $-i$ i, comeniert - choose not $p(\tau)$ but $x(T)$ as the unknown. Then we get the condition.

$$
\begin{equation*}
\varphi\left(\tau ; T, x(T), \lambda_{X}(T, x(T))\right)=x(\tau) \tag{13.2}
\end{equation*}
$$

(equivalent to (13.1)), from which we are to determine $x(T)$ as a function of $x(\tau)$. It $1 s$ well know in the theory of differential equations that the jacobiar

[^4]$$
\left[\frac{\partial x_{i}(\tau)}{\partial x_{j}(t)}\right]=\left[x_{i j}(\tau)\right]
$$
where $X($.$) is that solution of our canonical equations (10.1) which corres-$ ponds to the giver boundary condition and $\Sigma: \lambda_{x x}=a r e s$ the iocal solution of equation (13.2) (in the approximate sense, considering only the linear term in the taylor series of the left-hand side of (13.2)) requires kn wledge of the solution of the accessory problem. Moreover, a solution is possible if (usually also only if) $\operatorname{det} X(\tau) \neq 0$. So we see that the conjugate point condition is closely related to the solution of the "boundaryvalue problem" (13.2).

The engineering literature contains many misleading statements concerning the solution of the boundary-value problem. In effect this problem is merely a part of the classical theory of the accessory problem. We hasten to add that the entire theory is local. (If one had any mathematical idea concerning the global solution of the Founcurvenwe froblem, that would be nearly as much as a theory of the global accessory problem, that is to say, a global theory of the original nonlinear variational problem.)

The choice of $t=T$ as the starting point for the solution of the canonical equations (10.1) is quite arbitrary. We ynld have started also at $t=\tau$. Which of these choices is more sensible depends on the practical features of the problem.

Let us illustrate what would happen in the second case. (We let $T$ play the role of $\tau$. )
(2) Whe endpoint is completely constrained, $\therefore . e .19=\{0\}$. Now we must satisfy the condition

$$
\begin{equation*}
\varphi(\tau ; T, 0, y(T))=x(\tau) \tag{13.3}
\end{equation*}
$$

In this case $y(T)=$ free. The jacobian is again given by

$$
\left[\frac{\partial x_{i}(\tau)}{\partial p_{j}(T)}\right]=\left[x_{i j}(\tau)\right]
$$

(X suitably defined).
Both (13.2) and (13.3) can be expressed by a single formula with the aid of our parametrization. Thus in the first example we have that

$$
\left(x(T), \lambda_{x}(T, x(T))=(\mu, \Sigma \mu)\right.
$$

and in the second case

$$
(0, y(T))=(0, v)
$$

In the general case, we have
(13.4)

$$
(x(T), y(T))=(X(T) p, \quad Y(T) p)
$$

This gives our

SECOND MAIN THEOREM: The jacobian matrix

$$
\left[\frac{\partial x_{i}(\tau)}{\partial \rho_{j}}\right]
$$

of the general variational problem is given by the corresponding matrix $X(\tau)$.
An important reason for our parametric representation of extremals is to have a simple expression for the jacobian.
14. Two Important Iemmas: Now we wish to investigate the necessity of the condition (12.3).

It is clear that if this condition is not satisfied, then the problem is not well posed. For if $\operatorname{det} X\left(t_{1}\right)=0$ for some $t_{1} \in[\tau, T)$, then it is impossible to connect some point $\left(t_{1}, \xi_{1}\right)$ with the terminal set, $B$ extremely, i.e.,

$$
\xi_{1} \notin \text { range }\left[x\left(t_{1}\right)\right]
$$

However, even in this case it is conceivable that we might be able to conneat a point $\left(t_{1}, \xi_{1}\right)$ with the terminal set $\mathcal{A}$ in some nonextremal and therefore nonoptimal way. It turns out that this is not the case. In other words,
\{reachability of terminal surface $\}=\{$ optimal reachability $\}$
provided there is no conjugate point in the interval $[\tau, t$. .
Let us now make these notions precise.
IEMMA 1. If $X\left(t_{0}\right) \rho_{0}=0$ for some $\rho=\rho_{0}=\left(0, v_{0}\right), v_{0} \neq 0$, $\xi(t)=X(t) \rho_{o} \not \equiv 0$ on $\left[t_{o}, T\right)$ iff the boundary value problem is well posed over the interval $\left[t_{0}, T\right)$. [That is, given any state $x$ there is a control $u(0)$ which connects $\left(t_{0}, x\right)$ with $\left.(T, z), z \in h_{0}\right]$

Proof. Suppose $\xi(t)=X(t) \rho_{0} \equiv 0$ on $\left[t_{0}, T\right)$. Then

$$
\dot{\eta}=-F^{\prime}(t) \eta_{0}
$$

This equation can be explicitly solved; the answer is

$$
\eta(t)=\Phi^{\prime}(T, t) Y(T) \rho_{0}
$$

Then, since $X(T) \rho_{0}=\left(\mu_{0}, 0\right)=0$, the equation

$$
\dot{\xi}=F(t) \xi-G(t) R^{-1}(t) G^{\prime}(t) \Phi^{\prime}(T, t) Y(T) \rho_{0}
$$

has the solution

$$
\begin{aligned}
\xi(T)=\Phi\left(T, t_{o}\right) \xi\left(t_{0}\right) & =\left[\int_{t_{0}}^{T} \Phi(T, t) G(t) R^{-1}(t) G^{\prime}(t) \Phi^{\prime}(T, t) d t\right] Y(T) \rho_{o} \\
& =W\left(T, t_{o}\right) Y(T) \rho_{o} \\
& =0
\end{aligned}
$$

$W\left(T, t_{o}\right)$ is the reachability matrix; a point $(T, z), z \in \mathcal{A}$ is reachable from $\left(t_{0}, x\right)$ if $z-\Phi\left(T, t_{0}\right) x \in$ range $W\left(T, t_{0}\right)$ (see [5]). That is,

$$
\left.\mathrm{x}=\Phi\left(\mathrm{t}_{\mathrm{o}}, \mathrm{~T}\right)(\mathrm{w}+\mathrm{z}), \quad \mathrm{w} \in \text { range } \mathrm{w}, \quad \mathrm{z} \in-\mathbb{K}\right) .
$$

Thus the problem is well posed only if

$$
\begin{equation*}
\text { range } w+\mathcal{B}=X \text {. } \tag{14.2}
\end{equation*}
$$

Now $\left(0, v_{0}\right) \perp-<3$.
On the other hand, (14.1) and (11.7) show that

$$
W Y(T) \rho_{0}=W\left(0, v_{0}\right)=0
$$

so that $\left(0, v_{0}\right) \in$ null space $W$. Since $W$ is symmetric, this means that $\left(0, v_{0}\right) \perp$ range $W$. Hence $\left(0, v_{0}\right) \perp\left[\right.$ range $\left.W+h^{3}\right]$, and since $v_{0} \neq 0$ we have a contradiction to (14.2). This proves Lemma 1.

If the hypotheses of the lemma hold, we say that $t_{o}$ is a conjugate point (precise definition) of $T$. According to the lemma, a conjugate point is characterized by the fact that at least two distinct extremals connect the points $\left(0, t_{0}\right)$ and $(0, T) . \xi(t) \equiv 0$ is always an extremal; it corresponds to $\rho=0$. By the lemma the extremal $\xi(t)=X(t) \rho_{0}$ is distinct from $\xi(t) \equiv 0$.

If $\operatorname{det} X\left(t_{0}\right) \neq 0$, we may have also the case where $X\left(t_{0}\right) \rho=0$ and $\rho_{0}=\left(\mu_{0}, 0\right), \mu_{0} \neq 0$. In this case the extremal $\boldsymbol{\xi}(t) \equiv 0$ is obviously different from $\xi(t)=X(t) \rho_{0}$ because $x(T)=\left(\mu_{0}, 0\right) \neq 0$. When there is a $\rho_{0}$ with the latter properties, we say that $t_{0}$ is a focal point (precise definition) of $T$. Slightly imprecisely a focal point may be regarded as a generalization of a conjugate point and includes the latter as a special case. The optical intuition leading to the term "focal point" should be quite clear.

Another definition of the focal [conjugate] point is: there exist two distinct extremals which terminate at $x\left(t_{0}\right)=0$ [and begin at $x(T)=0$ ]. In view of our lemma, this is equivalent to the statement: there exists a $\rho_{0} \neq 0 \quad\left[\rho_{0} \neq 0\right.$ with $\left.v_{0} \neq 0\right]$ such that $x\left(t_{0}\right) \rho_{0}=0$.

IEMMA 2. Suppose that the boundary-value problem is well posed over any interval $[\tau, T), \tau<T$. (Refer Lemma 1 for detailed statement.) Then there is no focal point in $[\tau, T)$ if $\tau$ is taken to be sufficiently small.

Proof. If there is a focal point at $t=\tau$, then there is a $\rho_{0} \neq 0$ such that

$$
x(\tau)=X(\tau) \rho_{0}=0
$$

Let $r_{0}$ be the extremal which corresponds to $\rho_{0}$. In triew of formulas (14.1-2), it is clear that the performance index $V$ along $r_{0}$ is zero (since $x_{o}(\tau)=0$ ).

Now we define the scalar function

$$
\begin{equation*}
V(t, x)=\|x\|_{P(t)}^{2} \tag{14.3}
\end{equation*}
$$

by letting $P($.$) be given by (10.5), where$

$$
X(T)=\left(\begin{array}{cc}
I & 0 \\
0 & I
\end{array}\right), \quad Y(T)=\left(\begin{array}{ll}
Z & 0 \\
0 & 0
\end{array}\right)
$$

It is clear that $P(t)$ will be well defined (will exist) for $t$ near $T$ because $\operatorname{det} X(T)=I$ and therefore by continuity $\operatorname{det} X(t) \neq 0$ for $t$ near T. According to the theory discussed in Sects. 5 and 9, $V$ is a solution of the hamilton-jacobi equation corresponding to a new variational problem $P_{2} ; P_{2}$ is the same as the original problem $P$, (for which there exists a focal point) except for the fact that the boundary surface for $P_{2}$ is $\neq \mathbb{K}=\boldsymbol{H}$. Hence $\gamma_{0}$ is an extremal also for $P_{2}$ because it satisfies the boundary condition (trivially) for $P_{2}$. So the performance index $V$ for $r_{0}$ is 0 also for $P_{2}$.

The function $V$ defines a unique control law, which is linear. Hence in $P_{2}$ the optimal trajectory $r_{\infty}$ starting at $x(\tau)=0$ is the curve identically zero. Along this curve the performance index is obviously zero.

By Carathéodory's lemma (see [4]) the existence of a solution of the hamilton-jacobi equation implies that the optimal trajectories are unique. Both $\gamma_{0}$ and $\gamma_{\infty}$ are optimal because their performance index is 0 . We have a contradiction to uniqueness.

This completes the proof of the lemma.
We note also the

COROLLARY. Under the hypotheses of Lemma 1 , the focal points of $T$ are isolated.

Proof. If not, let $\left[t_{0}, t_{1}\right]$ be an interval of focal points. Since $X^{\prime}\left(t_{1}\right) Y\left(t_{l}\right)$ is symmetric, we can repeat the analysis of the lemma, choosing $t_{I}$ as $T$. Then the lemma shows that there are no focal points in the interval $\left[\tau, t_{1}\right]$ if $\tau$ is near $t_{1}$. Contradiction.

Notice also that our proof of Lemma 2 implies the

PROPOSITION. If $t_{1}<T$ is the focal point nearest to $T$ in prou blem $P_{1}$ and $t_{2}$ is the analogous focal point in $P_{2}$, then $t_{1} \leq t_{2}<T$.

- 15. Summary: We can now state our final result, which shows that the computational treatment of the general boundary conditions is identical with the treatment of the special case when $x(T)$ is free

THIRD MAIN THEOREM. Assume that the boundary-value problem is we 11 posed over any interval $[t, T$ ) (where $t \in[\tau, T$ )) and that $\tau$ is chosen so small that no focal point exists in the interval $[\tau, T$ ) (that is, $\operatorname{det} X(t) \neq 0$ on $[\tau, T))$.

Then the solution of the general problem may be obtained using the function $V$ defined via (9.4) by $P(t)$ which is given by (9.1'), where $X(T)$ and $Y(T)$ are determined by (10.1) and (10.2). This choice of initial conditions for (10.1) assumes that the terminal surface consists of the first $r$ of the $n$ (orthogonal) coordinate axes. The function $V$ so computed satisfies the relevant hamilton-jacobi equation for all $t \in[\tau, T$; if $t=T$, then $V(T, x)=\|x\|_{\Sigma}^{2}$ on $B$.

The statement: "the boundary-value problem is well posed over every interval $[t, T)^{\prime \prime}$ is satisfied, e.g., when the system (3.1) is completely controllable over every such interval. Our italicized statement is in fact equivalent in classical terminology to the statement "the problem is normal in every interval".

The theory can be carried out without such an assumption, as follows.
Suppose the problem is well posed merely with respect to the fixed interval $[\tau, T)$. Consider the linear space $\Gamma(t)$ of all points ( $t, x$ ) from which $\mathcal{K}$ may be reached at $t=T$. By definition of "well posed at $t=\tau^{\prime \prime}$ we have that $\Gamma(\tau)=$. But for $t>\tau \Gamma(t)$ may be a proper subspace of $X$.

By the theory of controllability, it follows very easily [IO] that Dim $\Gamma(t)$ is a piecewise integer-valued function, which cannot be decreased as $t \rightarrow \tau$. Moreover, there are but finitely many intervals on which this function has different values (because $\mathcal{X}$ is finite-dimensional). Hence let us
subdivide $[\tau, T]$ into maximal disjoint intervals on which dim $\Gamma(t)=$ constant. Each intcrval is olosed on the left and open on the right. We repeat the entire analysis (which is quite independent of the specification of the initial state $x(\tau)$ : all of our analysis holds for all initial states for which the boundary-value problem maikes sense) for each interval. Putting together the pieces, we get a result analogous to the third main theorem.

The possibility oin such a procedure was pointed out a long time ago by Carathéodory [1l], but his formulas are not explicit, contain some mistakes (rectified in Chapter 18 of [2]), and are not easy to read. Our present treatment is similar to Caratheodory's exposition of the theory of "second variation", [2, Chapter 15 ] which was concerned solely with the simple variational proDlems $(l=0, G=\therefore$ ), is the reader has seen, the Hamilton-Jacobi-Carathéodory-Bellman approach can give us the solution of the most general problem, and has the advantage in addition of yielding a single formula, (9.4), which covers all computing problems.

It is hardly necessary to point out that the theoretical part of our investigation is completed by applying the theory of the accessory problem to the formulas developed in Sect. 7. Most of the classical sufficiency proofs of the calculus of variations are done in this style. We omit the details, since they have no bearing on the computational problem.
16. Computation: The transition matrix for (10.1) can be computed easily only when all matrices are constants. In that case

$$
\begin{equation*}
\Theta(t, \tau)=\exp [(t-\tau) z] \tag{16.1}
\end{equation*}
$$

where

$$
Z=\left(\begin{array}{cc}
F & -G R^{-1} G^{\prime} \\
-Q & -F
\end{array}\right)
$$

The program is supplied with (16.1) and then computes $P(t)$ by substituting the four submatrices of $\Theta$ into one of the formula (10.5). In this way one obtains a stepwise solution of the riccati equation.

At each step $P$ is symmetrized before proceeding by replacing it with

$$
\frac{P(t)+P^{\prime}(t)}{2} .
$$

Symmetrization is absolutely essential because otherwise uncontrollable roundoff errors may accumulate in the antisymmetric part of $P(t)$.

The input to the program consists of the matrices $\Theta, R^{-1}{ }_{G}$, a symmetric $P(\tau)$, a sampling period $T$ at which intervals $P$ will be computed, a convergence criterion number $\epsilon$, a final time TF, and various printing codes.

The problem is terminated in one of two ways. Either the final time TT is reached or the convergence criterion is satisfied.

The convergence criterion is that

$$
\frac{\sum_{i=1}^{n}\left|p_{i i}(t+T)-p_{i i}(t)\right|}{\sum_{i=1}^{n}\left|p_{i i}(t+T)\right|}
$$

be less than the input number $\boldsymbol{\epsilon}$.
When $P(t)$ is computed, the matrix

$$
K(t)=R^{-1} G^{T} P(t)
$$

specifying the control law can be computed and printed. Print controls enable one to print $K$ or $P$ at every $N$ steps and at the final step.
17. Checks: A) The Program was run with

$$
F=\left[\begin{array}{ll}
0_{6} & I_{6} \\
0 & 0_{6}
\end{array}\right]
$$

where $0_{6}=$ six dimensional zero column vector and $I_{6}=6 \times 6$ identity matrix

$$
\begin{aligned}
G & =\left[\begin{array}{l}
1 \\
0_{6}
\end{array}\right], \quad Q=H^{\prime} H=7 \times 7 \text { matrix } \\
R & =[0.6075] \\
P(0) & =0.6075 \mathrm{I} \\
T & =-0.2 .
\end{aligned}
$$

This was iterated for ten steps and the result compared with a handcomputed result expressed exactly in four place decimals. $P$ appears in Fig. 2. The hand-computed $P$ is:

$$
P=\left[\begin{array}{lllllll}
0.2025 & 0.4050 & 0.4050 & 0.2700 & 0.1350 & 0.0540 & 0.0180 \\
0.4050 & 1.4175 & 2.0250 & 1.7550 & 1.0800 & 0.5130 & 0.1980 \\
0.4050 & 2.0250 & 3.8475 & 4.1850 & 3.1050 & 1.7280 & 0.7650 \\
0.2700 & 1.7550 & 4.1850 & 5.8275 & 5.4450 & 3.7170 & 1.9680 \\
0.1350 & 1.0800 & 3.1050 & 5.4450 & 6.6375 & 5.8410 & 3.8730 \\
0.0540 & 0.5130 & 1.7280 & 3.7170 & 5.8410 & 6.8319 & 5.9178 \\
0.0180 & 0.1980 & 0.7650 & 1.9680 & 3.8730 & 5.9178 & 6.8623
\end{array}\right] .
$$

B) The Program was run with

$$
\begin{aligned}
& F=\left[\begin{array}{ll}
0_{6}^{\prime} & 0 \\
-I_{6} & 0_{6}
\end{array}\right] \quad H=\left[\begin{array}{ll}
1 & 0_{6}^{1}
\end{array}\right] \\
& G=R^{-1}=7 \times 7 \text { zero matrix } \\
& Q=2.0250 \\
& P(0)=-0.2 I
\end{aligned}
$$

This was iterated for ten steps and the results compared with a handcomputed result which was expressed exactly in four place decimals. P appears in Fig. 3, $K$ is of course zero. The hand-computed result is:
$P=10 .\left[\begin{array}{rrrrrrr}2.6935 & -1.9759 & 1.2990 & -0.6720 & 0.2790 & -0.0900 & 0.0180 \\ -1.9750 & 2.2869 & -1.9710 & 1.2870 & -0.6480 & 0.2430 & -0.0540 \\ 1.2990 & -1.9710 & 2.2725 & -1.9350 & 1.2150 & -0.5400 & 0.1350 \\ -0.6720 & 1.2870 & -1.9350 & 2.1825 & -1.7550 & 0.9450 & -0.2700 \\ 0.2790 & -0.6480 & 1.2150 & -1.7550 & 1.8225 & -1.2150 & 0.4050 \\ -0.0900 & 0.2430 & -0.5400 & 0.9450 & -1.2150 & 1.0125 & -0.4050 \\ 0.0180 & -0.0540 & 0.1350 & -0.2700 & 0.4050 & -0.4050 & 0.2025\end{array}\right]$.
C) To obtain a problem whose answer we knew for all time, we ran the follew ing

$$
F=\operatorname{diag}(.1, .2, .5,1,2)
$$

$$
H^{\prime} \mathrm{QH}=\left[\begin{array}{ccccc}
.1 & .2 & .3 & .4 & .5 \\
.2 & .2 & .4 & .5 & .6 \\
.3 & .4 & .3 & .6 & .7 \\
.4 & .5 & .6 & .4 & .8 \\
.5 & .6 & .7 & .8 & .5
\end{array}\right]
$$

$G R^{-1} G^{\prime}=5 \times 5$ zero matrix $=P(0)$.
$P$ was computed at various times, we show in Fig. 4 and Fig. 5 the computed results at $t=.75$ and $t=3.7$. The answers are accurate in the seventh significant figure. The correct results are

$$
p_{i j}(t)=q_{i j} \frac{e\left(\lambda_{i}+\lambda_{j}\right) t-1}{\lambda_{i}-\lambda_{j}}
$$



Fig. 1
OEC 2,1964
-

0.59177990 E 01
0.3872993 Ol
.
_-_
_

Fig. 2
DEC 2.1964

- 

OEC 2,1964 -
MAIRIX P ( $0.37000000 E 011$.

| NUMBER OF ROWS 5 | numbeis of columns | 5 |  |  |
| :---: | :---: | :---: | :---: | :---: |
| 0.54796769600 | $0.13562386 E 01$ | 0.41036045 E 01 | 0.20929799 E 02 | $0.56368339 E 03$ |
| 0.13562386 E O1 | $0.16964725 \mathrm{E} \mathrm{O1}$ | 0.70455819 E 01 | 0.34906216 E 02 | 0.93488632 E 03 |
| 0.41030645 E OL | 0.70455819 E 01 | $0.11834189 \mathrm{E} \quad 02$ | 0.10249499E 03 | 0.29129970E 04 |
| 0.20929799 E 02 | 0.3490621 6t 02 | $0.10249499 E 03$ | $0.32699680 E 03$ | 0.17645368 E 05 |
| 0.50368339E 03 | 0.93488632 E 03 | 0.29129970E 04 | 0.17645368 E 05 | $0.33455532 \mathrm{E} \quad 06$ |

THE SAMPLED-DATA RICCAII PROGRAM

1. Description of the Problem: For many purposes, the variational theory presented in the preceding chapter is more conveniently applied in discretetime. This is the topic of the present chapter.
2. Theory: Consider the linear dynamical system
(2.1)

$$
x_{t+1}=\Phi_{t} x_{t}+\Gamma_{t} u_{t},
$$

where

$$
\begin{aligned}
t & =\text { integer }, \\
x_{t} & =(p \times 1) \text { the state vector, } \\
\Phi_{t} & =(p \times p) \text { transition matrix, a function of } t, \\
\Gamma_{t} & =(p \times q) \text { input matrix, a function of } t, \\
u_{t} & =(q \times I) \text { the control vector. }
\end{aligned}
$$

Such a system may arise in a variety of ways. Let us assume only that we are given a linear system, that is $\Phi_{t}$ and $\Gamma_{t}$ are independent of $x_{t}$ or $u_{t}$.

The control problem we will consider may be stated as follows. Given the desired value $x^{d}$ of the state vector, manipulate the sequence of control vectors $\left\{u_{t}\right\}$ in such a way as to bring the state vector $x_{t} \frac{\text { rapidly as close as possible to }}{} x^{d}$, and then keep the state
vector near $x^{d}$ at all times.

Let $Q$ be any nonnegative definite symmetric matrix. As before $\left\|x-x^{d}\right\|_{Q}^{2}$ will denote the quadratic form $\left(x-x^{d}\right)^{\prime} Q\left(x-x^{d}\right)$. This pseudo-metric (metric if $Q$ is positive definite) will be our definition of the distance between states. (We deviate intentionally from the point of view taken in Chapter VII in order to emphasize certain additional aspects of optimization.)

By static optimization we mean selecting a constant value $u^{0}$ of the control vector giving an equilibrium state $x^{*}$ of (1) lying as close as possible to $x^{d}$. Then $x^{*}$ and $u^{\circ}$ are characterized by the relations

$$
\begin{equation*}
x^{*}=\Phi x^{*}+\Gamma u^{\circ} \tag{2.2}
\end{equation*}
$$

and

$$
\left\|x^{*}-x^{\mathrm{d}}\right\|_{\mathrm{Q}}^{2}=\text { minimum }
$$

(We have assumed that $\Phi$ and $\Gamma$ are independent of $t$, because otherwise the problem would not be well defined.)

Such a $u^{\circ}$ exists, but knowing it may not provide a complete answer to our basic problem, because the equilibrium state $x^{*}$ may be unstable. Consider the scalar system

$$
x_{t+1}=2 x_{t}+u
$$

Assume $\mathrm{x}^{\mathrm{d}}=0$. Then $\mathrm{u}^{\circ}$ must be zero. But no initial state will go to zero if no control is used. Even if the initial state is $x_{0}=0$, because of the instability of the system small perturbations about zero will eventually become arbitrarily large. So the equilibrium state $x^{*}=0$ will not be maintained in practice. Note also that even if $x^{*}$ is globally asymptotically stable, there is no assurance that the approach to $x^{*}$ will be in any sense "rapid".

Hence static optimization is inadequate and we must consider dynamic optimization. We proceed to formulate the latter problem.

A performance index for the system (2.1) may be defined as:


Usually we normalize the time scale so that $t_{o}=0$ (and then we suppress $t_{o}$ as an argument of $\left.\forall \mathcal{H}.\right)$

We now define our control problem to mean that the control variables $u_{t}$ be selected in such a way as to minimize (2.3). This is what we shall mean by dynamic optimization.

We must find a sequence of vectors $\left\{u_{t}\right\} t=0, \ldots, T-1$ for which (2.3) assumes its minimum. At first sight it would appear that to obtain the optimal set $\left\{u_{t}\right\}$ we must optimize (2.3) with respect to all $u_{t}$ simultaneously, which is an elementary but very complicated job, at least for large $T$.

Fortunately, we can achieve a decisive simplication by making use of the following intuitively obvious but convenient observation emphasized by R. Bellman in the 1950's (but known at least since the l7th century).

PRINCIPLE OF OPTIMALITY. An optimal sequence $\left\{u_{t}^{0}\right\}$ of control variables has the property that, whatever the initial tate $x_{0}$ and the initial choice $u_{0}^{\circ}$ of control vectors, the remaining terms $u_{1}^{\circ}, u_{2}^{\circ}, \cdots$ must constitute an optimal sequence with respect to the state $x_{1}$ resulting from the choice of $u_{0}^{\circ}$.

Using the Principle of Optimality, we can obtain various expressions for the theoretical study and practical determination of the optimal control sequence. (Methods derived from the Principle of Optimality are known by the generic name of dynamic programming. Of course, dynamic programming is simply the discrete-time counterpart of the Hamilton-Jacobi theory discussed in Sect. 5 of the preceding chapter.) The reasoning used here and the
equations obtained are for the most part but slightly different from their continuous-time counterparts in the classical calculus of variations.

We observe first that (2.3) can be written in the form:

$$
\left.T x_{0}\right]=\left\{\left\|x_{1}-x^{a_{1}}\right\|_{Q_{1}}^{2}+\left\|u_{0}\right\|_{R_{1}}^{2}+T-1\left[x_{1}\right]\right\}
$$

Now let $\quad{ }_{T}^{O}\left[x_{0}\right]$ be the value of the performance index when the optimal sequence is used. Invoking the Principle of Optimality, we obtain a functional equation for

$$
\begin{aligned}
& { }_{\mathrm{T}}{ }^{\circ} \text { : } \\
& { }_{T}^{o}\left[x_{0}\right]=\min _{u_{0}, u_{1}, \ldots} \quad T^{\left[x_{0}\right]} \\
& =\min _{u_{0}}\left\{\left\|x_{1}-x^{d}\right\|_{Q_{1}}^{2}+\left\|u_{0}\right\|_{R_{1}}^{2}+{ }_{T-1}^{\left.\left[x_{1}\right]\right\} .}\right.
\end{aligned}
$$

This functional equation is solved by an iterative procedure. The successive optimal (minimum) performance indices $\quad{ }_{t}$ are connected by recursion relations:

$$
\begin{equation*}
\frac{o}{1}\left[x_{T-1}\right]=\underset{u_{T-1}}{\min }\left\{\left\|x_{T}-x^{\alpha_{1}}\right\|_{Q_{T}}^{2}+\left\|u_{T-1}\right\|_{R_{T}}^{2}\right\} \tag{2.6}
\end{equation*}
$$

$$
{ }_{k+1}^{0}\left[x_{T-k-1}\right]=\min _{u_{T-k-1}}\left\{\left\|x_{T-k}-x^{d}\right\|_{Q_{T-k}}^{2}+\left\|u_{T-k-1}\right\|_{R_{T-k}}^{2}+{ }_{k}^{0}\left[x_{T-k}\right]\right\}
$$

Substituting (2.1) into (2.5) we have

$$
\begin{equation*}
{ }_{1}^{0}\left[x_{T-1}\right]=\min _{u_{T-1}}\left\{\left\|\varnothing_{T-1} x_{T-1}+\Gamma_{T-1} u_{T-1}-x^{\alpha_{1}}\right\|_{Q_{T}}^{2}+\left\|u_{T-1}\right\|_{R_{T}}^{2}\right\} \tag{2.7}
\end{equation*}
$$

From the theory of the pseudo-inverse, we know that the minimum of this expression is attained when
(2.8)

$$
u_{T-1}^{o}=-\left(\Gamma_{T-1}^{1} Q_{T} \Gamma_{T-1}+R_{T}\right)^{\#}\left(\Gamma_{T-1}^{1} Q_{T}\left(\Phi_{T-1} x_{T-1}-x^{d}\right)\right)
$$

$$
=-K_{0} x_{T-1}+J_{0} x^{d}
$$

where \# denotes the Penrose-inverse of a matrix.
Substituting (2.8) into (2.7), we get

$$
{ }_{1}^{o}\left[x_{T-1}\right]=\left\|x_{T-1}\right\|_{P_{1}}^{2}-2 x_{T-1}^{\prime} U_{1} x^{d}+\left\|x^{d}\right\|_{S_{1}}^{2},
$$

where
(2.9)

$$
\begin{aligned}
& P_{I}=\left(\Phi_{T-I}-\Gamma_{T-1} K_{0}\right)^{\prime} Q_{T}\left(\Phi_{T-I}-\Gamma_{T-I} K_{0}\right)+K_{0}^{\prime} R_{T} K_{0}, \\
& U_{1}=-\left(\Phi_{T-1}-\Gamma_{T-K} K_{0}\right)^{\prime} Q_{T}\left(T_{T-1} J_{0}-I\right)+K_{0}^{*} R_{T} J_{0}, \\
& \left.\left.S_{1}=\left(\Gamma_{T-I} J_{0}-I\right)^{\prime} Q_{T}\right) \Gamma_{T-1} J_{0}-I\right)+J_{0}^{t} R_{T} J_{0} .
\end{aligned}
$$

Now we claim that

$$
{ }_{k}^{o}\left[x_{T-k}\right]=\left\|x_{T-k}\right\|_{P_{k}}^{2}-2 x_{n-k}^{s} U_{k} x^{d}+\left\|x^{d}\right\|_{S_{k}}^{2} .
$$

We will prove the assertion by induction. The statement has been already shown true for $k=1$. We assume it is true for $k-1$. Using (2.6) we write:

$$
\begin{aligned}
{ }_{k}^{o}\left[x_{T-k}\right] & =\min _{u_{T-k}}\left\{\left\|x_{T+1-k}-x^{d}\right\|_{Q_{T+1-k}}^{2}+\left\|u_{T-k}\right\|_{R_{T+1-k}}^{2}\right. \\
& \left.+\left\|x_{T+1-k}\right\|_{P_{k-1}}^{2}-2 x_{n+1-k}^{\prime} U_{k-1} x^{d}+\left\|x^{d}\right\|_{S_{k-1}}^{2}\right\} .
\end{aligned}
$$

Applying (2.1), this becomes

$$
\begin{aligned}
{ }_{k}^{0}\left[x_{T-k}\right] & =\min \left\{\left\|\Phi_{T-k} x_{T-k}+\Gamma_{T-k} u_{T-k}-x^{d}\right\|_{Q_{T+1}}^{2}\right. \\
& +\left\|u_{T-k}\right\|_{R_{T+1-k}}^{2} \\
& +\left\|\Phi_{T-k} x_{T-k}+\Gamma_{T-k} u_{T-k}\right\|_{P_{k-1}}^{2} \\
& \left.-2\left(\Phi_{T-k} x_{T-k}+\Gamma_{T-k} u_{T-k}\right)^{i} U_{k-1} x^{d}+\left\|x^{d}\right\|_{S_{k-1}}\right\}
\end{aligned}
$$

The minimum of this expression is attained when

$$
\begin{aligned}
u_{T-k}^{o} & =-\left[\Gamma_{T-k}^{\prime}\left(P_{k-1}+Q_{T+1-k}\right) \Gamma_{T-k}+R_{T+1-k}\right]^{\#} \\
\times\left[\Gamma _ { T - k } ^ { \prime } \left(P_{k-1}\right.\right. & \left.\left.+Q_{T+1-k}\right) \Phi_{T-k} X_{T-k}-\Gamma_{T-k}^{\prime}\left(U_{k-1}+Q_{T+1-k}\right) x^{d}\right] \\
& =-K_{k-1} x_{T-k}+J_{k-1} x^{d} .
\end{aligned}
$$

The fact that $u_{T-k}^{\circ}$ is a linear combination of $x_{T-k}$ and $x^{d}$ completes the proof, and we can obtain the following recursion formulae for $P_{k}, U_{k}$, and $S_{k}$ :

$$
(2.10)\left\{\begin{aligned}
P_{k}= & \left(\Phi_{T-k}-\Gamma_{T-k} K_{k-1}\right)^{\prime}\left(P_{k-1}+Q_{T+1-k}\right)\left(\Phi_{T-k}-\Gamma_{T-k} K_{k-1}\right) \\
& +K_{k-1}^{\prime} R_{k-1} K_{k-1} \\
-U_{k}= & \left(\Phi_{T-k}-\Gamma_{T-k} K_{k-1}\right)^{\prime}\left[\left(P_{k-1}+Q_{T+1-k}\right) \Gamma_{T-k} J_{k-1}-\left(U_{k-1}+Q_{T+1-k}\right)\right] \\
& -K_{k-1}^{\prime} R_{k-1} J_{k-1} \\
S_{k}= & \left(\Gamma_{T-k} J_{k-1}-I\right)^{\prime} Q_{T+1-k}\left(\Gamma_{T-k} J_{k-1}-I\right)+J_{k-1}^{\prime} R_{T+1-k} J_{k-I} \\
+ & S_{k-1}+J_{k-1}^{\prime} \Gamma_{T-k}^{\prime} P_{k-1} \Gamma_{T-k} J_{k-1}-J_{k-1}^{\prime} \Gamma_{T-k}^{\prime} U_{k-1}-U_{k-1}^{\prime} \Gamma_{T-k} J_{k-1}^{\prime}
\end{aligned}\right.
$$

Considerable simplification is possible after expansion and use of the pseudo-inverse lemma, $A^{\#} A A=A^{\#}$.

$$
\begin{gather*}
P_{k}=\Phi_{T-k}^{\prime}\left[\left(P_{k-1}+Q_{T+1-k}\right)-\left(P_{k-1}+Q_{T+1-k}\right) \Gamma_{T-k}\left(\Gamma_{T-k}^{\prime}\left(P_{k+1}+Q_{T+1-k}\right)\right.\right.  \tag{2.11}\\
\left.\Gamma_{T-k}+R_{T+1-k}\right\}_{T-k}^{*} \Gamma_{T-1}^{\prime}\left(P_{k-1}+Q_{T+1-k}\right) \Phi_{T-k}
\end{gather*}
$$

$$
\begin{equation*}
U_{k}=\left(\Phi_{T-k}-\Gamma_{T-k} K_{k-I}\right)^{\prime}\left(U_{k-1}+Q_{T+I-k}\right) \tag{2.12}
\end{equation*}
$$

$$
\begin{equation*}
K_{k}=\left[\Gamma_{T-k-1}^{\prime}\left(P_{k}+Q_{T-k}\right) \Gamma_{T-k-1}+R_{T-k}\right]_{\Gamma_{T-k-1}^{\prime}}^{\prime}\left(P_{k}+Q_{T-k}\right) \Phi_{T-k-1} \tag{2.13}
\end{equation*}
$$

$$
\begin{equation*}
J_{k}=\left[\Gamma_{T-k-1}^{:}\left(P_{k}+Q_{T-k}\right) \Gamma_{T-k-1}+R_{T-k}\right]_{T-k-1}^{\#}\left(U_{k}+Q_{n-k}\right) \tag{2.14}
\end{equation*}
$$

From the formulae for $P$, and $U$, we see that $P_{O}=U_{O}=0$.
Although the preceding manipulations have been rather tortuous, we now have quite explicit formulae for computing the control. We observe the important result:

Under the specified assumptions the optimal control vector is a linear (but time-dependent) function of the actual and desired states of the system.

Examination of the derivation shows that the control to be used in minimizing $F_{T}\left[x_{0}\right]$ is the sequence

$$
\begin{gathered}
u_{0}^{o}=-K_{T-1} x_{0}+J_{T-1} x^{d} \\
u_{1}^{o}=-K_{T-2^{x}} x_{1}+J_{T-2} x^{d} \\
\cdot \cdot \\
u_{T-k}^{o}=-K_{k-1} x_{n-k}+J_{k-1} x^{d} \\
u_{T-1}^{o}=-K_{0} x_{T-1}+J_{0} x^{d} .
\end{gathered}
$$

Note that the subscripts $t$ of $x$ and $u$ indicate the actual time, while the subscripts $k$ of $K, J, P$, etc. are "time to go" until $T$.

At this point it is appropriate to discuss the very important case where we wish to minimize the performance index over an infinite number of steps.

From the derivation we see that $P_{1}$ is computed using the transition relations and weighting coefficients applicable to the last interval considered in the performance index. But this has no meaning when we are optimizing over an infinite number of intervals. Taking a practical point of view, we choose some $T$ which in relation to the system parameters seems to be sufficiently large to allow the system to come to rest long before $t=T$. If the system is periodic over the entire range of optimization and completely controllable then we would expect that $K_{k}$ would tend to be periodic as $k \rightarrow \mathbb{T}$.

If the parameters of the system and performance index are constant, we have a much simpler situation. In this case, after using the initial control, we have exactly the same minimization problem since we must still optimize over an infinite number of steps. Thus we would expect to obtain in the limit $k \rightarrow \infty$ a constant value of the feedback matrices $K$ and $J$. If the system is completely controllable and $x^{d}$ is a possible equilibrium state of the system, then $P_{i}$ and $U_{i}$ approach limits and this expectation is furfilled.

Under these conditions we can generalize further. Let us assume that $x^{d} \neq 0$ and asymptotic approach to $x^{\mathrm{d}}$ is desired. This is impossible unless $x^{d}$ is in the range of $(I-\Phi)^{-1} T$. Even then if $R \neq 0$, $x$ will not approach $x^{d}$, but a balance will be reached minimizing the sum

$$
\left\|x-x^{\frac{a}{\|}}\right\|_{Q}^{2}+\|u\|_{R}^{2}
$$

Thus asymptotic approach to $x^{d}$ implies that we must ignore the cost of control because as $x \rightarrow x^{d}, u \rightarrow \Gamma^{\#}(I-\Phi) x^{d} \neq 0=$ const. It seems therefore that under certain circumstances it might be desirable to use a performance index of the form

$$
\left\|x-x^{d}\right\|_{Q}^{2}+\left\|u-u^{\alpha}\right\|_{R}^{2}
$$

where

$$
u^{d}=\Gamma^{\#}(I-\Phi) x^{d} .
$$

If we do this, we find that

$$
u=-K x+J x^{d}+L u^{d},
$$

where $K$ and $J$ are defined above and

$$
L=\left[\Gamma^{\prime}(P+Q) \Gamma\right]^{\#} \Gamma^{\prime} M R
$$

with

$$
M=-\left(I-\Phi^{\prime}+K^{\prime} \Gamma^{\prime}\right)^{-1} \Phi^{\prime}(P+Q) \Gamma\left[\Gamma^{\prime}(P+Q) \Gamma+R\right]^{\#} R .
$$

There are certain differences between the discrete and continuous control problems to which attention should be drawn. These follow mainly from the fact that in the discrete case $R$ may be singular. For instance, in order to take the state of a continuous system to the origin in finite time the ordinary quadratic performance index method cannot be used; instead the "Minimum Energy" trajectory is utilized. The difference between the two riccati equations is solely a matter of terminal conditions, it is true; nevertheless special treatment must be used. In the sampled case, these problems do not arise. If $s$ is positive definite, $Q$ and $R$
zer̂o matrices, and the system completely controllable, $P$ will be zero after at most $n$ (dim $x=n$ ) steps. (See Sect. 8 of previous chapter for notations.) This is the so-called "Dead Beat Control".

Physically the requirement that control be piecewise constant restricts the system response. In the continuous problem, sufficiently large control can make the state error arbitrarily small. This is no longer true in the discrete system. In the continuous system sufficiently large control can take the system to zero ("Minimum Energy Trajector") in arbitrarily small time. In the discrete system a certain number of sampling instants is required and no amount of extra control can reduce this number.
3. Computation: For the moment we will consider only the computation of $P_{k}$ and $K_{k}$.

Let us define

$$
P_{k}^{*}=P_{k}+Q_{T-k} ;
$$

then equation (2.11) can be written

$$
P_{k}^{*}=\Phi_{T-k}^{\prime}\left[P_{k-1}-P_{k-1} I_{T-k}\left(\Gamma_{T-k}^{\prime} P_{k-1}^{*} \Gamma_{T-k}+R_{T+1-k}\right\}^{*} T_{T-k}^{\prime} P_{k-1}^{*}\right] \Phi_{T-k}
$$

Then by (2.13)

$$
\left.\mathrm{K}_{\mathrm{k}}=\left[\mathrm{T}_{\mathrm{T}-\mathrm{k}-1}^{\prime} \mathrm{P}_{\mathrm{k}}^{* T} \mathrm{~T}_{\mathrm{T}-\mathrm{k}-1}+\mathrm{R}_{\mathrm{T}-\mathrm{k}}\right]^{\#_{\Gamma}^{\prime}}{ }_{\mathrm{T}-\mathrm{k}}\right] \Gamma_{\mathrm{T}-\mathrm{k}-1}^{\prime} \mathrm{P}_{\mathrm{k}}^{*} \Phi_{\mathrm{T}-\mathrm{k}-1}
$$

At the risk of being pedantic, we will outline very carefully the phasing of indices in $P$ and $K$.
$P_{0}$ is always zero.
$P_{I_{0}}$ is the value of the performance index obtained by using optimal control ${\underset{T}{T}}_{0}$ over the last interval only.

$u_{T-I}^{0}=-K_{0} x_{T-I}+J_{0} x^{d}$ where $K_{0}$ and $J_{o}$ are computed using $P_{o}^{*}$, not $P_{1}^{*}$.
$P_{T}^{*}=P_{T}+Q_{0}$, where $Q_{0}$ has not been defined (see (2.3)). This is purely a computational problem and merely requires that some matrix $Q_{o}$ be provided for the program.
$P_{k}=P_{k}^{*}-Q_{T-k}$, so if the performance index matrix $P_{k}$ is required, $Q_{T-k}$ must be subtracted from the program output $P_{k}^{*}$.

If comparisons are made between the discrete and continuous performance indices, we must use the redefinition

$$
\begin{equation*}
{ }_{T}\left[x_{0}\right]=\sum_{k=1}^{T}\left(t_{k}-t_{k-1}\right)\left[\left\|x_{k}-x^{\alpha}\right\|_{Q_{k}}^{2}+\left\|u_{k-1}\right\|_{R_{k}}^{2}\right] \tag{3.1}
\end{equation*}
$$

Computation of $U_{k}$ does not fall into the pattern given. However if $K_{k}$ converges to $K$ and $U_{k}$ to $U$ then from (1.9) we have

$$
U=(\Phi-\Gamma K)^{2}(U+Q) .
$$

Since we have $K$ available we can compute $U$ and thus $J$. Notice that although we need not have assumed $x^{d}$ constant our program can obtain $J$ only if $U$ converges, which probably will not occur unless $x^{d}$ is constent.

The form of the equation used in the machine is described in Chapter I, page 11 and Fig. I.

Some transformations are Inquired. In terms of Chapter I, Fig. I, we let

$$
\begin{aligned}
F_{M A C H} & =\phi_{\text {SYSTEM }} \\
\mathrm{PO}_{\text {MACH }} & =P_{\text {SYSTEM }}^{*} \\
G_{\text {MACH }} & =\Gamma_{\text {SYSTEM }}^{\prime} \\
R_{\text {MACH }} & =R_{\text {SYSTEM }} \\
Q_{M A C H} & =Q_{\text {SYSTEM }} \\
K_{\text {MACH }} & =K_{\text {SYSTEM }}
\end{aligned}
$$

Indexing of parameters in a nonstationary problem must be handled by proper programming of ASP, see, for instance, Problem C in Chapter IX.

Under certain circumstances $P^{*}$ will be independent of time. A relevant theory is:

THEOREM: Let $R=0, \Gamma^{\prime} P_{0}^{* \Gamma}$ be nonsingular and rank $\Gamma^{\prime} P_{0}^{*} \Gamma=$ rank $P_{0}^{*}$. Then $P_{0}^{*} \Gamma\left(\Gamma^{\prime} P_{0}^{*} \Gamma\right)^{-I^{\prime}} P_{0}^{*}=P_{0}^{*}$, implying that $P_{k}^{*}=Q=P_{0}^{*}$ for all k .

Proof. $P_{0}^{*}=Q=A A^{\prime}, \quad \Gamma^{\prime} A$ nonsingular (we make the trivial assumption that $\Gamma$ has maximal rank), then

$$
\begin{aligned}
& P_{O}^{*} \Gamma\left(T^{i} P_{O}^{*} \Gamma\right)^{-1} \Gamma^{i} P_{O}^{*} \\
& \quad=A A^{i} \Gamma^{\prime}\left(T^{i} A A^{i} T\right)^{-1} \Gamma^{i} A A=A A^{i}=P_{0}^{*}=Q .
\end{aligned}
$$

An important special case occurs when $\Gamma$ is a vector and rank $Q \Gamma=$ rank $Q$.

An analogous result states:

THEOREM: If $I$ is nonsingular, $P_{k}^{*}=Q$.
Proof. Consider $P_{0}^{*}-P_{0}^{*} \Gamma\left(T^{\prime} P_{o}^{*} T\right)^{\#} \Gamma^{\prime} P_{0}^{*}$. Since $\Gamma$ is nonsingular, multiply by $\Gamma^{\prime}$ and $\Gamma$. Then

$$
\Gamma^{i} P_{0}^{*} \Gamma-\Gamma P_{0}^{* *} \Gamma\left(\Gamma^{\prime} P_{0}^{*} \Gamma\right)^{\#} \Gamma^{\prime} P_{0}^{*} \Gamma ;
$$

by the first pseudo inverse lemma, this is the zero matrix.

All of these results are alike in saying that if $k$ states are penalized and there are $k$ independent control variables which can independently "reach" the $k$ weighted states, then the performance index is zero. Clearly if $R \neq 0$, this cannot be true.

PSEUD in SAMPL does not iterate. It uses Pl which is ordinarily $10^{-2}$. Therefore unless $R$ is a scalar $P l$ should be changed by PIZER to something like $10^{-6}$ or $10^{-7}$.
4. Checks: Input conforms to Chapter I notation, not to the system (2.1) described above.

$$
\begin{aligned}
& F=\left[\begin{array}{lll}
0 & 1 & 0 \\
0 & 0 & 0 \\
0 & 0 & 2
\end{array}\right] G^{\prime}=\left[\begin{array}{ll}
0 & 0 \\
2 & 0 \\
0 & 1
\end{array}\right] \\
& Q=\left[\begin{array}{lll}
3 & 1 & 0 \\
1 & 1 & 0 \\
0 & 0 & 1
\end{array}\right] \quad R=\left[\begin{array}{ll}
1 & 1 \\
1 & 2
\end{array}\right] .
\end{aligned}
$$

$K(0), P(1), K(1)$, and $P(2)$ appear as Fig. 2, 3, 4, and 5 and are correct to the given number of places.
5. Filtering Theory: In Sect. 2 we have set up a control problem for a discrete deterministic system and derived the appropriate equations for the optimal feedback and the minimum performance index. Through the Principle of Duality we know that these same equations represent the solution of an optimal filtering problem.

For pedagogical reasons, however, we prefer to derive the equations for the optimal filter ab initio.

$$
\begin{aligned}
x_{t+1} & =\Phi_{t} x_{t}+u_{t} \\
y_{t} & =H_{t} x_{t}+v_{t}
\end{aligned}
$$

(5.1)
where

$$
\begin{aligned}
t= & \text { integer } \\
\mathrm{x}_{\mathrm{t}}= & \text { the state vector } \\
\Phi_{t}= & \text { transition matrix, a function of } t \\
u_{t}= & \text { an element of a vector-valued independent } \\
& \text { gaussian random sequence } \\
H_{t}= & (q \times p) \text { output matrix, a function of } t . \\
v_{t}= & (q \times I) \text { an element of a vector-valued indepen- } \\
& \text { dent gaussian random sequence. }
\end{aligned}
$$

We assume that $E u_{t}=0, E v_{t}=0, E u_{t} v_{t}^{\prime},=0, E u_{t} u_{t}^{\prime}=Q_{t} \delta_{t t^{\prime}}$ and $E v_{t} v_{t}^{\prime}=R_{t} \delta_{t t}$, where $Q_{t}$ and $R_{t}$ are respectively ( $p \times p$ ) and ( $q \times q$ ) matrix, functions of $t$; we also assume that $\left[\Phi^{\prime}, H^{8}\right.$ ] is completely controllable, i.e. (5.1) is completely observable.

The filtering problem we will consider may be stated as follows.
Given the values of the output at $T$ times $\left\{y_{0}, y_{1}, \ldots, y_{T}\right\}$, determine an estimate $\hat{X}_{T+1}$ of $\mathrm{x}_{\mathrm{T}+1}$ such that $\mathrm{E}\left\|\mathrm{x}_{\mathrm{T}+1}-\hat{\mathrm{x}}_{\mathrm{T}+1}\right\|^{2}$ is minimum.

This statement has a formal resemblance to the usual least square fitting problem which may in turn be posed as a problem in orthogonal projections in an inner product space (see for instance the Orthogonal Projection Lemma in ChapterIV). Let us digress to show that this resemblance is more than formal.

Consider the real-valued random variables $y_{0}, y_{1}, \ldots, y_{T}$. The set of all real linear combinations of these form a vector space $Y_{T}$. (Remember $y_{t}$ does not denote the sample obtained at $t$ but the random variable at $t$
that is the set of all possible samples at $t$ with some distribution function.) Then any linear combination of the $y_{t}$ is also a random variable. Furthermore, in this vector space, an inner product may be defined $\left(y_{t}, y_{t},\right)=E y_{t} y_{t}$, But now that we are in an inner product space we can apply fourier analysis to our problem. The orthogonal projection lemma from ChapterIV tells us that $E\left\|X_{T+1}-\hat{x}_{T+1}\right\|^{2}$ will be minimum if $\hat{X}_{T+1}$ is the orthogonal projection of $x_{T+1}$ on $Y_{T}$, provided we restrict $\hat{x}_{T+1}$ to be a linear functional on $Y_{T}$.

It is interesting to have the following theorem which tells us that the orthogonal projection on $Y_{T}$ in the case we consider, actually gives the minimum value of $E\left\|X_{T+1}-\stackrel{X}{X}_{T+1}\right\|^{2}$.

THFOREM: Let $\left\{x_{i}\right\},\left\{y_{j}\right\}$ be random sequences with zero mean. We observe $y_{0}, y_{1}, \ldots, y_{T}$. If either
(A) the random sequences are gaussian; or
(B) the optimal estimate is restricted to be a linear function on $Y_{T}$ and the function to be minimized is $E\left\|x_{T+1}-\hat{X}_{T+1}\right\|^{2}$ then the optimal estimate of $x_{T+1}$ given $y_{O}, \ldots, y_{T}$ is the orthogonal projection of $x_{T+1}$ on $Y_{T}$.

In the sequel, we shall be dealing mainly with vector valued random variables. In that case we have only to remember that $Y_{T}$ is an $m(T+1)$ dimensional space and $Y_{T+1}$ is $m(T+2)$ dimensional. This is actually the only novelty to the analysis -- at each step we increase by $m$ the dimension of the space into which we are projecting. The notation to be used in this case will be explained at each step. Furthermore we will minimize not just $E\left\|x_{T+1}-\hat{x}_{T+1}\right\|^{2}$ but even $E\left(x_{T+1}-\hat{x}_{T+1}\right)_{i}^{2}$ that is, minimize each component of the error $E\|x-\hat{x}\|^{2}$ separately. Iet us assume that the $\left\{y_{t}\right\}$ have been orthonormalized to $\left\{\epsilon_{t}\right\}$. In $R^{m}$ we mean by this that $\left(\epsilon_{t}, \epsilon_{t}\right)=\delta_{t t}:$ However the $j^{\text {th }}$ component $\epsilon_{t j}$ of $\epsilon_{t}$ is a random variable and it is these that must be orthonormalized, i.e. $E \epsilon_{t j} \epsilon_{t^{\dagger} \ell}=\delta_{t t^{\prime} k \ell}=0$ unless $i=j=k=\ell$. This is conveniently expressed by writing $E \epsilon_{t} \epsilon_{t},=\delta_{t t}: I_{m}$.

Purely algebraically, we know that

$$
\begin{equation*}
\left.\hat{x}_{\mathrm{T}+1}=\sum_{t=0}^{\mathrm{T}}\left(\mathrm{x}_{\mathrm{T}+1}\right), \epsilon_{\mathrm{t}}\right) \epsilon_{\mathrm{t}} . \tag{5.2}
\end{equation*}
$$

By this formula we mean that every component of $\mathrm{X}_{\mathrm{T}+1}$ is projected into $Y_{T}$

$$
\begin{equation*}
\left(\hat{x}_{T+1}\right)_{j}=\sum_{t=0}^{T}\left(\left(x_{T+1}\right)_{j}, \epsilon_{t}\right) \epsilon_{t} . \tag{5.3}
\end{equation*}
$$

Since $\epsilon_{t}$ is an m-vector, we can write (5.2) more explicitly as

$$
\left(\hat{x}_{T+1}\right)_{j}=\sum_{t=0}^{T} \sum_{k=1}^{m}\left(\left(x_{T+1}\right)_{j}, \epsilon_{t k}\right) \epsilon_{t k}
$$

which has a clearer representation as

$$
\text { (5.4) } \quad \hat{x}_{T+1}=\sum_{t=0}^{T} E\left(x_{T+1} \epsilon_{t}^{\prime}\right) \epsilon_{t}
$$

In other words, $\hat{X}_{T+1}$ is a random variable expressed as the sum of random variables $\epsilon_{t}$ with coefficients determined by the expected values $E\left(X_{T+1} \epsilon_{t}^{1}\right)$.

Using (5.1) in (5.2) we get

$$
\begin{aligned}
\hat{x}_{T+1} & =\sum_{t=0}^{T}\left(\left(\Phi_{T} x_{T}+u_{T}\right), \epsilon_{t}\right) \epsilon_{t} \\
& \left.=\Phi_{T} \sum_{t=0}^{T}\left(x_{T}, \epsilon_{t}\right) \epsilon_{t}+\sum_{i=0}^{T}\left(u_{T}, \epsilon_{t}\right) \epsilon_{t}\right)
\end{aligned}
$$

Since $\left\{u_{t}\right\}$ is uncorrelated, we have $\left(u_{T}, \epsilon_{t}\right)=0$ for $i=0, \ldots$. , by (5.1). Thus

$$
\hat{x}_{T+I}=\Phi_{T}\left[\hat{x}_{T}+\left(x_{T}, \epsilon_{T}\right) \epsilon_{T}\right]
$$

Now what is $\epsilon_{T}$ ? It is the component of $y_{T}$ orthogonal to $Y_{T-1}$, normalized. Let us observe that $\left(y_{T}-H_{T} \hat{X}_{T}\right)$ is orthogonal to $Y_{T-I}$. We know that

$$
E\left(x_{T}-\hat{x}_{T}\right) y_{t}^{\prime}=0 \quad t=1, \ldots, T-1
$$

So $E\left(H x_{T}-\hat{H x}_{T}\right) y_{T}^{\prime}=0$ and $E\left(y_{T}-H x_{T}\right) y_{t}^{\prime}=E v_{T} y_{t}^{\prime}=0, \quad t=1, \ldots, T-1$. And since $\left(y_{T}-H \hat{X}_{T}\right)$ lies in $Y_{T}$ it must be a multiple of $\epsilon_{T}$. In the usual analysis where $y_{T}$ is one dimensional, we would say a scalar multiple, but here we can say only that

$$
\left(y_{T}-\hat{H x_{T}}\right)=A_{\epsilon T}
$$

where $A$ is nonsingular.
We have, therefore, shown that $\hat{x}_{T}$ is generated in a system

$$
\hat{x}_{T+I}=\hat{x}_{T}+K_{T}\left(y_{T}-\hat{H x_{T}}\right)
$$

Now let us determine $K_{T}$.
We know that $\tilde{x}_{T+1}=x_{T+1}-\hat{x}_{T+1}$ is orthogonal to $Y_{T}$. From the discussion above we know that this means

$$
E \tilde{x}_{T+1} y_{t}^{\prime}=0 \quad \text { for } \quad t=1, \ldots, T
$$

Hence

$$
\Phi_{T} E \tilde{x}_{T} y_{t}^{2}-K_{T} H_{T} E \tilde{x}_{T} y_{t}^{\prime}+E u_{T T} y_{t}^{:}-K_{T} E v_{T} y_{t}^{:}=0
$$

Again we have $\left(u_{T}, y_{t}\right)=0$ for $t=0, \ldots, T$. By optimality of $\hat{x}_{T}$, . $\left(\tilde{x}_{T}, y_{t}\right)=0$ for $t=0, \ldots, T-1$. Because $v_{T} x_{t}^{\prime}=0$ for all $t$ and $v_{T} v_{t}=R_{T} \delta_{t T}$, we have $E v_{T} y_{t}^{\prime}=R_{T}$. So we finally arrive at
(5.5)

$$
\begin{aligned}
& \Phi_{T} \tilde{X X}_{T} y_{T}^{\prime}=K_{T}\left(H_{T} \tilde{X}_{T} y_{T}+R_{T}\right) \\
& \tilde{E X}_{T} v_{T}^{\prime}=E \tilde{x}_{T} \tilde{x}_{T} H_{T}^{\prime}+E \tilde{x}_{T} v_{T}+E \tilde{x}_{T} \hat{x}_{T} H_{T}^{\prime}
\end{aligned}
$$

We know from fourier series that $\left(\tilde{x}_{T}, \hat{x}_{T}\right)=0$.

$$
\begin{aligned}
E \tilde{x}_{T} y_{T}^{\prime} & =E \tilde{x}_{T} x_{T} H_{T}^{\prime}+E \tilde{x}_{T} v_{T}^{\prime} \\
E \tilde{x}_{T} v_{T} & =E \tilde{x}_{T} v_{T} H_{T}^{\prime}+E x_{T} v_{T}^{\prime} \\
& =E \hat{x}_{T} v_{T}^{\prime}
\end{aligned}
$$

But $\hat{x}_{T}$ is orthogonal to $\epsilon_{T}$, so

$$
\begin{aligned}
& \left(\hat{x}_{T},\left(y_{T}-H_{T} \hat{x}_{T}\right)^{\prime}\right)=0 \\
= & \left(\hat{x}_{T},\left(H_{T}\left(x_{T}-\hat{x}_{T}\right)+v_{T}\right.\right. \\
= & \hat{x}_{T} v_{T}^{\prime}=0 .
\end{aligned}
$$

Let us denote $\tilde{E X}_{T} \tilde{x}_{T}$ by $P_{T}$ and attempt to find a recursion scheme for $P_{T}$.

$$
\begin{aligned}
P_{T+I} & \left.=\Phi_{N}-K_{N} H_{N}\right) P_{N}\left(\Phi_{N}-K_{N} H_{N}\right)^{\prime}+\left(\Phi_{N}-K_{N} H_{N} \tilde{x}_{N} u_{N}\right. \\
& -\left(\Phi_{N}-K_{N} H_{N}\right) \tilde{x}_{N} V_{N} K_{N}^{\prime} R_{N} K_{N}^{\prime} \\
& =\left(\Phi_{N}-K_{N} H_{N}\right) P_{N}\left(\Phi_{N}-K_{N} H_{N}\right)^{\prime}+Q_{N}+K_{N} R_{N} K_{N}^{\prime}
\end{aligned}
$$

After a similar reduction we obtain

$$
\begin{aligned}
P_{n=1} & =\Phi_{N}\left[P_{N}-P_{N} H_{N}^{\prime}\left[H_{N} P_{N} H^{\prime}{ }_{N}+R_{N}\right]\right]^{\#} H_{N} P_{N} \Phi_{N}^{\prime}+Q_{N} \\
K_{N} & =\Phi_{N} P_{N} H_{N}^{\prime}\left[H_{N} P_{N} H_{N}^{\prime}+R_{N}\right]^{\#} \\
\hat{x}_{I} & =\Phi_{0} \hat{x}_{0}+K_{0}\left(y_{0}-H_{0} \hat{x}_{0}\right)
\end{aligned}
$$

Since (5.5) must be satisfied exactly, not in the least squares sense, it is necessary to justify the use of the pseudo-inverse in the formula for $K_{T}$. The justification is that a solution always exists since

$$
\text { Range }\left[\mathrm{HPH}^{\prime}+\mathrm{R}\right] \text { ) Range } \mathrm{HP}
$$

provided $P$ and $R$ are nonnegative definite symmetric. This assertion is proved in the appendix to the chapter on approximation of an impulse response.

These formulae require initial conditions $P_{o}$ and $\hat{x}_{0}$ which may be otained for instance as follows.

By our assumption of complete observability

$$
\left[H^{1}, \Phi^{\mathbf{1}} \mathrm{H}^{1}, \Phi^{\mathbf{1}^{2}} \mathrm{H}^{1}, \ldots, \Phi^{\mathrm{n}^{\mathrm{n}-1} \mathrm{H}^{2}}\right]
$$

has maximal rank. Let $q$ be the number such that

$$
\Lambda^{\prime}=\left[H^{\prime}, \Phi^{\mathbf{y}} \mathrm{H}^{\mathrm{y}}, \ldots, \Phi^{1 q-1} \mathrm{H}^{\mathrm{t}}\right]
$$

has maximal rank.
Then

$$
Y=\left[\begin{array}{l}
y_{0} \\
y_{I} \\
\cdot \\
\cdot \\
y^{q-1}
\end{array}\right]=\Lambda x_{0}+\Omega
$$

where

$$
\Omega=\left[\begin{array}{c}
v_{0} \\
v_{1}+H u_{0} \\
v_{2}+H \Phi u_{0}+H u_{1} \\
v_{3}-H \Phi^{2} u_{0}+H \Phi u_{1}+H u_{2}
\end{array}\right]
$$

Our primary concern in an initial estimate $\hat{\mathrm{x}}_{\mathrm{O}}$ is that it be unbiased, i.e.

$$
\begin{aligned}
E\left(x_{0}-\hat{x}_{0}\right) & =0 \\
E\left(x_{0}-K Y\right) & =E(I-K \hat{A}) x_{0}-E K \Omega \\
& =E(I-K \Lambda) x_{0} .
\end{aligned}
$$

In order to guarantee that this is zero, we must choose $K=\Lambda^{\#}$. It is then possible to compute $E \tilde{x}_{o}^{\tilde{x}_{0}^{\prime}}=\Lambda^{\#} E \Omega \Omega^{\prime} \Lambda^{\prime \prime}$, and, letting

$$
\hat{\mathrm{x}}_{\mathrm{O}}=\Phi^{\mathrm{k}_{\Lambda} \#_{\mathrm{Y}}}
$$

and

$$
P_{0}=\Phi^{k} \Lambda^{\#} E \Omega \Omega \Lambda^{\#} \Phi^{2} k
$$

we are ready to start our recursion scheme.
This brief analysis brings out the importance of an unbiased initial $\hat{x}_{0}$ since the derivation of the minimum variance estimate requires the previous $\tilde{x}$ to be unbiased.
se an example to help those who are confused by the outer products of Euv.... an vectors, e.g. Exx', which appear to be inner products in the probak: ir space, let us point out the following precise analogy.

Let $f^{\prime}=\left(f_{1}, \ldots, f_{n}\right)$ be a row vector of $n$ functions which are Iebesgue square integrable on $[0,2 \pi]$. We desire the $m^{\text {th }}$ Fourier approximant for $f$. The easiest way to write the solution is by representing the coefficients of the Fourier series as an outer product:

$$
\hat{\mathrm{f}}=\frac{1}{2 \pi}\left\{\int_{0}^{2 \pi} \frac{1}{2} f d t+\sum_{i=1}^{m}\left[\int_{0}^{2 \pi} f(\cos i t) d t, \int_{0}^{2 \pi} f(\sin i t) d t\right]\left[\begin{array}{ll}
\cos & i t \\
\sin & i t
\end{array}\right]\right\}
$$

The significant property here is that in both the example and the problem itself there is not merely a minimization of

$$
\|\hat{f}-\dot{f}\|^{2} \text { or } E\|\hat{x}-x\|^{2}
$$

but minimization is taking place component-wise: That is, we are actually minimizing each

$$
\left(\hat{f}_{i}-f_{i}\right)^{2} \quad \text { and } \quad E(\hat{x}-x)_{i}^{2} \quad i=1, \ldots, n^{2}
$$

Thus each component of $x$ is projected into the probability space and at each step more than one new dimension is being added to the space into which we are projecting. In the Fourier approximation we are projecting each component of $f$ into the function space spanned by

$$
\{\cos i t, \sin i t\} \quad i=0, \ldots, m
$$

and at each step we add two to the dimension of the fitting space. (It is not universally known, but the $m^{\text {th }}$ Fourier approximant is "best" in the least squares sense.)

SAMPL


Fig. 1
AUTOMATIC SYNTHESIS PROGRAM DEC 5. 1964

## MATRIX PT 21

EXPONENT 0

ALPHA $=0.22521415 E=00$

## CHAPTER IX

## COMPUTATION OF TIME HISTORIES

1. Description of the Problem: The entire manual is concerned with finite dimensional linear dynamical systems. That is, processes determined by linear differential or difference equations. This being the case, one of the most important problems is to obtain the time history of the state.

As we have seen in Chapter II, this involves computation of the transition matrix -- ordinarily a very straightforward process. In this chapter we shall consider several numerical difficulties which can arise. In general these belong to two categories: poor conditioning and nonstationarity.

ASP has two formats for displaying transient behavior. We will illustrate both of these and discuss their respective virtues.
2. Theory and References: Theoretical background for this material is contained in Chapter II and Acrivos, see $3 . B$ ) below. Acrivos is concerned with discrete systems but in the digital computer we are always constrained to discretize so that much of this material is pertinent to both continuous and discrete systems.

We shall now consider several distinct problems (A, B, C below) to familiarize the reader with techniques which are repeatedly used in later applications.

3A. The Specific Problem: We begin by computing the transition matrix of
$(3 A .1) \quad \dot{x}=\left[\begin{array}{cc}0 & \frac{\pi}{10} \\ -\frac{\pi}{10} & 0\end{array}\right] x, \quad \Phi(t)=\left[\begin{array}{cc}\cos \frac{\pi}{10} t & \sin \frac{\pi}{10} t \\ -\sin \frac{\pi}{10} t & \cos \frac{\pi}{10} t\end{array}\right]$.

In the computer we have no method of functional expression, so we must compute $\Phi$ at selected points in time. For convenience we ask for printout at fixed intervals, say, $\tau=.5$.

4A. Equations and Procedure: We will compute

$$
\Phi(.5)=e^{.5 F}
$$

and then use the relationship

$$
\Phi(.5 \mathrm{k})=\Phi^{\mathrm{k}}(.5)
$$

5A. Results: The ASP program used to compute such a transiton matrix may be seen in Fig. I. Results are good, as would be expected in such a trivial problem. The errors are larger than can be legimately blamed on the fact that $\pi / 10$ can not be accurately entered in the machine. For instance, the eirror in sine at $k=10$, where the argument of trigonometric terms should be $\pi / 2$, is $.24 \cdot 10^{-6}$, but the errors in $\pi / 10$ should be less than $1 \cdot 10^{-8}$ and the derivative of sine at this point is nearly zero. So it appears that the errors are largely accumulated computational errors.

The rather large sampling period makes it difficult to check phase precisely. Nevertheless it is possible to say that these are genuine errors in the computation of $\Phi$ rather than phase errors caused by incorrect values of the argument. In the first place 0.5 enters the machine exactly. Secondly, the errors increase linearly with time and the value of the determinant decreases linearly. If a phase error were contributing the cosine term would not have errors increasing linearly with time and the determinant would remain constant. Notice that there is an extremely small phase error as measured by the sine terms being nonzero.


$$
.24 \cdot 10^{-6}
$$

$.5 \cdot 10^{-6}$
$50\left[\begin{array}{ll}-.99999756 & .5476 \cdot 10^{-6} \\ -.5476 \cdot 10^{-6} & -.99999756\end{array}\right]$

$$
2.43 \cdot 10^{-6}
$$

$$
4.8 \cdot 10^{-6}
$$

$100\left[\begin{array}{ll}.99999513 & -.1051 \cdot 10^{-5} \\ .1051 \cdot 10^{-5} & . .99999513\end{array}\right]$
$4.87 \cdot 10^{-6}$
$9 \cdot 7 \cdot 10^{-6}$
$200\left[\begin{array}{ll}.99999024 & -.2023 \cdot 10^{-5} \\ .2023 \cdot 10^{-5} & .99999513\end{array}\right]$
$9 \cdot 75 \cdot 10^{-6}$
$19.5 \cdot 10^{-6}$.

One interesting aspect of the computation was that throughout this fairly long transient the numbers which should have been equal were equal.

6A. Numerical Considerations: Observe that the previous $F$ matrix was in good form for computation. If we take the same problem and change only the units in which the components of $x$ are expressed, we could obtain the mathematically identical system

$$
\dot{y}=\left[\begin{array}{cc}
0 & \frac{\pi}{10} \cdot 10^{6} \\
-\frac{\pi}{10} \cdot 10^{-6} 0
\end{array}\right] y, \Phi(t)=\left[\begin{array}{cc}
\cos \frac{\pi}{10} t & 10^{6} \sin \frac{\pi}{10} t \\
-10^{-6} \sin \frac{\pi}{10} t & \cos \frac{\pi}{10} t
\end{array}\right] .
$$

In this case $.5\|F\|>10$ so $\tau$ will be halved until $\frac{.5}{2^{k}}\|F\|<10$ (see Chapter II) and the exponential squared $k$ times. In this example $k$ was 14 and $\tau$ was $\frac{.5}{16,384} \approx 3 \cdot 10^{-5}$. Because of this all the significance was contained in the sine term since the cosine to eight decimal places was one. This seriously affected the accuracy. For one thing notice that terms which should be equal are not precisely so.
$5\left[\begin{array}{ll}.2608 \cdot 10^{-7} & .99770785 \cdot 10^{6} \\ -.99770787 \cdot 10^{-6} & .3353 \cdot 10^{-7}\end{array}\right]$

$$
.22 \cdot 10^{-2} \quad .44 \cdot 10^{-2}
$$

$50\left[\begin{array}{ll}-.97731353 & .2617 \\ -.2647 \cdot 10^{-12} & -.97731354\end{array}\right]$
$2.2 \cdot 10^{-2} \quad 4.4 \cdot 10^{-2}$

$$
4.4 \cdot 10^{-2} \quad 8.8 \cdot 10^{-2}
$$

$8.8 \cdot 10^{-2}$
$17 \cdot 6 \cdot 10^{-2}$

Not only does this cause loss of accuracy but it also wastes time in the exponential routine. This problem is a very serious numerical one, it is difficult to tell whether a number is small because it expresses an unimportant coupling or because the system is given in a poorly chosen basis.

In this case $\left(\frac{\pi}{10}\right) \cdot 10^{-6}$ is vital to the system although it is much smaller than the other matrix elements. Usually we will try to equalize elements as much as possible by using diagonal transformations. No more complicated transformations are attempted as a rule.

7A. Remarks: In this simple case where we know the transition matrix, we can consider the problem to be discrete and load $\Phi(.5)$ into the machine. Clearly this is the most machine-efficient process as it avoids the exponential computation. But it means also that the programmer must compute sine $\frac{\pi}{20^{\circ}}$. Since the last step is laborious, it is better to load $F$ into the machine and let it compute $\Phi(.5)$.

Another decision to be made when computing time histories is whether or not to use TRNSI. TRNSI cannot be used with nonstationary systems. If a complete homogeneous solution is required TRNSI should not be used; it is inefficient. If a complete solution, including control variables is required TRNSI should not be used if $n>7$. In fact the use of TRNSI should be confined to the case where only one or two initial vectors are to be considered and the number of outputs is less than seven. A drawback of IRNSI is that it has only a four-decimal-place print format; if the system is well-conditioned this should not be a serious objection. In programmed transients, however, we can compute in a well-conditioned basis and retransform for printing with no accumulating error due to poor conditioning. Clearly this cannot be done in TRNSI.

To cut down on the paper volume of output, we did not use the Fig. I ASP Program, but instead that appearing in Fig. 2. This presents the output in a "packed" form which uses the output routine, and hence writes a new page less frequently. Since Fortran uses blocked output, there is no significant saving of machine time, and it makes output somewhat more difficult to read, but the factor of 10 decrease in pages is worth come inconvenience.

3B. The Specific Problem: As a second example let us consider a system given by Andreas Acrivos, "The Transient Response of Stagewise Processes", Jour. SIAM; 4 (March 1956):
(3B.1) $\dot{x}=\left[\begin{array}{ccc}0 & 435 \cdot 21 & 355 \cdot 54 \\ -2.0892 \cdot 10^{-2} & -2.4507 & 0.6577 \\ -0.0386 \cdot 10^{-2} & 1.4507 & -2.7634\end{array}\right] x+\left[\begin{array}{l}1 \\ 0 \\ 0\end{array}\right] u$.

Notice that the units (of physical quantities) have been poorly chosen. We can easily transform to the system
(3B.2) $\dot{\mathbf{y}}=\left[\begin{array}{ccc}0 & 4.3521 & 3.5554 \\ -2.0892 & -24507 & 0.6577 \\ -0.0386 & 1.4507 & -2.7634\end{array}\right] y+\left[\begin{array}{l}1 \\ 0 \\ 0\end{array}\right] u$.
using the transformation
(3B. 3)

$$
y=\left[\begin{array}{ccc}
1 & 0 & 0 \\
0 & 100 & 0 \\
0 & 0 & 100
\end{array}\right] x
$$

We will run a transient response of the system to $u=10$. in both the transformed and untransformed system to analyze the effects of the transformation. In addition we will obtain a few points of the frequency response $\phi$ using the transformed system (3B.2).

The eigenvalues are given as

$$
\begin{gathered}
\lambda_{1}=-3.7778 \\
\lambda_{2,3}=-0.7180 \pm i 3.0179 \\
-254-
\end{gathered}
$$

making the shortest time constant about . 27 and the largest about 1.4.
Let us use a print interval then of .05 and a final time of 7.5 . 4B. Equations and Procedure: To obtain the transient response, we let $\Phi=\Phi(.05)$,

$$
\Gamma=\int_{0}^{0.05} \Phi(\tau) \mathrm{d} \tau\left[\begin{array}{l}
1 \\
0 \\
0
\end{array}\right]
$$

and compute

$$
x(.05(k+1))=\Phi x(.05 k)+\Gamma u
$$

To obtain a point on the frequency response, we enlarge the system by a harmonic oscillator feeding into $x_{1}$ and run the free motion. After all transients have decayed, the amplitude and phase may be calculated.

$$
F=\left[\begin{array}{ccccc}
0 & 4.3521 & 3.5554 & 1 & 0 \\
-2.081 & -2.4507 & 0.6577 & 0 & 0 \\
-0.0386 & 1.4507 & -2.7634 & 0 & 0 \\
0 & 0 & 0 & 0 & \omega \\
0 & 0 & 0 & -\omega & 0
\end{array}\right]
$$

The program used to do this appears in Fig. 4.
The transient response could also have been computed (probably a little less efficiently) by this same method, using a fourth order system (adding an eigenvalue $=0$ ).

5B. Results: If we consider only the particular solution, this appears to be an ideal situation in which to use TRNSI. We need only one vector solution of three components and the solution provided by Acrivos is accurate
only to three significant figures. However, we wish to compare results obtained for systems (which is (3B.1) and (3B.2), so we will use the program in Fig. 3 (which is virtually the same as that in Fig. 2) in order to obtain more significant figures in the output.

There was very little difference in the computation using scaled and unscaled values, both were accurate to the number of significant figures given by Acrivos. At $t=7.75$ we had:

| x transformed | x untransformed |
| :--- | :--- |
| 1.5908521 | 1.5908545 |
| -1.5968528 | $-1.5968528 \cdot 10^{-2}$ |
| -0.86253438 | $-0.86253363 \cdot 10^{-2}$. |

The correct results are (transformed):
$x=\left[\begin{array}{r}1.600 \\ -1.595 \\ -0.860\end{array}\right]-\left[\begin{array}{l}5.641 \cdot 10^{-2} \\ 0.300 \\ -0.427\end{array}\right] e^{-3.7778 t}$

$$
+e^{-.718 t}\left[\begin{array}{r}
1.544 \\
-1.895 \\
-0.433
\end{array}\right] \cos 3.0179 t+\left[\begin{array}{l}
2.876 \\
0.075 \\
0.637
\end{array}\right] \sin 3.0179 t
$$

The computed response of $x_{1}$ is graphed in Fig. 5, where the largest time constant (1.39) and the frequency may be checked easily.

The transfer function for $x_{1}$ is $\frac{s^{2}+5.2141 s+5.81814}{(s+3.7778)\left((s+0.718)^{2}+(3.0179)^{2}\right)}$
which aids in checking the frequency response. The initial response to an input of $\sin t$ is graphed in Fig. 6. From the transfer function we compute the amplitude to be .207 with a phase lead of about . 40 radians. The digital output after only one full cycle of the input indicates an amplitude of . 208 and a phase lead of . 40 radians.

As in the transient response, we see here the prime virtue of the computer with no intellectual effort and for modest computer charges we can obtain quite reasonably accurate quantitative information about the system response, such as overshoot and terminal value in the transient, phase shift and amplitude in the frequency response -- even for a much larger system than one for which we could practically carry out the required hand computation.

It hardly seems necessary here to illustrate the use of ASP in obtaining the time history of a discrete system because, as we have seen, all systems are discretized before consideration by the computer. A system which is initially discrete deletes the exponentiation operation but otherwise requires the same treatment.

3C. The Specific Problem: It is advisable however, to consider also a time-varying system. Probably the simplest and most easily checked is the 3essel function $J_{0}(t)$. This function is generated by the equation

$$
\dot{x}=\left[\begin{array}{cc}
0 & 1 \\
-1 & -\frac{1}{t}
\end{array}\right] x ;
$$

if $x_{1}(0)=1, \quad x_{2}(0)=0$, then $x_{1}(t)=J_{0}(t)$. To avoid the pole at $t=0$ we will begin the trajectory at $t=.1$, where $x_{1}=.99750623, x_{2}=-.049750934$.

We made this run for several meshes on the $F$ matrix to show how the accuracy improves as the mesh becomes smaller. Accuracy will be checked against the Jahnke-Emde four decimal place tables.

First we set up a $t$ mesh such that in any interval, the sample used does not differ by more than $k$ percent in norm from the actual $F$.

This is most simply done by letting ASP compute the system matrices. Fig. 7 shows the program used to compute the $F$ matrices and run the transient when $k=20$.

The trajectory was run for $k=1,10$, and 20. The results for $k=10$ and 20, along with $J_{0}$, are graphed in Fig. 8. The graph for $k=1$ was indistinguishable from $J_{0}$.

```
            BEGIN
            LOAD T,Z1,ND, I, F,
            ETPHI F, T,PH,
            RINT Z1, I,PHI
HEAD IMULT PH, I, 1,
            ADD T,Z1, Z1,
            RINT Z1, 1,PHI
            EQUAT 1, I,
            IF ND,Z1,HEAD 1
            END1- 5
\begin{tabular}{lll} 
Z1 & 1 & 1 \\
ND & 0 & \\
& 1 & 1
\end{tabular}
\begin{tabular}{cccc}
1. & & 0
\end{tabular}
```



```
                                    1.
                .3141592654
                -.3141592654
O
```

FIG. 1

```
    EEGIN
    LOAD T,ZI,ND,PR, I,F,
    ETPHI F, T,PH,
    RINT Z1, I,PHI
HEAAD
IMULT PH, I, 1.
MULT PH, 1 2,
MULT PH, 2 3,
MULT PH, 3 4,
MULT PH, 4 5,
MULT PH, 5 6,
MULT PH, 6 7.
MULT PH, 7 8,
MULT PH, 8 9,
MULT PH, O I,
JUXTR 1, 2, Al,
JUXTR A1 3, A2,
JUXTR A2 4, A3,
JUXTR A3 5, A4,
JUXTR A4 6, A5,
JUXTR A5 7, A6.
UUXTR AG 8, A7,
UUXTR A7 9, A8,
UUXTR AB I, A9,
ADD Z1,PR, Z1,
RINT Z1, Ag,PHI
IF ND,Z1,HEAD 1
END
    .5
\begin{tabular}{ll}
1 & 1 \\
0 & 1
\end{tabular}
        201.
            1 
0 .3141592654 -.314159264
```

FIG. 2


FIG. 3


FIG. 4



Fig. 6

```
            NOV 17.1964
            BEGIN
            LOAD -5,TA,TO,T1,S1,S2,BE,ND,XO,M1,M3,F1,35,FI,EC
            RINT }\times0.\times
            EQUAT TO. T,T1,T2
            ADD TO,TA, PT.
HEAD4 IF T2,FI,HEAD6
                            MULT SI,BE, DI,
                            ADD D1.S2, D1.
                            SUET EEE,S2, DZ,
                            MULT BE,D2, D3,
                            PSEUO D1,+ D1,RK.
                            MULT D1,D3, BE,
                                    EQUAT T2,T1,F1,F,
                                    IF EE,M1,HEADS
                                    FQUAT EC,BE,FI,T2
                            IF .5..5.HEAD10
HEADG EQUAT F1, F,35,T5
            IF -5..5,HEAD3
HEAD9 PSEVO BE,+ T2,RK
HEADIOMULT BE,M1. M2
            ADD M2,M3, F1
            ADD T1.T2. T1
            MULT -5.T1, T5
HEAD3 IF T5,PT,HEADI
            SUBT T5, T, T3.
            EQUAT TS, T,
            IF .5..5.HEAD2
HEAD1 SUGT PT, T, T3
            EQUAT PT, T,
                            \triangleDD PT,TA, PT
HEADZ ETPHI F,T3.PH,
                            MULT PH, XO, }\times1
                        EQUAT }\times1,\timesO
                            IF T,TS,HEAD4
                            RINT T, XO, X
                            IF T.ND,HEAD5 HEAD3
HEADS END
\begin{tabular}{lll}
1 & & 1 \\
1 & \(\cdot 5\) & 1 \\
1 & \(\cdot 2\) & 1 \\
1 & \(\cdot 1\) & 1
\end{tabular}
- 128205128
\begin{tabular}{lll}
1 & & 1 \\
\(1 \cdot 4\) & \\
1 & & 1 \\
1 & .4 & 1 \\
\(7 \cdot 8\) & \\
1 & & 1
\end{tabular}
Fig. 7
\begin{tabular}{|c|c|c|c|c|c|}
\hline & \[
\begin{aligned}
& 6 \\
& 2
\end{aligned}
\] & & \multicolumn{3}{|c|}{2} \\
\hline \multirow[t]{13}{*}{.90750623} & & & 50934 & -. 049750934 & .99750623 \\
\hline & 2 & 2 & & & \\
\hline & 0 & & 0 & 0 & -1. \\
\hline & 2 & 2 & & & \\
\hline & 0 & & 1 。 & -1. & 0 \\
\hline & 2 & 2 & & & \\
\hline & 0 & & 1 。 & -1. & \(-7 \cdot 8\) \\
\hline & 1 & 1 & & & \\
\hline & \(1 \cdot 530\) & & & & \\
\hline & 1 & 1 & & & \\
\hline & 5. & & & & \\
\hline & 1 & 1 & & & \\
\hline & - 2 & & & & \\
\hline
\end{tabular}

FIG. 7


Fig. 8

\section*{CHAPIER X}

\section*{STABIIITY COMPUTATIONS}
1. Description of the Problem: In the analysis of dynamical systems, one of the most fundamental questions is whether or not a given system is asymptotically stable. For a linear system in which the characteristic polynomial is readily available, the Routh-Hurwitz criterion is quite satisfactory for hand calculation. With the advent of Lyapunov techniques there is a desire to obtain not only information about stability, but also a Lyapunov function. In this chapter we will demonstrate some ASP methods for doing this.
2. Theory and References: For Lyapunov stability theory and definitions of stability see
[I] R. E. Kalman and J. E. Bertram", Control System Analysis and Design via the "Second Method" of Lyapunov; Journal of Basic Engineering, June, 1960.
[2] H. S. Wall, "Polynomials Whose Zeroes have Negative Real Parts", American Mathematical Monthly, 52, (1945) No. 6.
[3] Anthony Ralston, "A symmetric Matrix Formulation of the Hurwitz-routh Stability Criterion", IEEE Transactions on Automatic Control, July 1963.
[M] P. C. Parks, "Lyapunov and the Schur-Cohn Stability Criterion", IEE Transactions on Automatic Control, January 1964.

A different proof of the results of Ralston and Parks is given in
[5] R. E. Kalman, "On the Hermite-Fujiwara Theorem in Stability Theory", Quarterly of Applied Mathematics, 1965.
3. The Specific Problem: Given a continuous dynamical system

\section*{(3.1)}
\[
\dot{\mathrm{x}}=\mathrm{Fx}
\]
or a discrete dynamical system
\[
\begin{equation*}
\mathrm{x}_{\mathrm{k}+1}=\Phi \mathrm{x}_{\mathrm{k}}{ }^{\bullet} \tag{3.2}
\end{equation*}
\]

We wish to determine 1) whether the system is asymptotically stable; 2) if so a Lyapunov function; 3) from this Lyapunov function we want to gain some idea of the relative stability of different state variables.

ASP has one very simple method of determining stability. Given a discrete system (3.2), perhaps obtained from a continuous system (3.1) by \(\Phi=e^{\tau F}\), we need only raise \(\Phi\) to very high powers, and see if its norm is, in the limit, increasing or decreasing.

This satisfies in a direct way requirement l), but that is all.
4. Equations and Procedure: To obtain a Lyapunov function \(V\) for a linear stationary system (3.1) we must find a symmetric matrix \(P\) and a positive definite matrix \(Q\) such that
\[
\begin{equation*}
P F+F^{\prime} P=-Q \tag{4.1}
\end{equation*}
\]
or for the system (3.2) such that
\[
(4.2) \quad \Phi^{\prime} P \Phi-P=-Q
\]

The usual procedure is to select a positive definite matrix \(Q\) and find the corresponding \(P\). Unless \(F\) has an eigenvalue with zero real part or, correspondingiy, \(\Phi\) has an eigenvalue of unit magnitude, there exists a unique solution to these problems for all Q. Then the system is stable if \(P\) is positive definite.

There exists a straightforward matrix inversion method of solving these equations (Bellman, INIRODUCTION TO MATRIX ANALYSIS, p. 231) but setting up the required matrix by means of ASP would be extremely tedious and

Moreover, the matrix would be of order \(\left(\frac{n^{2}+n}{2}\right)\) where \(F\) is of order n. If \(n\) is 8 , this would require the inversion of a rather wellpopulated matrix of order 36; a task which, besides being beyond the formal limits of ASP is likely to involve considerable numerical difficulties.

The method which we will use to obtain \(P\) relies upon the riccati and sampled riccati equations to find the equilibrium points of the equations
(4.3a)
\[
\dot{P}=F^{\prime} P+P F+Q
\]
and
\[
\begin{equation*}
P_{k+1}=\Phi^{\prime} P_{k} \Phi+Q . \tag{4.3~b}
\end{equation*}
\]

If the equilibrium points are reached, they represent the required solutions of the algebraic equations. The principal drawback of this scheme is that an equilibrium point will be reached only if the system is asymptotically stable. This precludes determining the number of unstable roots of \(F\) by determining the number of negative roots of \(P\). However, it provides a very quick test to see if the system is unstable, for in such a case, the riccati equation does not converge. This will be illustrated in what follows.

We will apply our procedures to a continuous system with eigenvalues \((-1,-2,-3 \pm 2 i,-3 \pm 4 i,-4,-5)\). The system will appear in four forms: 1) continuous, with \(F\) in companion form; 2) discrete, with \(\Phi\) in companion form; 3) continuous, with \(F\) in "scrambled" form obtained by a similarity transformation; 4) discrete, with \(\Phi\) the exponential of \(F\) in the 3) form.

For 1) and 2) we shall obtain Lyapunov functions by the methods described in [3] and [4]. This will provide some check on the accuracy of the method. For 3) and 4) we shall use the identity matrix for \(Q\) and obtain a matrix \(P\). This will enable us to give some statements ajout relative stability of the various components, as follows.

When obtaining \(P\) according to (4.1), we have that
\[
\begin{equation*}
x^{\prime}(0) P x(0)=\int_{0}^{\infty} x^{\prime}(t) Q x(t) d t \tag{4.4}
\end{equation*}
\]
and using (4.2)
\[
\begin{equation*}
x_{0}^{\prime} P x_{0}=\sum_{k=1}^{\infty} x_{k}^{\prime}{ }_{k} Q x_{k} \tag{4.5}
\end{equation*}
\]

Therefore the diagonal terms of \(P\) will tell us the value of the integral and sum (4.3) and (4.4) when \(x_{o}\) is in turn each vector of the usual orthonormal basis. If \(Q=I\), then larger terms correspond to components with larger time constants.
5. Results: This material will provide one of the very best illustrations of the fact that diagonal and scalar transformations, easily derived and applied, are essential to the successful use of ASP (see section 6 of this chapter).

The characteristic polynomial for the eigenvalues we have chosen is
\[
\begin{equation*}
s^{8}+23 s^{7}+267 s^{6}+1782 s^{5}+7663 s^{4}+21324 s^{3}+36669 s^{2} \tag{5.1}
\end{equation*}
\]
\[
+34470 s+13000
\]

The matrix \(Q\) corresponding to this polynomial for the special Lyapunov function given by Parks is twice the outer product of the vector
\[
a^{2}=(0,34470,0,21324,0,1782,0,24)
\]
with itself. That is, \(Q=2 a a^{\prime}\). Note that \(a^{\prime}\) consists of every second coefficient in (5.1). The corresponding \(P\) appears in Fig. 1.

The entire system was transformed by \(T, F^{*}=T F T^{-1}\), where \(T=\operatorname{diag}\left(10^{3}, 10^{3}, 10^{3}, 10^{3}, 10^{3}, 10^{2}, 10,1\right)\) and the resulting \(F\) and Q used in the program appearing in Fig. 2. This gave the very reasonably
accurate \(P\) appearing in Fig. 3, with a maximum error of about 3 in the sixth significant figure. This matrix had rank eight with a very high confidence level. That is (see Chapter V) with \(P_{2}=l\), we had the following table of \(\rho\) and rank
\begin{tabular}{c|c} 
rank & \(p\) \\
\hline 6 & \(.29 .10^{-2}\) \\
7 & \(.85 \cdot 10^{-3}\) \\
8 & \(.11 .10^{-5}\)
\end{tabular}

One aspect of this computation is that the zeroes appearing in \(P\) do not have identically zero derivatives, hence they must decay to zero and their accuracy can never be better than that of the larger terms. This of course is not peculiar to this method of computation. The same inaccuracies would occur in the inversion technique.

To obtain \(\Phi\) in companion form we need to select some time interval \(\tau\) over which to compute \(e^{\tau F}\). Having arbitrarily selected \(\tau=.25\) we have the problem of computing the characteristic polynomial. It would not have been unreasonable to compute it by hand, but after all we should use ASP, so we decided to compute the characteristic coefficients as the components of the solution of
\[
\left[\Gamma, \Phi \Gamma, \Phi^{2} \Gamma, \ldots, \Phi^{7} \Gamma\right] x=\Phi^{8} \Gamma
\]
where \(\Gamma\) is some vector such that \([\Phi, \Gamma]\) is completely controllable.* Even then we had the choice of what form to use for \(F\). Feeling that computing \(\Phi\) from \(F\) in companion form would perhaps provide the more difficult problem, we desided to do that; so we let \(\Gamma^{\prime}=(0,0,0,0,0,0,0,1)\) and \(\Phi=e^{\cdot 2} F\). Note that \((\Phi, \Gamma)\) is completely controllable because \((F, \Gamma)\) is.

\footnotetext{
*This method of computing the coefficients of the characteristic equation of a matrix goes back to the celebrated Russian applied mathematician (Krylov).
}

The only check which we performed on these calculations was to compare the first and last coefficients obtained in this way with the determinant of \(\Phi\) as computed analytically \(\left(e^{-6 .}=.0024787524\right)\) and with the trace of \(\Phi\) as computed by the machine (3.37923825).

The characteristic polynomial as computed was
\[
\begin{aligned}
s^{8} & +3.37923745^{7}+5.0860058 s^{6} \\
& +4.5157148 s^{5}+2.6094069 s^{4}+1.0075931 s^{3} \\
& +.25321779 s^{2}+0.37539943 s+.0024787312
\end{aligned}
\]
which agrees very well in the two given coefficients. Assuming that we were working with the true coefficients we computed \(Q\) for the LyapunovParks (Schur-Cohn) method and used SAMPL in the program shown in Fig. 4 to compute \(P\) for \(Q=a a^{\prime}\), where
\[
\begin{aligned}
a^{\prime}= & (.99999386,-3.3791469,5.0853854 \\
- & 4.5132249,2.6029441,-.99640206 \\
& .24061150,-.029163730) .
\end{aligned}
\]

This is also the first row of \(P\) and may be compared with the results printed in Fig. 5. This matrix has a rank of only six,
\begin{tabular}{l|l} 
rank & \(\rho\) \\
\hline 4 & \(\cdot 3810^{-3}\) \\
5 & \(\cdot 75 \cdot 10^{-4}\) \\
6 & \(\cdot 54 \cdot 10^{-4}\) \\
7 & \(.23 \cdot 10^{-3}\)
\end{tabular}
which is disappointing, since six-decimal accuracy was achieved in the first row of \(P\). This is not, however, as important as it appears. We shall illustrate our reasoning in Section 7 of this chapter. When using the differential equation (4.3a) to obtain the \(P\) matrix as an equilibrium point, the question is not so much whether the equilibrium is indefinite but whether it exists. There exist unique solutions to (4.1) and (4.2) but they are (for positive definite Q) positive definite only if \(F\) and \(\Phi\) are asymptotically stable. On the other hand the solutions to our differential equations are always nonnegative definite and if (F, Q) (or ( \(\Phi, Q)\) ) is completely controllable they are positive definite (not necessarily computationally). This allows us to use the nonnegative definite option in PSEUO to compute rank, but it prevents us from ever reaching an equilibrium if the system is not asymptotically stable.

To illustrate the general use of ASP in creating Lyapunov functions, we take \(F\) in a "scrambled" form (Fig. 6) obtained by a similarity transformation and using \(Q=I\) run the program shown in Fig. 7. This eventually converged, to the P in Fig. 8, indicating stability, but had a rank of 7:
\begin{tabular}{c|c} 
rank & \(p\) \\
\hline 5 & \(.20 \cdot 10^{-3}\) \\
6 & \(\cdot 90 \cdot 10^{-4}\) \\
7 & \(.80 \cdot 10^{-4}\) \\
8 & \(.10 \cdot 10^{-3}\)
\end{tabular}

Again using a sampling interval of .25 , we obtained \(\Phi\) for the scrambled system and obtained the sampled Lyapunov function generated by (4.3). Instead of using \(Q=1\), we used \(Q=.25 \cdot I\), since this should be approximately the same as Fig. 8. The resulting \(P\) appears in Fir. 9 notice that it is very similar to Fig. 8, the differences being int od. by sampling.

Now looking at the matrix \(P\) in Fig. 8 we can say that transients following initial conditions in \(x_{1}\) will involve much smaller excursions than those in (for instance) \(\mathrm{x}_{3}\).

The following table of \(\|x\|\) following initial conditions in \(x_{1}\) and \(x_{3}\) illustrates this very well.
\begin{tabular}{l|r|r}
t & \(\mathrm{x}_{1}\) & \(\mathrm{x}_{3}\) \\
\hline 0 & 1.0 & 1.0 \\
.25 & 2.1 & 21.0 \\
.5 & 1.9 & 20.0 \\
.75 & 1.3 & 15.0 \\
1.0 & .66 & 7.8 \\
1.25 & .25 & 2.7 \\
1.5 & .05 & 1.9
\end{tabular}
6. Numerical Considerations: The system provides an excellent illustration of how important diagonal and scalar transformations are in ASP. Despite the fact that the eigenvalues of \(F\) are close together, operating in a companion basis gives very large ratios of numbers in the \(F\) matrix. As we see in (5.1) the largest element in \(F\) is 36669. and the smallest is 1. However the 1 is not ignorable since it provides a vital link in the topology of the system. Adding to the numerical problem is the fact that the \(P\) and \(Q\) matrices produced by the Lyapunov-Parks method have extremely large elements and are very poorly conditioned.

For these reasons we find certain very simple transformations necessary. Looking at the input in Fig. 2 we see that the system has been transformed so that the largest element/smallest element ratio is now 36.669 instead of 366669., and the same ratio in \(Q\) is \(\frac{1188}{3.18}\) instead of \(\frac{1188180900}{576}\). In addition to this transformation we equalize \(\|Q\|\) and \(\|F\|\) before computing the solution to the riccati equation.

To illustrate the effect of the two operations, we made three runs over 1000 computing intervals.
1) With no transformation, no equalization.
2) With equalization, no transformation.
3) With transformation, no equalization.

In 1) the most significant fact is that the size of \(\|Q\|\) makes the computing interval so small that convergence is not approached. This gives a double argument for these operations -- they improve accuracy and save machine time.

In 2), slightly better results were obtained, the diagonal elements (compare with Fig. 1) are
\[
\begin{gathered}
\left(9 \cdot 2 \cdot 10^{6}, 5 \cdot 4 \cdot 10^{7}, 6 \cdot 7 \cdot 10^{7}, 2 \cdot 0 \cdot 10^{7}, 2 \cdot 4 \cdot 10^{6}, 1 \cdot 3 \cdot 10^{5}\right. \\
\left.1 \cdot 9 \cdot 10^{3}, 2 \cdot 0 \cdot 10\right)
\end{gathered}
\]

In 3) results were even better
\[
\begin{gathered}
\left(1.3 .10^{8}, 5.1 .10^{8}, 3.1 .10^{8}, 6.8 .10^{7}, 6.3 .10^{6}, 2.5 .10^{5},\right. \\
\left.4.1 .10^{3}, 2.3 .10\right)
\end{gathered}
\]

Notice that better is a relative term here, since none of these answers is acceptable.

It is not impossible that 3) could ultimately have converged to the correct answer, but we have illustrated our main point, that on any basis of accuracy or cost, simple transformations are essential.

That they are not always vital is illustrated by our experience in computing the characteristic equation of \(e^{.25 F}\). It is quite evident here that a better job of inversion could be done if the columns of
\[
\left[\Gamma, \Phi \Gamma, \ldots, \Phi^{\top}{ }_{5}\right]
\]
are normalized.
However in the present case no benefit was gained by so doing. Apparently the spread of eigenvalues ( \(e^{-.25}\) to \(e^{-1.25}\) ) was not large enough to demand such sophistication.

Another artifice which can be used to save time and improve accuracy is the use of a changing time interval. In these runs we have used the largest computing interval possible, as indicated by the coding in Fig. 2 and Fig. 7. We then tried taking the output of this program and using it as input to another in which the computing interval had been decreased by a factor of ten. Unfortunately for illustrative purposes, this gave no improvement in accuracy.

Another observation about the mode of convergence . Using the maximum computing interval, we got better accuracy with an error criterion of \(10^{-6}\) than with \(10^{-8}\). This was because the error never went under \(10^{-8}\), hence we were given the \(1000^{\text {th }}\) iterant. By this time the error was no longer decreasing, it was just randomly distributed in the \(10^{-5}-10^{-7}\) range. An error criterion of \(10^{-6}\) therefore selected a slightly better iterant.

One option in RICAT which has helped to improve accuracy is to use the transpose instead of the inverse when the riccati equation is linear (see Chapter IV). This saves time, and according to past experience, it improves accuracy. Here it did not. The matrices quoted above were all computed using the transpose, in Fig. 10 the inverse was used (compare with Fig. I and Fig. 3) and the accuracy was only slightly improved.
7. Remarks: To illustrate how convergence implies stability, rega 'less of the rank of \(P\), we took
\[
F=\operatorname{diag}\left(10^{-2},-2,-3 \pm 2 i,-3 \pm 4 i,-4,-5\right)
\]
used the same "scrambling" transiormation to produce the \(\mathrm{F}^{*}\) in Fig. 8, and tried to obtain a Lyapunov function.

The diagonal terms of the matrix obtained after 1000 iterations are all larger than those obtained previously. All but the third and fifth are quite close to the previous ones. Furthermore the percentage difference of successive iterants is decreasing. The following table shows, however, that the matrix is in no sense converging and displays an unbounded growth indicating instability.
\begin{tabular}{l|l|l|l}
\(a_{33}(k)\) & \(a_{55}(k)\) & \(k\) & \(\rho(k)\) \\
\hline \(1.2 .10^{5}\) & \(.26 .10^{5}\) & 100 & \(.2 .10^{-2}\) \\
\(1.5 .10^{5}\) & \(.39 .10^{5}\) & 200 & \(.1 .10^{-2}\) \\
\(1.8 .10^{5}\) & \(.52 .10^{5}\) & 300 & \(.1 .10^{-2}\) \\
\(2.1 .10^{5}\) & \(.66 .10^{5}\) & 400 & \(.1 .10^{-2}\) \\
\(2.5 .10^{5}\) & .80 & 500 & \(.1 .10^{-2}\) \\
\(2.8 .10^{5}\) & \(.95 .10^{5}\) & 600 & \(.1 .10^{-2}\) \\
\(3.1 .10^{5}\) & \(1.1 .10^{5}\) & 700 & \(.9 .10^{-3}\) \\
\(3.5 .10^{5}\) & \(1.2 .10^{5}\) & 800 & \(.9 .10^{-3}\) \\
\(3.8 .10^{5}\) & \(1.4 .10^{5}\) & 900 & \(.8 .10^{-3}\) \\
\(4.2 .10^{5}\) & \(1.6 .10^{5}\) & 1000 & \(.8 .10^{-3}\)
\end{tabular}

We append a few Parks-Iyapunov and Schur-Cohn functions. We will give \(F, P\), and \(Q\) where \(V=x^{\prime}(t) P x(t)\) is a possible Lyapunov function for the system \(\dot{x}=F x\left(x_{k+1}=F x_{k}\right)\) and \(P F+F^{\prime} P+Q=0 \quad\left(P=F^{\prime} P F+Q\right)\). That is, if \(F\) is stable,
\[
\begin{aligned}
x^{\prime}(0) p x(0) & =\int_{0}^{\infty} x^{\prime}(t) Q x(t) d t \\
\left(x_{0}^{\prime} P x_{0}\right. & \left.=\sum_{i=1}^{\infty} x_{i}^{2} Q x_{i}\right)
\end{aligned}
\]

Parks - Lyapunov
\[
\begin{gathered}
F=\left[-a_{1}\right] \quad P=\left[a_{1}\right] \quad Q=2 a_{1}^{2} \\
F=\left[\begin{array}{cc}
0 & 1 \\
-a_{2} & -a_{1}
\end{array}\right] \quad P=\left[\begin{array}{cc}
a_{1} a_{2} & 0 \\
0 & a_{1}
\end{array}\right] \quad Q=2\left[\begin{array}{cc}
0 & 0 \\
0 & a_{1}^{2}
\end{array}\right]
\end{gathered}
\]
\(F=\left[\begin{array}{cccc}0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -a_{4} & -a_{3} & -a_{2} & -a_{1}\end{array}\right] P=\left[\begin{array}{cccc}a_{3} a_{4} & 0 & a_{1} a_{4} & 0 \\ 0 & a_{2} a_{3}-a_{1} a_{4} & 0 & a_{3} \\ a_{1} a_{4} & 0 & a_{1} a_{2}-a_{3} & 0 \\ 0 & a_{3} & 0 & a_{1}\end{array}\right]\)
\(Q=2\left[\begin{array}{cccc}0 & 0 & 0 & 0 \\ 0 & a_{3}^{2} & 0 & a_{1} a_{3} \\ 0 & 0 & 0 & 0 \\ 0 & a_{1} a_{3} & 0 & a_{1}^{2}\end{array}\right]\)


\[
\begin{aligned}
& F=\left[-a_{1}\right] \quad P=\left(1-a_{1}{ }^{2}\right) \quad Q=\left(1-a_{1}\right)^{2} \\
& F=\left[\begin{array}{cc}
0 & 1 \\
-a_{2} & -a_{1}
\end{array}\right] \quad P=\left[\begin{array}{cc}
1-a_{2}{ }^{2} & a_{1}\left(1-a_{2}\right) \\
a_{1}\left(1-a_{2}\right) & 1-a_{2}^{2}
\end{array}\right] \\
& Q=\left[\begin{array}{c}
\left(1-a_{2}^{2}\right)^{2} \\
a_{1}\left(1-a_{2}^{2}\right)\left(1-a_{2}\right)
\end{array}\right. \\
& \left.\begin{array}{c}
a_{1}\left(1-a_{2}^{2}\right)\left(1-a_{2}\right) \\
a_{1}^{2}\left(1-a_{2}\right)^{2}
\end{array}\right] \\
& F=\left[\begin{array}{ccc}
0 & 1 & 0 \\
0 & 0 & 1 \\
-a_{3} & -a_{2} & -a_{1}
\end{array}\right] \\
& Q=\left[\begin{array}{ccc}
\left(1-a_{3}^{2}\right)^{2} & \left(1-a_{3}^{2}\right)\left(a_{1}-a_{2} a_{3}\right) & \left(1-a_{3}^{2}\right)\left(a_{2}-a_{1} a_{3}\right) \\
\text { symmetric } & \left(a_{1}-a_{2} a_{3}\right)^{2} & \left(a_{1}-a_{2} a_{3}\right)\left(a_{2}-a_{1} a_{3}\right) \\
& & \left(a_{2}-a_{1} a_{3}\right)^{2}
\end{array}\right]
\end{aligned}
\]
\[
P=\left[\begin{array}{ccc}
\left(1-a_{3}^{2}\right) & a_{1}-a_{2} a_{3} & a_{2}-a_{1} a_{3} \\
\text { symmetric } & 1+a_{1}^{2}-a_{2}^{2}-a_{3}^{2} & a_{1}-a_{2} a_{3} \\
& & 1-a_{3}^{2}
\end{array}\right]
\]
\[
\begin{aligned}
F= & \text { companion }\left(a_{8}, a_{7}, a_{6}, a_{5}, a_{4}, a_{3}, a_{2}, a_{1}\right) \\
Q= & a a^{\prime} \\
a= & {\left[\left(1-a_{8}^{2}\right),\left(a_{1}-a_{7} a_{8}\right),\left(a_{2}-a_{6} a_{8}\right),\left(a_{3}-a_{5} a_{8}\right),\left(a_{4}-a_{4} a_{8}\right),\right.} \\
& \left.\left(a_{5}-a_{3} a_{8}\right),\left(a_{6}-a_{8}\right),\left(a_{7}-a_{1} a_{8}\right)\right] .
\end{aligned}
\]

Some sidelights were discovered during the development of this chapter. Despite the fact that they are not new and not difficult to prove, they seem to be sufficiently interesting in themselves to warrant inclusion.
1. Let \(F\) be a matrix in companion form, and \(\lambda\) an eigenvalue of \(F\). Then \(\left(1, \lambda, \ldots, \lambda^{\mathrm{n}-1}\right)\) is an associated eigenvector.
2. Let \(\Lambda=\operatorname{diag}\left(\lambda_{i}\right) \quad \lambda_{i} \neq \lambda_{j} \quad\) if \(i \neq j\). Then
\[
\left[\begin{array}{llll}
1 & 1 & - & 1 \\
\lambda_{1} & \lambda_{2} \cdots \cdots- & \lambda_{n} \\
\cdots- & \cdots & \cdots & - \\
\lambda_{1}^{n-1} & \lambda_{2}^{n-1} & \cdots & -\cdots
\end{array} \lambda_{n}^{n-1}\right]
\]
is nonsingular and
\[
V \Lambda V^{-1}=C
\]
where \(C\) is in companion form.

Proof: It is well known that the Vandermonde determinant of distinct numbers is nonzero, hence \(\nabla^{-1}\) exists. The first \(n-1\) rows of \(V \Lambda\) are the same as the last \(n-1\) rows of \(V\). Hence the first \(n-1\) rows of \(V \Lambda V^{-1}\) are in companion form. But \(\Lambda\) is similar to \(V \Lambda V^{-1}\) so \(V \Lambda V^{-1}=C\), the companion form of \(\Lambda\).

Alternately from 1. above, \(V\) is the matrix of eigenvectors, so if \(C\) is the companion form of \(\Lambda, V^{-1} C V=\Lambda\).
3. If \(V\) is an invertible matrix such that the first \(n-1\) rows of \(V F\) are the last \(\mathrm{n}-1\) rows of V , then \(\mathrm{VFV}^{-1}\) is the companion form of F .
4. The minimal polynomial of a companion matrix \(F\) is its characteristic polynomial.

Proof: Case 1. The last row of \(F\) is zero. Then \(F\) is a maximal Jordan block and its minimal polynomial is \(S^{n}=0\).

Case 2. If some coefficient of the characteristic polynomial is nonzero, so is some coefficient \(b_{p}\) of the minimal polynomial \(\sum_{\ell=0}^{m} b_{\ell} F^{\ell}=\left[a_{i j}\right]\). Because \(F\) satisfies the minimal polynomial, \(a_{l, p+1}=0\). Consider the terms in \(a_{1, p+1}\). They consist of \(b_{p} \neq 0\) occurring in \(b_{p} F^{p}\), and no other term unless \(m=n\).
5. Let \(J\) be a single Jordan block with eigenvalue \(\lambda\). Then
\begin{tabular}{|c|c|c|c|c|c|}
\hline & 1 & 1 & 1 & & 1 \\
\hline & \(\lambda\) & \(\lambda+1\) & \(\lambda+1\) & & \(\lambda+1\) \\
\hline & \(\lambda^{2}\) & \(\lambda^{2}+2 \lambda\) & \((\lambda+1)^{2}\) & & \((\lambda+1)^{2}\) \\
\hline \(\mathrm{V}=\) & \(\lambda^{3}\) & \(\lambda^{3}+3 \lambda^{2}\) & \(\lambda^{3}+3 \lambda^{2}+3 \lambda\) & & \((\lambda+1)^{3}\) \\
\hline & \(\lambda^{4}\) & \(\lambda^{4}+4 \lambda^{3}\) & \(\lambda^{4}+4 \lambda^{3}+6 \lambda^{2}\) & & \((\lambda+1)^{4}\) \\
\hline & \[
\lambda^{n-1}
\] & \[
\mathrm{I}_{+}+(\mathrm{n}-1) \lambda^{\mathrm{n}-2}
\] & \[
\lambda^{n-1}+(n-1) \lambda^{n-2}+\frac{(n-1)(n-2)}{2} \lambda^{n-3}
\] & & \({ }^{-}{ }^{-}\) \\
\hline
\end{tabular}
is nonsingular and \(\mathrm{VJV}^{-1}\) is the companion form for J .
Proof: Subtract the \(j^{\text {th }}\) column of \(V\) from the \((j+1)^{s t}, j=n-1\), \(\mathrm{n}-2, \ldots\), . This leaves V in lower triangular form with \(l\) on the diagonal, hence \(\mathrm{V}^{-1}\) exists.

The first \(n-1\) rows of \(V J\) are the last \(n-1\) rows of \(V\), the conclusion follows from 3.
6. Let \(J\) be an \(n \times n\) matrix in Jordan form. It follows from 4. and the fact that the minimal polynomial is an invariant, that \(J\) has a companion form only if distinct Jordan blocks have distinct eigenvalues. We show now that \(J\) has a companion form if distinct Jordan blocks have distinct eigenvalues.

Proof: We will define a transforming matrix \(T\) satisfying 3 .
Consider a \(k \times k\) Jordan block \(M\) in \(J\). From 5 we have a \(V\) which would put this block in companion form. Extend \(V\) to an \(n \times k\) matrix in the obvious way; alternatively, take the first \(k\) column of the \(V\) which puts a single \(n \times n\) Jordan block in companion form.

Let these \(k\) columns be the \(k\) columns of \(T\) which are multiplied with M.

Do this for all Jordan blocks. This completely defines T. Now if \(T\) is nonsingular it satisfies 3. and we are through.

By the method used in 5. we can reduce this question to that of the singularity of column juxtaposes of matrices
\[
\left.\left[\begin{array}{ccccc}
1 & 0 & 0 & 0 & - \\
\lambda & 1 & 0 & 0 & - \\
\lambda^{2} & 2 \lambda & 1 & 0 & - \\
\lambda^{3} & 3 \lambda^{2} & 3 \lambda & 1 & - \\
- & - & - & - & - \\
- & - & - & - & - \\
- & - & - & - & - \\
- & \lambda^{n} & (n-1) \lambda^{n-1} & \binom{n}{2} \lambda^{n-2} & \binom{n}{3} \lambda^{n-3}
\end{array}\right]-\right]
\]
with distinct eigenvalues \(\lambda\).
Now prove the assertion by induction.
In 5. we showed it true for one eigenvalue.
If one of the eigenvalues is zero it is easy to reduce \(T\) to \(a\) form which is singular only if the induction hypothesis is violated.

If none of the \(\lambda\) 's are zero: Let \(\lambda\) be the eigenvalue with the largest Jordan block and \(\mu\) some other eigenvalue. Then dividing the \(\lambda\) columns by \(\mu\) and subtracting from the \(\mu\) columns we can obtain an equivalent problem with a zero eigenvalue.




II
\(م_{4}\)


Fig. 2


Fig. \(ع\)
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 \(\square\)


BEGIN
```

TRANP $F, G, F$,
SAMPL $F T, Q, G, R, Q, D, P C, \quad P, K, A L$,

```
RINT P. P
PSEUO P.+ 1PI.RK,PRINT
END
\begin{tabular}{|c|c|c|c|c|}
\hline \multicolumn{5}{|l|}{8 8} \\
\hline 0 & 1. & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 1. & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 1. \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 1. & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 1. & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 1. & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 1. & -. 002478734 & . 037539967 & -. 2532183768 & 1.007595337 \\
\hline \[
-2.6094121455
\] & \[
4.515722478
\] & -5.08601306 & 3.37924 & \\
\hline . 999987712 & -3.379126186 & . 08535415 & -4.513197187 & 2.6029281135 \\
\hline -. 99639594 & .2406100256 & -. 029163549818 & -3.379126186 & 11.4186341 \\
\hline -17.1842646 & 15.2508502 & -8.79573063 & 3.366988986 & -. 8130616294 \\
\hline . 09854852922 & 5.08535415 & -17.1842646 & 25.86114466 & -22.9514881 \\
\hline 13.23697395 & -5.067088497 & 1.223602229 & -. 1483088067 & -4.513197187 \\
\hline 15.2508502 & -22.9514881 & 20.36919915 & -11.74767219 & 4.496986614 \\
\hline -1.085933835 & -1316224729 & 2.6029281135 & -8.79573063 & 13.23697395 \\
\hline -11.74767219 & 6.775318018 & -2.593578874 & . 5262982962 & -.07591155911 \\
\hline -. 99639594 & 3.366988986 & -5.067088497 & 4.496986614 & -2.593578874 \\
\hline . 9928170691 & -. 2397457987 & . 02905880071 & . 2406100256 & .8130616294 \\
\hline 1.223602229 & -1.085933835 & -626298296 & -. 2397457987 & . 0578938958 \\
\hline -.007017128937 & -.029163549818 & . 0.09854852922 & -. 1483088067 & . 1316224729 \\
\hline -. 07591155911 & .02905880071 & -.007017128937 & . 0008505231475 & \\
\hline & & & & \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & & \\
\hline 1 & 1 & & & \\
\hline 0 & & & & \\
\hline 1 & 2 & & & \\
\hline \(1 \cdot E-7\) & 1. & & & \\
\hline 1 & 4 & & & \\
\hline 0 & 100. & 1. & 1000. & \\
\hline
\end{tabular}

Fig. 4

\section*{MATRIX \(P\)}
NUMBER OF ROWS 8 NUMBER OF COLUMNS 8




0.58378630 E 01 - 0.99620940 E 0 _ 0.
105E 02
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|}
\hline \[
\begin{aligned}
& -0.45132231 E \quad 01 \\
& -0.13231401 E \text { OZ }
\end{aligned}
\] & \[
\begin{array}{ll}
0.20307245 \mathrm{E} & 02 \\
0.26022442 \mathrm{E} & 01
\end{array}
\] & -0.43268226E & & \(0.57597196 E\) & 02 & -0.52421236E & 02 & 0.32916105 E & \\
\hline \[
\begin{array}{ll}
0.26029401 E & C 1 \\
0.20303351 E & 02
\end{array}
\] & \[
\begin{array}{lll}
-0.13233040 E & C 2 \\
-0.451 .16063 E & 01
\end{array}
\] & 0.32917666 E & 02 & \(-0.52421236 \mathrm{E}\) & 02 & 0.57594770 E & 02 & \(-0.43263954 E\) & 02 \\
\hline \[
\begin{array}{ll}
-0.99639608 E & O C \\
-0.20550682 \mathrm{E} & 02
\end{array}
\] & \[
\begin{array}{r}
0.58382457 E \\
0.50829767 E \\
\hline
\end{array}
\] & -0.17213748E & 02 & \(0.32916105 E\) & 02 & -0.43263954E & 02 & 0.38214687 E & 02 \\
\hline \[
\begin{aligned}
& 0.24060622 \mathrm{E}-0 \mathrm{C} \\
& 0.12412692 \mathrm{E}
\end{aligned}
\] & \[
\begin{aligned}
& -0.16610840 \mathrm{E} 01 \\
& -0.33770088 \mathrm{E}
\end{aligned}
\] & \(0.58378630 E\) & 01 & -0.13231401E & 02 & 0.20303351 E & 02 & -0.20550682E & 02 \\
\hline \[
\begin{aligned}
& -0.29161556 \mathrm{E}-01 \\
& -0.33770088 \mathrm{E} \text { 01 }
\end{aligned}
\] & \[
\begin{array}{r}
0.24058066 \mathrm{E}-00 \\
0.99910301 \mathrm{E} 00
\end{array}
\] & \[
-0.99620940 \mathrm{E}
\] & 00 & 0.26022442 E & 01 & -0.45116063E & 01 & 0.50829767 E & 01 \\
\hline
\end{tabular}

FIG. 5


BEGIN
LOAD F, Q,ZR,LT, C, D,PC,2.,PO
MULT 2.. \(Q\). \(P\)
NORM F. NF,
NORM P, NP,
PSEUO NP, NP,RK,
MULT NF,NP, LM,
\(\begin{array}{llll}\text { MULT } & \text { LM, } P, & Q, \\ \text { SUBT } & \text { ZR, } & F, & \text { MF, }\end{array}\)
TRANP F, FT.
JUXTC MF,ZR, TP,
\(\begin{array}{ll}\text { JUXTC Q.FT, } & B T \text {, } \\ \text { JUXTR TP.BT, } & \text { TH, }\end{array}\)
NORM TH, NT.
PSEUO NT, NT,RK,
MULT LT,NT, T,
ETPHI TH. T.PH. PRINT
MULT LM,PO, ZR,
PSEUO LM, LM•RK,
RICAT ZR,PH, C, D,PC, P, K,AL,
MULT LM, P, R,
RINT R, P
PUNCH R. \(Q\),
PSEUO R,+ 1PI•RK,PRINT
END
\begin{tabular}{|c|c|c|c|c|}
\hline \multicolumn{5}{|l|}{\(8 \quad 8\)} \\
\hline -7. & \(2 \cdot\) & -35. & 18. & -21. \\
\hline 6. & 2. & -8. & -6. & 5. \\
\hline -54. & 44. & -18. & 18. & 24. \\
\hline -12. & 8. & 0 & 41. & -16. \\
\hline 30. & 0 & 4. & 16. & 0 \\
\hline -16. & 48. & -84. & 0 & -42. \\
\hline -48. & 8. & -12. & 0 & -63. \\
\hline 24. & -46. & 0 & -6. & -24. \\
\hline 0 & 24. & -72. & 123. & 0 \\
\hline 61. & 72. & -12. & 10. & 0 \\
\hline 54. & -20. & 36. & 0 & 1. \\
\hline 20. & 0 & -20. & 60. & -101. \\
\hline 0 & -54. & -60. & 5. & \\
\hline 8 & 8 & & & \\
\hline 1. & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 1. \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 1. & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 1. & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 1. & 0 & 0 & 0 \\
\hline 0 & \(\bigcirc\) & 0 & 0 & 0 \\
\hline 1. & 0 & 0 & 0 & 0 \\
\hline 0 & \(\bigcirc\) & 0 & 0 & 1. \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 1. & \\
\hline
\end{tabular}

Fig. 7


Fig. 7

\(\square\)
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\(\begin{array}{lll}0.44810817 E & 03 & -0.12370304 E-02 \\ 0.31199912 E & 02 & -0.36114717 E-04\end{array}\) - _ _ _
\(\begin{array}{ll}-0.12370304 \mathrm{E}-\mathrm{C} 2 & 0.98676633 \mathrm{E} \\ -0.12361985 \mathrm{E}-\mathrm{C3} & 0.34469945 \mathrm{E}\end{array}\)
-0.12361985 E-c3 0.34469945E O2
-0.27721113E 03 -0.90876401E-03
\(0.84558530 \mathrm{E} 02-0.31612076 \mathrm{E}-04\)
\(-0.23160005 F-03 \quad 0.24097717 E 03\) 0.21323988 E 02
\(0.23165947 \mathrm{E} \quad 02-0.84354330 \mathrm{E}-04\) \(0.16258796 \mathrm{E} 02-0.22669186 \mathrm{E}-05\)
\(-0.82607347 E-04 \quad 0.88914763 E \quad 02\)
\(0.29948283 \mathrm{E}-05\) 0.17820000E 02
\(\begin{array}{rrr}0.31199912 \mathrm{E} & 02 & -0.12361985 \mathrm{E}-03 \\ 0.46259999 \mathrm{E} & 02 & 0.22877160 \mathrm{E}-06\end{array}\) 0.2287160 -
\(\begin{array}{ll}0.36114717 E-04 & 0.34469945 E ~ 02 \\ 0.22877160 E-06 & 0.23999999 E ~ 02\end{array}\)
FIG. 10

\section*{ASYMPIOIIC BEHAVIOR OF ROOIS OF THE CLOSED-IOOP SYSIEM}
1. Description of the Problem. We shall examine the behavior of the closed loop poles of optimal systems as the weighting factor for the control energy tends to zero.
\[
\begin{equation*}
\frac{Y(s)}{U(s)}=\frac{b_{m} s^{m}+b_{m-1} s^{m-1}+\ldots+b_{1} s+b_{0}}{s^{n}+a_{n-1} s^{n-1}+\ldots+a_{1} s+a_{0}} \tag{1.1}
\end{equation*}
\]
with an associated system in control canonical form,
\[
\begin{align*}
& \dot{x}=F x+G u \\
& y=H x \tag{1.2}
\end{align*}
\]
where \(\mathrm{F}=\)

\(G^{\prime}=(0,0, \ldots, I)\)
\(H=\left(b_{o}, b_{1}, \ldots, b_{m}, 0,0, \ldots, 0\right)\).
We wish to optimize the functional
\[
\begin{equation*}
\int_{0}^{\infty}\left(\|y\|^{2}+r\|u\|^{2}\right) d t \quad(r=\text { scalar }) \tag{1.3}
\end{equation*}
\]
and then examine the eigenvalues of the optimal system matrix \(F\) - GK as \(r\) tends to 0 .
2. Theory and References: For the procedures involved in optimization see Chapter VII.

The asymptotic behavior of the closed loop poles is described in
[1] R. E. Kalman, "When is a Linear Control System Optimal?", Journal of Basic Engineering, March, 1964.

The relevant result is this: as \(r \rightarrow 0\) in (1.3) \(m\) of the closed loop poles will go to the \(m\) zeroes of (l) in the left-half plane (or their reflections about the imaginary axis, if some of the zeros are in the righthalf plane) and the other \(n-m\) poles will converge to a butterworth pattern with radius
\[
\left(\frac{a_{0}^{2} b_{m}^{2}}{b_{0}^{2}}+\frac{b_{0}^{2}}{r}\right)^{\frac{1}{2(n-m)}}
\]

The following proposition supplements the results of the reference, providing a simpler derivation of the product of the roots, though not specifying where the individual roots are located.

PROPOSITION. Given the transfer function
\[
\frac{Y(s)}{U(s)}=\frac{b_{m} s^{m}+b_{m-1} s^{m-1}+\ldots+b_{1} s+b_{0}}{x^{n}+a_{n+1} s^{n-1}+\ldots+a_{1} s+a_{0}}
\]

If we optimize
\[
\int_{0}^{\infty}\left(y^{\prime} y+r u^{2}\right) d t
\]
the product of the roots of the optimal closed loop system matrix will be
\[
\begin{equation*}
\sqrt{a_{0}^{2}+\frac{b_{0}^{2}}{r}} \tag{2.1}
\end{equation*}
\]

Proof: The product of the closed-loop poles is invariant under a change of basis. Therefore we may choose the control-canonical representation with \(F\) in companion form,
\[
G^{\prime}=[0,0, \ldots, 0,1]
\]
and
\[
H=\left[b_{0}, b_{1}, \ldots, b_{m} 0,0, \ldots, 0\right]
\]

Then the closed loop matrix \(F-r^{-1} G^{2} P\) is also in companion form and the product \((-1)^{n} \pi \lambda_{i}\) of its roots is \(\left(a_{0}+r p_{I n}\right)\), where \(P\) satisfies the relation
\[
\dot{P}=P F+F^{\prime} P+H^{\prime} H-r^{-1} P G G^{\prime} P=0
\]

To determine \(p_{1 n}\), we note that
\[
\dot{p}_{l n}=0=-2 p_{l n} a_{0}+b_{0}^{2}-l p_{l n}^{2}
\]
so that
\[
p_{1 n}=r\left[-a_{0} \pm \sqrt{a_{0}^{2}+r^{-1} b_{0}^{2}}\right]
\]
and \((-1)^{n} \pi \lambda_{i}=\sqrt{a_{0}^{2}+r^{-1} b_{0}^{2}}\). Since we know that the constant term of the characteristic polynomial of \(r^{-I_{G G}}{ }^{\top} P\) must be positive, it follows that
\[
p_{1 n}=r\left[-a_{0}+\sqrt{a_{0}^{2}+r^{-1} b_{0}^{2}}\right]
\]
and (2.1) is proved.
If \(m=0\), then as \(r \rightarrow 0\) the closed-loop poles approach a butterworth pattern with radius
\[
\left(a_{0}^{2}+r^{-1} b_{0}^{2}\right)^{\frac{1}{2 n}}
\]

If the open-loop transfer function has \(m\) zeroes, then the other \(n-m\) poles will approach a butterworth pattern with radius
\[
\left(\frac{a_{0}^{2} b_{m}^{2}}{b_{0}^{2}}+\frac{b_{m}^{2}}{r}\right)^{\frac{1}{2(n-m)}}
\]
3. The Specific Problem: We took the following four transfer functions

(D)
with poles at \(\pm 1,-1 \pm i, 1 / 2 \pm i\), and zeroes at \((B) \pm 1\), \(1 \pm i\), and (D) \(-1 \pm i\).

We selected control-canonical coordinates with
\[
F=\left[\begin{array}{cccccc}
0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 \\
2.5 & .5 & -1.25 & .5 & -.25 & .5
\end{array}\right], \quad G=\left[\begin{array}{c}
0 \\
0 \\
0 \\
0 \\
0 \\
1
\end{array}\right]
\]
and
\[
\begin{array}{rl}
\mathrm{H}_{\mathrm{A}} & =[1 \\
1 & 0 \\
0 & 0 \\
H_{B} & =[1 \\
\hline 1 & 0 \\
-1 & 0 \\
\hline
\end{array}
\]

Then systems (B) and (D) are not completely observable, because of cancellation of a factor between the numerator and denominator of the transfer functions.
4. Results: Using the program appearing in Fig. l, we obtained the closed loop system matrices \(F\) - GK which minimize the performance index
\[
\int_{0}^{\infty}\left[(H x)^{2}+r u^{2}\right] d t
\]
\[
r^{-1}=.1,1 ., 10,30,100,300,1000,3000 .
\]

Using a separate (non-ASP) program we then obtained the eigenvalues ff these matrices. The results are graphed in Fig. 2, 3, 4 and may be ;ummarized as follows:
1) As \(r^{-1} \rightarrow 0\), the closed loop eigenvalues are "the same" as the spen loop eigenvalues with negative real parts. In this case they are \(-1,-1,-1 \pm i,-1 / 2 \pm i\).
2) The eigenvalues of (C) and (D) were the same, as the lemma in jection 6 of this chapter assures us. The performance indices were different of course.
3) Observability does not seem to affect the conclusions, in both (B) and (D) the expected behavior occurred.

In the graphs, the straight lines are the asymptotes of the roots. The circles have radius
\[
\left(\left|b_{m}\right| \sqrt{a_{o}^{2}+r^{-1}}\right)^{\frac{1}{6-m}}
\]
5. Numerical Problems: There were no numerical problems in ASP, however there are some points of interest. In Fig. I the code from
\begin{tabular}{lrrr} 
NORM & Q, & NQ, & \\
MULT & SJ, & C, & C,
\end{tabular}
is an equalization of \(\left\|H^{1} H\right\|\) and norm \(\left\|G r^{-1} G^{1}\right\|\) to cut down on computer time and help accuracy. This will be done routinely in all such optimization problems.

Fig. 5 is a table for system (A) showing the max value of the performance index and the times required for convergence using different values of \(r^{-1}\). \(\tau\) is the time step used in the riccati equation, \(N\) the number of steps required for convergence, \(T\) the total time required for convergence.
\(p_{i i} \max\) is the largest diagonal element of the performance index matrix in the computer weighting, \(p_{i i} \max\) normalized returns it to the weighting (4.1).

Roughly we may say that if the equalization had not been done then for \(\mathrm{r}^{-1}=3000\) we would have had \(\tau=\frac{9}{3000+6} \approx .003\) instead of \(\tau=\frac{9}{\sqrt{3000}+6} \approx\).15. Disregarding the accuracy problem, this would have caused \(N\) to be over 3000 .

The other coding aspect is the method of introducing a sequence of \(r^{-1}\), s. This is done very nicely by using a LOAD in the loop. However it is most convenient not to have to use a counter in the loop. This may done merely by terminating with an error return. Following the last \(R I\), FORTRAN finds an input error and ejects, which is satisfactory if this is in the last ASP program. A less time consuming method (and the only method possible if another ASP program follows) is to follow the last \(R I\) with a dummy RI having the wrong dimension. This causes an ASP (not FORIRAN) error which goes on to the next BEGIN card.
6. Appendix: We shall give here a necessary and sufficient condition for the irrelevance of off diagonal terms in the error weighting of a cost functio

Let us consider a single input, stationary, real linear system
\[
\dot{x}=F x+g u
\]
with performance index
\[
\begin{equation*}
\int_{0}^{\infty}\left[\|x\|_{Q}^{2}+u^{2}\right] d t . \tag{6.1}
\end{equation*}
\]

We know [l] that the optimal feedback gain \(k\) which specifies the control law: \(u=-k{ }^{\prime} x\) ) will be the same for the different performance indices (1) implied by the error weighting matrices \(Q_{1}\) and \(Q_{2}\) if
\[
\begin{equation*}
\|\Phi(s) g\|_{Q_{1}}^{2}=\|\Phi(s) g\|_{Q_{2}}^{2} \quad \text { for all pure imaginary } s, \tag{6.2}
\end{equation*}
\]
where \(\Phi(s)=s I-F)^{-1}\).

Let \(r_{i}(s)=((s) g)_{i}\) and \(r_{i}(s)=\frac{r_{i}(s)}{r_{j}(s)}\), where \(r_{i j}(s)\) is a rational function of \(s\). We will show that \(q_{k \ell}=q_{\ell k}\) has no effect upon (2) if and only if \(r_{k \ell}(i \omega)\) is pure imaginary, or, more simply, if and only if \(r_{k l}(s)\) is an odd function of the real variable \(s\).

What is needed is a necessary and sufficient condition for the coefficlient of \(q_{k \ell}\) in (2) to be zero. But this coefficient is
\[
\left[\bar{r}_{k}(i \omega) \gamma_{\ell}(i \omega)+\bar{\gamma}_{\ell}(i \omega) r_{k}(i \omega)\right]=2 \operatorname{Re} \bar{\gamma}_{k}(i \omega) \gamma_{\ell}(i \omega)
\]

The necessary and sufficient condition that the real part of the product \(\overline{\mathrm{w}} \mathrm{Z}\) be zero is that \(\mathrm{w}=\mathrm{icz}\), where c is a real constant. A necessary and sufficient condition that \(\operatorname{Re} \bar{\gamma}_{k}(i \omega) r_{\ell}(i \omega)=0\) then is that \(\gamma_{k}(i \omega)=i f(\omega) \gamma_{l}(i \omega)\) where \(f(\omega)\) is real. But this says precisely that \(r_{k \ell}(i \omega)\) is imaginary. But if \(r_{k \ell}(i \omega)\) is imaginary, then \(r_{k \ell}(i \omega)+\overline{r_{k \ell}(i \omega)}=r_{k \ell}(i \omega)+r_{k \ell}(-i \omega)=0\). But this says that \(r_{k \ell}(s)\) is an odd function.

Clearly this condition cannot be determined Prom the open loop alone, but if \(\dot{x}_{k}=\mathrm{cx}{ }_{\ell}\) then \(s r_{k}(s)=c r_{\ell}(s)\) and the condition is satisfied. On the other hand if \(\dot{x}_{k}=c x_{\ell}+u\), then the condition is satisfied if and only if \(\gamma_{\ell}(s)\) is an even function of the real variable \(s\).

As an example, consider a system in characteristic form
\[
F=\left[\begin{array}{cccc}
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
\cdot & \cdot & \cdot & \cdot \\
0 & 0 & 0 & 1 \\
-a_{0} & -a_{1} & -a_{g} & -a_{n-1}
\end{array}\right] G=\left[\begin{array}{c}
0 \\
0 \\
\cdot \\
\cdot \\
\cdot \\
0 \\
1
\end{array}\right]
\]
then \(r_{i}(s)=s^{i-1}\) and if \(Q\) is replaced by

i.e., \(q_{i j}\) is set equal to 0 when \(i+j=o d d\), the control law remains the same.

This observation saves a little computing time and explains a phenomenon which might appear odd if encountered for the first time.

The situation will occur in Chapter XVII and appears to be true also after the introduction of sampling.


Fig. 1


Fig. 1

LOCATION OF ROOTS
NUMERATOR \(=1\).

\(r^{-1}=3000\)
\(r^{-1}=1000\)
\(r^{-1}=300\)
\(r^{-1}=100\)
\(r^{-1}=30\)
\(r^{-1}=10\)
\(r^{-1}=0\)

Fig. 2

LOCATION OF ROOTS


Fig. 3

LOCATION OF ROOTS


Fig. 4

Numerator \(=1\).
\begin{tabular}{rlllccc}
\(r^{-1}\) & \(\tau\) & \(N\) & \(T\) & \(P_{i i^{m a x}}\) & \(P_{i i} \max\) normalized & 1 \\
.1 & 1.425 & 17 & 24.2 & 638 & 2020. & 3 \\
1. & 1.286 & 16 & 20.6 & 213 & 213. & 3 \\
10. & .982 & 17 & 16.7 & 96 & 30.4 & 3 \\
30. & .784 & 23 & 18.0 & 81 & 14.8 & 3 \\
100 & .563 & 28 & 15.8 & 77 & 7.7 & 3 \\
300 & .386 & 32 & 12.4 & 89 & 2.1 & 2 \\
1000 & .239 & 46 & 11.0 & 117 & 2.8 & 2
\end{tabular}

FIG. 5

\section*{CHAPIER XII}

MATCHING DYNAMICS
1. Description of the Problem: We are interested here in the construction of a control system to force the output of a given system to have specified dynamics. Two interesting features of our specific example should be noted. (i) The process of matching dynamics will be simplified because in our given system
\[
\dot{\mathrm{x}}=\mathrm{Fx}+G \mathrm{u},
\]
\[
\begin{equation*}
y=H x, \tag{1.1}
\end{equation*}
\]

HG will be the zero matrix. (ii) Because the desired dynamics already match certain modes of (the open-looP) \(F\), we will find that the performance index is not positive definite, but merely nonnegative definite.
2. Theory and References: Source material for the problem was obtained from Dynamic Optimization of Continuous Processes, J. G. Balchen, published at Trondheim, Norway by Instituitt for Reguleringstenchnik (1961).

The method for obtaining specified dynamics will now be derived. We wish to change the lagrangian so as to minimize \(\|\dot{y}-L y\|_{Q}^{2}\) instead of \(\|y\|_{Q}^{2}\). The idea is to make the output obey approximately the dynamics of some desired system
(2.1)
\[
\dot{y}=\mathrm{Ly}
\]

Notice that this differs from the so-called "model-follower" problem (see Chapter XVIII)in which we wish to minimize \(\left\|y-y_{d}\right\|_{Q}^{2}\), where \(y_{d}\) is a solution of the system (2.1).

This problem then is to minimize the integral of
\[
\|\dot{y}-L y\|_{Q}^{2}+\|u\|_{R}^{2}=\|H F x+H G u-L H x\|_{Q}^{2}+\|u\|_{R}^{2}
\]

We will for the moment make the simplifying assumption that \(H G\) is zero, as would be satisfied, for instance, by any impulse response matrix \(T(t, \tau)\) such that \(T(\tau, \tau)\) is the zero matrix, or, equivalently, by any transferfunction matrix \(Z(s)\) in which every numerator has degree at least two less than its denominator. This gives us an equivalent system (with the usual lagrangian) which is unchanged except that a new output has been deinfed:
\[
\begin{equation*}
y_{1}=(H F-L H) x \tag{2.2}
\end{equation*}
\]

Obviously the controllability has not been affected. So we need examine only the observability matrix,

To decide whether or not (2.3) is completely observable requires rather advanced algebraic analysis. In the simplest case, we have the following result:
\[
\begin{aligned}
& \text { If } p=1 \text {, so that } L=\lambda(1 \times 1 \text { matrix), then (2.3) is completely } \\
& \text { observable iff } \lambda \neq \text { eigenvalue of } F .
\end{aligned}
\]

This follows immediately if we observe that (2.3) is (F - \(\lambda I\) ) times the usual observability matrix
\[
\begin{equation*}
\left[H^{\imath}, F^{\prime} H^{\prime}, \ldots, F^{n^{n-1}} H^{\prime}\right] \tag{2.4}
\end{equation*}
\]

Now let us consider the changes in the riccati equation which take place because of the new lagrangian. We will no longer assume that \(H G\) is zero. We will however show that the performance index is still a quadratic form in \(x\left(t_{0}\right)\) and formally derive the differential equation which the matrix of that form must satisfy.
- We have the lagrangian
\[
T=\frac{1}{2}\|H(F x+G u)-L H x\|_{Q}^{2}+\frac{1}{2}\|u\|_{R}^{2}
\]
and the hamiltonian
\[
) t=\min _{u}\left[\mathscr{X}+p^{\prime}(F x+G u)\right]
\]

This gives
\[
u=-A^{-1}\left[G^{\prime} p+B x\right]
\]
where
\[
A=\left[N^{\imath} Q N+R\right], \quad N=H G
\]
and
\[
B=N^{\prime} Q M, \quad M=(H F-I H)
\]

The hamilton-jacobi equation is
\[
\frac{\partial v^{\circ}}{\partial t}+\pi=0,
\]
where
\[
2 \partial \mathcal{C}=\|M x\|_{Q}^{2}+2 p^{\prime} F x+\left\|G^{\prime \prime} p+N^{\prime} Q M x\right\|_{A^{-1}}^{2}
\]

Its solution can be given by assuming
\[
v^{0}=\frac{1}{2}\|x\|_{P}^{2}
\]
where \(P\) is symmetric. This leads to the riccati equation
\[
\begin{aligned}
-\dot{P}=F^{\prime} P & +P F-P G A^{-1} G^{t} P+M^{\mathbf{t}} Q M-M^{\mathbf{t}} Q N A^{-1} N^{\mathbf{t}} Q M \\
& -P G A^{-1} N^{\mathbf{t}} Q \mathrm{Q}-\mathrm{M}^{\mathbf{y}} Q N A^{-1} \mathrm{G}^{\mathbf{t}} \mathrm{P}
\end{aligned}
\]

Collecting terms we see that this equation is identical with a standard riccati equation if the parameters of the latter are defined as
\[
\begin{aligned}
& \hat{F}=F-G A^{-1} N^{t} Q M, \quad \hat{G}=G, \quad \hat{H}=M \\
& \hat{R}=A \\
& \hat{Q}=Q-Q N A^{-1} N^{\prime} Q
\end{aligned}
\]

Thus the new hamiltonian function fits into the standard computational scheme.
3. The Specific Problem. We are given the impulse response matrix
\[
T(s)=\left[\begin{array}{ccc}
\frac{1}{(s+1)\left(s+\frac{1}{2}\right)(s+2)} & \frac{10}{(s+10)\left(s+\frac{1}{3}\right)\left(s+\frac{1}{2}\right)} & \frac{1}{(s+1)\left(s+\frac{1}{2}\right)} \\
\frac{-s+\frac{3}{4}}{\left(s+\frac{1}{4}\right)(s+1)^{2}(s+2)} & \frac{-4}{(s+5)(s+1)(s+2)} & \frac{4}{(s+1)(s+2)}
\end{array}\right]
\]

From this we obtain the time domain representation
\(T(t)=\left[\begin{array}{l}\frac{4}{3} e^{-\frac{1}{2} t}-2 e^{-t},+\frac{2}{3} e^{-2 t} \frac{180}{29} e^{-\frac{1}{3} t}-\frac{120}{19} e^{-\frac{1}{2} t}+\frac{60}{551} e^{-10 t},-2 e^{-\frac{1}{2} t}+2 e^{-t} \\ \frac{64}{63} e^{-\frac{1}{4} t}+\frac{5 e^{-t}}{9}-\frac{7}{3} t e^{-t}-\frac{11}{7} e^{-2 t},-e^{-t}+\frac{4}{3} e^{-2 t}-\frac{1}{3} e^{-5 t}, 4 e^{-t}-4 e^{-2 t}\end{array}\right]\)
and then obtain a canonical realization by means of the system (1.1). (See pp. 340-356, final report NAS2-1107, July 1964).

We can tell a priori that the dimension of any realization is at least eight since there are seven eigenvalues one of which appears squared in \(T(s)\) or, equivalently, multiplied by \(t\) in \(T(t)\). A little further analysis shows
that the dimension is at least nine since the coefficient matrix associated with the eigenvalue -2 is of rank two. (ibid.)

Furthermore we can tell that the system is not completely controllable by any single input nor completely observable by any single output. This follows from the fact that not all eigenvalues appear in any column or row.

Using Method A, (Ibid.) , we can obtain the following canonical realization.
\[
\begin{aligned}
& F=\operatorname{diag}\left(-\frac{1}{4},-\frac{1}{3},-\frac{1}{2},-2,-2,-5,-10,\left(\begin{array}{llllllll}
-1 & 1 \\
0 & -1
\end{array}\right),-1\right) \\
& H=\left[\begin{array}{llllllllll}
0 & \frac{180}{29} & 1 & 1 & 0 & 0 & \frac{60}{551} & 0 & \frac{6}{7} & 1 \\
\frac{64}{63} & 0 & 0 & 0 & 1 & 1 & 0 & 1 & -\frac{3}{7} & 0
\end{array}\right] \\
& G^{\prime}=\left[\begin{array}{llllllllll}
1 & 0 & \frac{4}{3} & \frac{2}{3} & -\frac{11}{7} & 0 & 0 & -\frac{4}{9} & -\frac{7}{3} & 0 \\
0 & 1 & -\frac{120}{19} & 0 & \frac{4}{3} & -\frac{1}{3} & 1 & -1 & 0 & 0 \\
0 & 0 & -2 & 0 & -\frac{4}{4} & 0 & 0 & 4 & 0 & 2
\end{array}\right]
\end{aligned}
\]

This realization was checked by comparing the step response computed by the ASP program appearing in Fig. I with that shown in Balchen p. 38 and also by checking the terminal values of the response with those computed directly from \(T(s)\).

We computed the controllability matrix using \(u_{1}\) only, in the program appearing in Fig. 2. This should give us a matrix of rank five; it is evident from the placement of zeroes in the first column of \(G\) that we will lose \(-\frac{1}{3},-5,-10\), and -1 and it is clear from elementary controllability theory that we must lose also one of the eigenvalues -2 . This demonstrates the advantages of having the system in canonical form, for the question is not so easily answered by numerical means.

Let us examine the situation in some detail for the insight it may give in the general problem of rank determination. Four rows and columns of \(W\) will be identically zero and thereby simplify the problem. We let \(p_{1}\) and \(p_{2}\) (see Chapter \(V\) ) both be \(10^{-4}\), thus helping to ensure that most of the possible ranks will be considered and their errors printed. The times referred to are the times over which the controll. ability matrix integral is calculated.

At . 2 W was so poorly conditioned that in spite of the small \(p_{2}\), the rank was given as two. The first pivntal element was 1.34, the third was \(1 \cdot 10^{-6}\).

At . 4 the first pivotal element was 3.34, the fifth was \(1 \cdot 10^{-8}\) and the sixth was negative. The errors however, after changing \(p_{2}\) to 1 , were

thus indicating that the pseudo-inversion error is not a satisfactory test for determining rank.

At . 6 the first pivotal element was 6.3, the fifth was . \(2 \cdot 10^{-7}\) and the sixth was negative. The errors were
\begin{tabular}{rl} 
rank 3 & \(\cdot 5 \cdot 10^{-3}\) \\
4 & .3 \\
5 & 2.
\end{tabular}

At .8 the first pivotal element was 14.5 , the fifth was \(.5 \cdot 10^{-7}\), the sixth was \(.14 \cdot 10^{-7}\) both well down in the noise level of the initial
pivot: The errors were
\[
\begin{array}{rl}
\text { rank } 3 & .1 \cdot 10^{-3} \\
4 & .3 \cdot 10^{-1} \\
5 & .6 \\
6 & 8 .
\end{array}
\]

This pattern then continues for as long as \(W\) was computed.
Very similar results were obtained when the controllability matrix was computed using all three inputs except that the difficulties increased because of the extra four dimensions and because the spread of eigenvalues which was \(\left(-\frac{1}{4},-2\right)\) when \(u_{1}\) was used, becomes \(\left(-\frac{1}{4},-10\right)\) when all three are used. Since the elements of \(W\) are roughly proportional to \(e^{-\left(\lambda_{i}+\lambda_{j}\right) t}\) this increase in spread can be expected to cause difficulties.

At . 2 the first pivot was 10 , the tenth \(.2 \cdot 10^{-8}\). The minimum error of \(.4 \cdot 10^{-4}\) occurred at a rank of 6 .

At . 4 the first pivot was 149, the tenth .2 • \(10^{-6}\). The minimum error of \(.6 \cdot 10^{-4}\) occurred at a rank of 6 . These minima were not very definite
\[
\begin{array}{lll}
5 & .1 \cdot 10^{-3} & .9 \cdot 10^{-4} \\
6 & .4 \cdot 10^{-4} & .3 \cdot 10^{-4} \\
7 & .3 \cdot 10^{-3} & .7 \cdot 10^{-4}
\end{array}
\]

This pattern continued with the smallest error slipping back to smaller ranks until abruptly at \(1.4 \quad p_{2}\) could not force the error smaller and only two pivots were made on the -10 and -5 eigenvalues, the two pivotal elements being \(1 \cdot 10^{10}\) and \(.2 \cdot 10^{3}\). These numbers completely obscured the contributions of smaller eigenvalues.
4. Equations and Procedure. We now wish to design an optimal control so. that \(y_{1}\) behaves as \(\dot{y}_{1}=-y_{1}\) and \(y_{2}\) behaves as \(\dot{y}_{2}=-2 y_{2}\). This gives us the performance index
\[
\begin{equation*}
\int_{0}^{\infty}\left[\left(\dot{\mathrm{y}}_{1}+\mathrm{y}_{1}\right)_{\mathrm{q}_{11}}^{2}+\left(\dot{\mathrm{y}}_{2}+2 \mathrm{y}_{2}\right)_{\mathrm{q}_{22}}^{2}+\mathrm{u}^{\prime} \mathrm{Ru}\right] d t \tag{1.1}
\end{equation*}
\]
where \(L\) can be rewritten as
\[
L=\|(H F-L H) x\|_{Q}^{2}+\|u\|_{R}^{2}
\]
where \(Q=\operatorname{diag}\left(q_{11}, q_{22}\right)\) and \(L=\operatorname{diag}(-1,-2)\).
This simple form for \(L\) occurs because \(H G=[0]_{2,3} 3^{*}\). We know this is correct because each denominator in \(T(s)\) is of degree at least two greater than its numerator, equivalently \(\left.T(t)\right|_{t=0}=H G=[0]_{2,3^{\circ}}\)

Because of this, we need only define \(\hat{H}=H F-I H\) and then compute the gains for the optimal regulators of the system \([\hat{H}, F, G]\).

However, because \(F\) and \(L\) have two common eigenvalues, the system \([\hat{H}, F]\) has an observable space of dimension eight. We expect therefore to obtain a performance index matrix \(\mathrm{P}(0)\) of rank eight and to find that the vectors
\[
\left[\begin{array}{llllllllll}
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0
\end{array}\right]
\]
and
\[
\left[\begin{array}{llllllllll}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1
\end{array}\right]
\]
are costless (lie in the null space of \(P(0)\) ). This will be true only if the vectors lie in the null space of \(P(\infty)\), but we are letting \(P(\infty)=[0]_{10,10}\).
\(\overline{{ }^{*}[0]_{m, n} \text { means } m \times n \text { zero matrix }}\)
"This follows from the fact that these vectors will give the correct response without control effect a fact which can be seen formally from the two zero columns of
\[
H F-L H=\left[\begin{array}{cccccccccc}
0 & \frac{120}{29} & \frac{1}{2} & -1 & 0 & 0 & -\frac{540}{551} & 0 & 0 & 0 \\
\frac{16}{9} & 0 & 0 & 0 & 0 & -3 & 0 & 1 & \frac{4}{7} & 0
\end{array}\right]
\]
5. Results: Using the program appearing in Fig. 3, the performance index and optimal gain matrices were computed (Fig. 4 and 5). Fig. 6 illustrates \(y_{1,10}(t)\) which is uncontrolled, being the desiced response \(e^{-t}\) anyway, together with \(y_{1,4}(t)\) which, uncontrolled would have the response \(e^{-2 t}\), also illustrated. These results were obtained using the program in Fig. 7.

BEGIN
LOAD F. G, H. T.Z1,ND.
\begin{tabular}{|c|c|c|c|c|}
\hline HEAD 1EAT
MULT & \multicolumn{4}{|l|}{\[
\begin{aligned}
& \mathrm{F}, \mathrm{Z1}, \mathrm{PH}, \mathrm{IN} \\
& \mathrm{H}, \mathrm{IN}
\end{aligned}
\]} \\
\hline MULT & 1 & G & & SR \\
\hline RINT & 21 & & SR & ST \\
\hline ADD & Z1 & T & \multicolumn{2}{|l|}{Z1} \\
\hline IF & ND & 21 & HEA & D \\
\hline END & & & & \\
\hline
\end{tabular}
\begin{tabular}{|c|c|c|c|c|}
\hline \multirow[t]{2}{*}{-. 250} & 0 & 0 & 0 & 0 \\
\hline & 0 & 0 & 0 & 0 \\
\hline \multirow[t]{2}{*}{0} & -. 333333333 & 0 & 0 & 0 \\
\hline & 0 & 0 & 0 & 0 \\
\hline \multirow[t]{2}{*}{0} & 0 & -. 5 & 0 & 0 \\
\hline & 0 & 0 & 0 & 0 \\
\hline \multirow[t]{2}{*}{0} & 0 & 0 & -2. & 0 \\
\hline & 0 & 0 & 0 & 0 \\
\hline \multirow[t]{2}{*}{0} & 0 & 0 & \(\bigcirc\) & -2. \\
\hline & 0 & 0 & 0 & 0 \\
\hline \multirow[t]{2}{*}{\(-5.0\)} & 0 & 0 & 0 & 0 \\
\hline & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & -10. & 0 & 0 & 0 \\
\hline \multirow[t]{2}{*}{0} & 0 & 0 & 0 & 0 \\
\hline & 0 & -1. & 1. & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & -1. & 0 \\
\hline \multirow[t]{2}{*}{0} & 0 & 0 & 0 & 0 \\
\hline & 0 & 0 & 0 & -1. \\
\hline G 10 & 3 & & & \\
\hline 1. & 0 & 0 & 0 & 1. \\
\hline \multirow[b]{2}{*}{0} & 1.3333333 & & -2. & \\
\hline & 0 & & & 4. \\
\hline 0 & -. 33333333 & 0 & 0 & 1. \\
\hline \multirow[b]{2}{*}{0} & -. 44444444 & -1. & 4. & \\
\hline & 0 & 0 & 0 & 2. \\
\hline \(\mathrm{H} \quad 2\) & 10 & & & \\
\hline 0 & 6.2068966 & 1. & 1. & 0 \\
\hline 0 & . 10889292 & 0 & & \\
\hline 1.0158730 & 0 & 0 & 0 & \\
\hline 1. & 0 & 1. & & 0 \\
\hline T 1 & 1 & & & \\
\hline \multicolumn{5}{|l|}{- 2} \\
\hline Z1 1 & 1 & & & \\
\hline \multicolumn{5}{|l|}{0} \\
\hline ND 1 & 1 & & & \\
\hline 16. & & & & \\
\hline
\end{tabular}

Fig. 1

EEGIN
LOAD P1,P2.Z1,PC.D2.D3.T1.ND,ZR,WO. 1.RI.F. G. WRITE 1 THIS PROGRAM COMPUTES THE CONTROLLABILITY MATRIX FOR THE WRITE SYSTEM
WRITE - XDOT \(=F * \times+G * U\)
PIZER P1.P2,
TRANP G. GT,
\(\begin{array}{ccc}\text { MULT } & \text { RI.GT, } & \text { C, } \\ \text { MULT } & \text { G. C, } & \text { Q. }\end{array}\)
NORM F. NF.
NORM Q. NQ.
PSEUO NQ, NQ.RK
MULT NF,NQ, LM,
\(\begin{array}{lcc}\text { MULT LM. Q. } & \text { Q. } \\ \text { MULT LM.WO. } & \text { WO }\end{array}\)
TRANP F, FT.
SUBT ZR, \(F\), MF,
\(\begin{array}{lll}J U X T C & F T, Z R, & 1, \\ J \cup X T C & Q, M F, & 2,\end{array}\)
JUXTR 1. 2. 3.
RINT \(3 \cdot 3\)
ETPHI 3.T1,PH,T9,
MULT T9.Dこ, 04.
MULT T1.D3. D5.
ADD D4.D5. D.
PSEUO LM, LN,RK.
HEAD IRICAT WO.PH, C, D,PC, WO, K.AI.
ADD Z1.Ti, Z1,
PSEUO WO. + IWI,AL, PRINT
\(\begin{array}{lll}\text { MULT LN,WO. } & \text { W. } \\ \text { RINT } 2 I \cdot & \text { W. W }\end{array}\)
IF ND.Z1.HEAD 1


Fig. 2


Fig. 2

\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)

Fig. 2
\(\qquad\)

BEGIN
LOAD TT, D,D1,PC, F, G, Q,RI,ZR,T1,XO,ND,R1,RZ,XX, H,Q1,
TRANP H , HT
\(\begin{array}{llll}\text { MULT } & \text { HT } & 8, & Q \\ \text { SUBT } & \text { ZR, } & F, & 1,\end{array}\)
\(\begin{array}{lll}\text { TRANP } & F, & F T, \\ \text { TRANP } & G, & G T,\end{array}\)
MULT RI,GT• \(C\),
MULT G. C, 5,
NORM \(Q\). NQ.
NORM 5, N5.
PSEUO NQ, PQ,RK
MULT PQ,N5, M1,
DECOM M1, S,SJ,ER,PE, E,RK.
MULT \(S, Q\), \(Q\),
MULT SJ, 5, 5,
MULT SJ, C, C,
BLOT NQ.
\(\begin{array}{lll}\text { JUXTC } & 1,5, & 2, \\ J U X T C & Q, F T, & 3,\end{array}\)
JUXTR 2, 3, PH,
NORM PH, NP,
PSEUQ NP, NP,RK
MULT NP,TT,
\(\frac{\text { RINT }}{\text { ETPHI } \mathrm{PH}, \mathrm{PH}}\)
MULT T,D1, 4,
ADD \(4 \cdot D^{\circ}\) D.
RICAT Q,PH, C, D,PC, XX, P, K,AL,
RINT P.PER K, K
IF AL, D.ZILCH
WRITE THE PRECEDING MATRICES WERE THE MATRIX P OF THE
WRITE PERFORMANCE INDEX AND THE FEEDBACK GAIN MATRIXK.
SUBT F,GK, CF,
ETPHI CF,T1.P1,
HEAD IMULT K, XO, KX,
JUXTR XO,RZ, 6,
RINT RI, \(7, \frac{7}{2}\)
MULT P1, \(\times 0, \quad \times 0\),
ADD R1,T1, RI,
\begin{tabular}{ll} 
IF & ND,R1, HEAD 1 \\
\hline IF & TT,TT,HEAD 2
\end{tabular}

- 3 Fig. 3


Fig. 3


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\(\qquad\)
\(\qquad\)
\(\qquad\)

Fig. 3

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Fig. 6

BEGIN
LOAD F, G. H. T,Z1,ND,K I
MULT G,K, GK
SUBT FSGK, CF
ETPHI CF, T.PH
HEAD 1MULT H, I, \(\quad\) Y
\(\begin{array}{lll}\text { MULT } & \mathrm{PH}, \mathrm{I}, & \mathrm{I} \\ \mathrm{ADD} & \mathrm{Z} 1, \mathrm{~T}, & \mathrm{Zi},\end{array}\)
IF ND,Z1,HEAD 1



Fig. 7
\begin{tabular}{|c|c|c|c|c|}
\hline \[
\begin{aligned}
& 3.9075574 \\
& -2.8574571
\end{aligned}
\] & 37.43898
-2.348452 & 4.3875866 & -6.7588778 & -41919892E-6 \\
\hline 17.169672 & -9.652482 & -1.1691411 & 1.4517066 & -. \(15456941 \mathrm{E}-9\) \\
\hline -25.951548 & 1.9231991 & 9.4811624 & 2.2779363
5.6479795 & -13085039E-6 \\
\hline 110 & 10 & & & 27773E-11 \\
\hline 1. & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 1. & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 1. & 0 & 0 \\
\hline 0 & 0 & 0 & 1. & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 1. \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 1. & 0 & 0 & 0 & 0 \\
\hline 0 & 1. & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 1. & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 1. & 0 \\
\hline 0 & 0 & 0 & 0 & 0 \\
\hline 0 & 0 & 0 & 0 & 1. \\
\hline
\end{tabular}

Fig. 7

\section*{CHAPIER XIIII}

\section*{AN OPTIMAL CONIINUOUS TIME FIIIER}
1. Description of the Problem: We shall consider a special data-smoothing problem encountered in determining the position and velocity of a spsce vehicle. This will provide a convenient illustration of the hamiltonian technique for obtaining solutions of the variance equation. The example shows also how to obtain the model of the random process directly from physical considerations.

The physical picture is as follows. The position of a satellite is measured by means of a radio signal. It is assumed that the measurement contains additive noise which may be taken to be approximately gaussian and white relative to the bandwidth of the satellite motion. A second measurement of the satellite motion is available from an accelerometer. This reading is also subject to noise; but here the noise is due to drift and other very slowly varying effects, and may be considered to be a constant random variable during the interval of interest. The motion of the satellite is linearized and assumed to be one-dimensional, and subject to a constant, gaussian random acceleration.

The problem is to design an optimal filter which provides the best running estimates of the position and velocity of the satellite based on the two types of measurement noise and the variance of the acceleration.
2. Theory and References: For a derivation of the variance equation, see Chapter V.

The problem was suggested by the follpwing paper:
[I] E. I. Peterson, "Optimization of multi-input time-varying systems subject to multiple or redundant nonstationary inputs". Proc. First Internationid Congress on Automatic Control, (Moscow 1960) Butterworths 1961. See also:

\section*{[2] R. E. Kalman, Discussion of Peterson's paper, in the same Próceedings.}
3. The Specific Problem: The assumptions are formalized by setting up a model for the message process. Let \(z_{1}\) denote the radio signal and \(a_{1}\) the reading of the accelerometer. Both signals are supposed to be known exactly. The equation of motion (linearized, one-dimensional, with unit mass) is
\[
\ddot{x}=a(t)=\text { acceleration }=\text { constant }=a
\]
where \(a\) is a gaussian random variable with zero mean. The accelerometer measures a plus a constant gaussian random variable \(b\) with zero mean (the bias error of the accelerometer):
\[
a_{1}=a+b
\]

Let \(E a^{2}=r_{a}\) and \(E b^{2}=r_{b}\). We assume that \(a\) and \(b\) are uncorrelated (hence, by gaussianness, independent) and set
\[
\rho=\frac{r_{a} r_{b}}{r_{a}+r_{b}}
\]

We replace \(a_{1}, b\) by two new random variables \(u_{1}\) and \(x_{3}\) which are orthogonal to each other (and thus, by gaussianness, independent); \(u_{1}\) is exactly known and \(x_{3}\) is to pe estimated:
\[
u_{1}=e_{r_{b}}^{a_{1}}, \quad x_{3}=\frac{\rho_{a_{1}}}{r_{1}}-b
\]

Then the equations of motion are:
\[
\dot{\mathrm{x}}=\mathrm{x}_{2}, \quad \dot{x}_{2}=a=a_{1}-b=u_{1}+x_{3}
\]

The model is now fully described, and we have:
(3.1) \(F=\left[\begin{array}{lll}0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0\end{array}\right], \quad G=\left[\begin{array}{l}0 \\ 1 \\ 0\end{array}\right], \quad\) and \(H=\left[\begin{array}{lll}1 & 0 & 0\end{array}\right]\).

The variance equations are
\[
\begin{align*}
& \mathrm{d} \mathrm{\sigma}_{11} / \mathrm{dt}=2 \sigma_{12}-\sigma_{11}^{2} / \mathrm{r}_{11}, \\
& \mathrm{~d} \mathrm{\sigma}_{12} / \mathrm{dt}=\sigma_{13}+\sigma_{22}-\sigma_{11} \sigma_{12} / r_{11}, \\
& \mathrm{~d} \sigma_{13} / \mathrm{dt}=\sigma_{23}-\sigma_{11} \sigma_{13} / r_{11},  \tag{3.2}\\
& d \sigma_{22} / d t=2 \sigma_{23}-\sigma_{12}^{2} / r_{11}, \\
& d \sigma_{23} / d t=\sigma_{33}-\sigma_{12} \sigma_{13} / r_{11}, \\
& d \sigma_{33} / d t=-\sigma_{13}^{2} / r_{11} .
\end{align*}
\]

The Hamiltonian equations are
(3.3)
\[
\left[\begin{array}{l}
\dot{x}_{1} \\
\dot{x}_{2} \\
\dot{x}_{3} \\
\dot{p}_{1} \\
\dot{p}_{2} \\
\dot{p}_{3}
\end{array}\right]=\left[\begin{array}{cccccc}
0 & 0 & 0 & 1 / r_{11} & 0 & 0 \\
-1 & 0 & 0 & 0 & 0 & 0 \\
0 & -1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 . & 0 \\
0 & 0 & 0 & 0 & 0 & 1 . \\
0 & 0 & 0 & 0 & 0 & 0
\end{array}\right] \cdot\left[\begin{array}{l}
x_{1} \\
x_{2} \\
x_{3} \\
p_{1} \\
p_{2} \\
p_{3}
\end{array}\right] .
\]

The traisition matrix corresponding to these equations is easily found. (The axith power of the matrix on the right-hand side of (3.3) is zero.) The r is:
\((3.4) \Theta(t, 0)=\left[\begin{array}{cccccc}1 & 0 & 0 & t / r_{11} & t^{2} / 2 r_{11} & t^{3} / 6 r_{11} \\ -t & 1 & 0 & -t^{2} / 2 r_{11} & -t^{3} / 6 r_{11} & -t^{4} / 24 r_{11} \\ t^{2} / 2 & -t & 1 & t^{3} / 6 r_{11} & t^{4} / 24 r_{11} & t^{5} / 120 r_{11} \\ 0 & 0 & 0 & 1 & t & t^{2} / 2 \\ 0 & 0 & 0 & 0 & 1 & t \\ 0 & 0 & 0 & 0 & 0 & 1\end{array}\right]\).

We assume that the initial value of \(\Sigma(0)\) is: \(\sigma_{11}(0)=\sigma_{22}(0)=0\), while \(\sigma_{33}(0)=\rho\) is the effect due-to the bias in the reading of the accelerometer. (Of course, all off-diagonal terms of \(\Sigma(0)\) are zero.) Using (3.4) we find that the solution of the variance equation corresponding to these initial conditions is:
\(\Sigma(t)=\frac{r_{11}}{t^{5} / 20+r_{11} / p}\left[\begin{array}{lll}t^{4} / 4 & t^{3} / 2 & t^{2} / 2 \\ t^{3} / 2 & t^{2} & t \\ t^{2} / 2 & t & 1\end{array}\right]\).

It is easily verified by direct substitution that this is indeed a solution of the variance equation which satisfies the initial conditions stated above.

The optimal time-varying gains can now be obtained at once from the relation \(K(t)=\Sigma(t) H^{1} R^{-1]}\) they are:
\[
k_{11}(t)=t^{4} / 4 \alpha(t), k_{21}(t)=t^{3} / 2 \alpha(t), k_{31}(t)=t^{2} / 2 \alpha(t)
\]
where
\[
\alpha(t)=t^{5} / 20+r_{11} / p
\]
(3.5) \(\left[\begin{array}{l}d \hat{x}_{1} / d t \\ d \hat{x}_{2} / d t \\ d \hat{x}_{3} / d t\end{array}\right]=\left[\begin{array}{ccc}-t^{4} / 4 \alpha & 1 & 1 \\ -t^{3} / 2 \alpha & 0 & 1 \\ -t^{2} / 2 \alpha & 0 & 0\end{array}\right] \cdot\left[\begin{array}{l}\hat{x}_{1} \\ \hat{x}_{2} \\ \hat{x}_{3}\end{array}\right]+\left[\begin{array}{c}t^{4} / 4 \alpha \\ t^{3} / 2 \alpha \\ t^{2} / 2 \alpha\end{array}\right] z_{1}+\left[\begin{array}{c}0 \\ u_{1} \\ 0\end{array}\right]\).

This differential equation is difficult to solve. Considerable simplification is obtained by introducing a new set of state variables:
\[
\begin{array}{ll}
w_{1}=\hat{x}_{3} & 2 \hat{x}_{1}=t^{2} w_{1}+w_{2}+t w_{3} \\
w_{2}=2 \hat{x}_{1}-t \hat{x}_{2} & \hat{x}_{2}=t w_{1}+w_{3}, \\
w_{3}=\hat{x}_{2}-t \hat{x}_{3}, & \hat{x}_{3}=w_{1} .
\end{array}
\]

Then by (3.5)
\[
\left[\begin{array}{l}
d w_{1} / d t \\
d w_{2} / d t \\
d w_{3} / d t
\end{array}\right]=\left[\begin{array}{ccc}
-t^{4} / 4 \alpha & -t^{2} / 4 \alpha & -t^{3} / 4 \alpha \\
0 & 0 & 0 \\
0 & 0 & 0
\end{array}\right]\left[\begin{array}{c}
w_{1} \\
w_{2} \\
w_{3}
\end{array}\right]\left[\begin{array}{c}
t^{2} / 2 \alpha \\
0 \\
0
\end{array}\right] z_{1}+\left[\begin{array}{c}
0 \\
-t \\
1
\end{array}\right] u_{1} .
\]

The transition matrix corresponding to this equation is
\[
\Psi^{(w)}(t, \tau)=\left[\begin{array}{ccl}
\beta / \alpha & -\delta / 2 \alpha & -(\gamma-\delta \tau / 2) / \alpha \\
0 & 1 & t-\tau \\
0 & 0 & 1
\end{array}\right]
\]
where
\[
\beta(\tau)=\tau^{5} / 20+r_{11} / p, \gamma(t, \tau)=\left(t^{4}-\tau^{4}\right) / 8, \delta(t, \tau)=\left(t^{3}-\tau^{3}\right) / 6
\]

Thus the transition matrix corresponding to (3.5) is found to be
\[
\Psi^{(\hat{x})}(t, \tau)=\left[\begin{array}{ccc}
\alpha-\delta t^{2} / 2 & (t-\tau) \alpha-(\gamma-\delta \tau) \tau^{2} / 2 & \left(\tau^{2} / 2-t \tau\right) \alpha+\left(\beta+\gamma \tau-\delta \tau^{2} / 2\right) t^{2} / 2 \\
-\delta t & \alpha-(\gamma-\delta \tau) t & -\alpha \tau+\left(\beta+\gamma \tau-\delta \tau^{2} / 2\right) t \\
-\delta & -(\gamma-\delta \tau) & \beta+\gamma \tau-\delta \tau^{2} / 2
\end{array}\right]
\]
4. Results: Using the program appearing in Fig. I we obtained the covariance matrix for the system (3.1) with \(Q=0\) and \(R=.5\). At \(t=.95\), the variance matrix should have been:
\[
\Sigma=\left[\begin{array}{ccc}
.352674 & .74247275 & .78155026 \\
& 1.5631005 & 1.6453690 \\
\text { sym. } & & 1.7319673
\end{array}\right]
\]
and actually was computed to be
\[
\Sigma=\left[\begin{array}{ccc}
.35267451 & .7424271 & .78155027 \\
& 1.5631005 & 1.6453691 \\
\text { sym. } & & 1.7319676
\end{array}\right]
\]

The transition matrix of the optimal filter as computed by sampling the optimal filter gain at intervals of .05 was, at \(t=1\)
\[
\Phi(1,0)=\left[\begin{array}{rrr}
.72218 & .79251 & .41728 \\
-.55489 & .58507 & .83441 \\
-.55461 & -.41522 & .83412
\end{array}\right]
\]
and should have been
\[
\Phi(1,0)=\left[\begin{array}{rrr}
.722222 & .791666 & .416666 \\
-.555555 & .583333 & .833333 \\
-.555555 & .416666 & .833333
\end{array}\right]
\]

This shows that the sampling is being done correctly. Accuracy of the transient can be improved by increasing the sampling rate.

JAN. 26. 1965
BEGIN
LOAD AS.Z1.D2.RC. T.D3. I.VO.ON.GS.ZRAFSEHSURNOND.
MULT RN.HS, 21.
TRANP HS, HTe
MULT HT.21, 22.
TRANP FS. 1.
TRANP GS. GT.
MULT GS.ON, 27
MULT 27.GT 29
\(\begin{array}{llll}\text { JUXTC } 23 & 22 & 24 \\ \text { JUXTC } 29 & \mathrm{FS} & 25\end{array}\)
JUXTC 29 FS 25
\(\begin{array}{lrrr}\text { JUXTR } & 24 & 25 & 26 \\ \text { MULT } & 5 & T & T 1\end{array}\)
ETPHI 26 T1.28.T2
MULT T2.D2. D4.
ADD D4.D3 D,
RICAT VO.28.21. D.PC, VO.KN.A1.
ETPHI 26. T.28.T2
MULT T2 D2 D4
ADD D4.D3.
HEAD 1 TRANP KN. KF.
MULT KF,HS. 2
SUBT FS, 2. CF,
ETPHI CF, T,PH,
MULT PH, I, I,
RINT T1, VO,VAR
ADD Tle Te Tl.

RICAT VO.28.21. D.PC, VO.KN,A1.
IF ND,Z1.HEAD 1
END
\begin{tabular}{lll}
.5 & 1 & 1 \\
21 & \(1^{.5}\) & 1 \\
02 & \(1^{0}\) & 0 \\
& & 0
\end{tabular}
\(P C \quad 1 \quad 0\)
\(T \quad 1{ }^{0} 1\)
D3 \(\quad 1 \quad 3\)
\(\begin{array}{cccccc}1 & 3^{0} & 3 & 0 & 1 & \\ & 1 \cdot & & 0 & 0 & 0 \\ & 0 & 0 & 0 & 10\end{array}\)
Vo \(\begin{array}{rlll}3 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0\end{array}\) \(\qquad\)


Fig. 1

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\(\qquad\)

Fig. 1

\section*{CHAPIER XIV}

\section*{LOSS OF CONIROLLABILITY BY SAMPLING}
1. Description of the Problem: We take a transfer function; after obtaining an irreducible representation and discretizing, we find the "deadbeat" control law. This control law is a function of the sampling interval and we will examine the behavior of the control and the closed loop transients, particularly in the vicinity of points where controllability is lost.
2. Theory and References: In addition to Chapter VIII,see: [I] R. E. Kalman, "On the General Theory of Control Systems", Proc. lst International Congress in Automatic Control, Moscow (1960); published by Butterworths, London (1961), [2] R. E. Kalman, Y. C. Ho and R. Narendra, "Controllability of Linear Dynamical Systems", Contributions to Differential Equations, vol. I, no. 2 .

We will preface our results with some remarks about deadbeat control in general. Consider a completely controllable system
\[
x_{k+1}=\Phi x_{k}+\Gamma u_{k}
\]

We assume that \(\operatorname{det} \Phi \neq 0\).
Deadbeat control of a sampled system is any control law which takes the state of the system to zero in finitely many ( \(=\mathrm{N}\) ) steps. Since
\[
\begin{equation*}
x_{n}-\Phi^{n} x_{0}=\Phi^{n-1} \Gamma u_{0}+\Phi^{n-2} \Gamma u_{1}+\ldots+\Phi \Gamma_{n-2}+\Gamma u_{n-1} \tag{2.1}
\end{equation*}
\]
it is clear from complete controllability that deadbeat control exists and that we never have to use more than \(N=n\) steps. However, the control law is generally not unique. This is because (2.1) admits many control sequences
\[
u_{0}, u_{1}, \ldots, u_{n-1}
\]
as a solution. Even if \(N=N_{0}=\) minimum number of steps necessary to take every state to 0 , the solution may be nonunique. There is one case when the solution is unique (and \(N_{0}=n\) ): if \(m=l\), the vectors \(\Phi^{-1} \Gamma, \ldots, \Phi^{-N} \Gamma\) are linearly independent and span the state space if and only if \(N=n\). In this case we may conclude that any method which takes every state \(x_{o}\) to 0 in \(n\) steps must yield the same control law.

Thus (recall Chapter VIII) we let \(Q_{n}=I, R_{n}=0\), and \(Q_{k}=R_{k}=0\) for \(1 \leqq k<n\), and compute a time-varying closed-loop control law using the sampled data riccati equation. According to the preceding considerations, we must thereby obtain a control law which is in the case \(m=1\) identical with the unique deadbeat control law (for if not, \(x_{n}^{\prime} I x_{n} \neq 0\) for some vector \(x_{n}\), which would contradict optimality.) In the general case, \(m \neq 1\), the situation is very much more complicated.

The riccati equation usually yields a time-varying control law. In the present problem a special situation arises, as follows.

Let the control law given by the riccati equation be
\[
u_{k}=-K_{k} x_{k}, \quad k=0, \ldots, n-1 .
\]

It is a most interesting fact that \(K_{0}\) also defines a deadbeat control law. In other words (recall uniqueness), we have along every optimal trajectory
\[
\begin{equation*}
u_{k}=-K_{o} x_{k}=-K_{k} x_{k}, \quad k=0, \ldots, n-1 \tag{2.2}
\end{equation*}
\]

According to this equation, we can always use a constant control law defined via \(K_{0}\). This fact is well known (see [1]); but the proof usually requires ad hoc argument. Here we shall give a direct proof based on the riccati equation.

First we note that the optimal transition matrix \(\Phi_{i}\) corresponding to the state transition \(x_{n-i}\) to \(x_{n-i+1}\) is given by
\[
\begin{equation*}
\Phi_{i+1}=\left[I-\Gamma\left(\Phi_{1} \ldots \Phi_{i} \Gamma\right)^{\#} \Phi_{I} \ldots \Phi_{i}\right] \quad i=0, \ldots, n-1 . \tag{2.3}
\end{equation*}
\]

We prove this by induction. \(\Phi_{1}\) is determined by the requirement
\[
0=x_{n}=\Phi x_{n-1}+\Gamma u_{n-1} ;
\]
hence
\[
k_{n+1}=-\Gamma_{\Phi}^{\#}
\]
and
\[
\Phi_{1}=\Phi-\Gamma \Gamma^{\#} \Phi=\left(1-\Gamma \Gamma^{\#}\right) \Phi .
\]

In the second step,
\[
0=x_{n}=\Phi_{1} x_{n-1}=\Phi_{1}\left(\Phi x_{n-2}+\Gamma u_{n-2}\right) ;
\]
hence
\[
k_{\mathrm{n}-2}=-\left(\Phi_{I} \Gamma\right)^{\#} \Phi_{1} \Phi
\]
and
\[
\Phi_{2}=\Phi-\Gamma\left(\Phi_{1} \Gamma\right)^{\#} \Phi_{1} \Phi_{.}
\]

The general case may be proved similarly.
So far all calculations are valid for any \(\Gamma\).
Now we shall assume that \(m=1\) and write \(\Gamma\) as \(\gamma\). Then
\[
\begin{equation*}
\Phi_{n}^{k} \Phi^{-k} r=0 \quad \text { for all } k=1, \ldots, n \tag{2.4}
\end{equation*}
\]
(2.4) shows, by complete controllability, that the \(n\)-fold application of \(\Phi_{\mathrm{n}}=\left(\Phi-\gamma K_{0}\right)\) will take every state into 0 in at most \(n\) steps. Since there is only one way of accomplishing this, \(K_{o}\) defines the optimal control law. Thus the time-optimal control law may be computed by the riccati equation when \(m=1\).

To prove (2.4), we note that
(2.5)
\[
(A \gamma)^{\#}=\gamma^{I} A^{\prime} /\|A \gamma\|^{2}
\]
for any matrix \(A\).
If \(k=1\), (2.4) follows at once from (2.3) and (2.5).
If \(k=2\), we calculate
\[
\Phi_{n} \Phi^{-2} \gamma=\left[I-r r^{\prime} \Phi_{1}^{\prime} \ldots \Phi_{n-1}^{\prime}\left\|\Phi_{1} \ldots \Phi_{n-1} \gamma\right\|^{2} \Phi_{1} \ldots \Phi_{n-1}\right]^{-1} r .
\]
gut
\[
\Phi_{n-1} \Phi^{-1} r=0
\]
by direct computation. Hence, using (2.5) for \(k=1\),
\[
\Phi_{\mathrm{n}}^{2} \Phi^{-2} \gamma=\Phi_{\mathrm{n}} \Phi^{-1} r=0
\]
the general case is established similarly.
This is the deadbeat transition matrix for the last step. Recursively define
\[
\varphi_{i+I}=\varphi-\Gamma\left(\prod_{j=1}^{i} \varphi_{j} \cdot \Gamma\right)^{\#} \prod_{j=1}^{i} \varphi_{j} \cdot \varphi
\]
egg.
\[
\varphi_{3}=\varphi-\mathbb{I}^{\prime}\left(\varphi_{1} \varphi_{2} \Gamma\right)^{\#} \varphi_{1} \varphi_{2} \varphi_{0}
\]

These define the deadbeat transition matrices \(\Phi_{i}\) from the \((n-i)^{\text {ty }}\) step to the \((n-i+1)^{\text {th }}\) step. We claim that
\[
\begin{aligned}
\varphi_{i}^{j} \varphi^{-k} \Gamma=0 \text { for } \quad j & =1, \ldots, i \\
k & =1, \ldots, j .
\end{aligned}
\]

Proof: By induction on \(i\).
\[
\varphi_{\perp} \varphi^{-1} \Gamma=\Gamma-\Gamma \Gamma^{\#} \Gamma=0 .
\]

Crucial to all this is the property of controllability. In fact, controllability for a single-input nonsingular discrete system can be characterized as the existence of a \(K\) such that \(\Phi-\Gamma K\) is simılar to a single Jordan block with zero eigenvalue. Notice that no \(\Phi\) whose rank is less than n-l can be single input controllable. We see also that controllability of a discrete system does not guarantee that we can transfer from any state to any other unless \(\Phi\) is nonsingular.

Even if \([\varphi, \Gamma]\) is derived from a completely controllable continuous time system it is possible for complete controllability to be lost by the introduction of sampling. This may occur (see the reference [2]) when the system is discretized with an interval \(\sigma\) such that
\[
\left\{\begin{array}{l}
\operatorname{Im}\left[\lambda_{i}-\lambda_{j}\right]=2 \pi \frac{q}{\sigma}  \tag{2.6}\\
q= \pm 1, \pm 2, \ldots,
\end{array}\right.
\]
for any two eigenvalues \(\lambda_{i}, \lambda_{j}\) such that \(\operatorname{Re}\left[\lambda_{i}-\lambda_{j}\right]=0\).
This condition is necessary and sufficient for a single input system and is independent of the choice of \(\Gamma\). That is the system is no longer single-input controllable. Recall that this occurs if the discretized system matrix has more than one Jordan block associated with a given eigenvalue.
3. The Specific Problem. We take the transfer function
\[
\begin{equation*}
T(s)=\frac{s+3 / 2}{(s+2)\left(s^{2}+\frac{\pi^{2}}{9}\right)\left(s^{2}+\frac{4 \pi^{2}}{9}\right)} \tag{3.1}
\end{equation*}
\]
and an irreducible realization
\[
H=[1,3 / 2,0,0,0]
\]
\(F=\left[\begin{array}{ccccc}0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ -9.620509 & -1.8103254 & -10.966226 & -5.4831135 & -2 .\end{array}\right]\)
\(G^{\prime}=[\quad 0\)
0
0
0
\(1]\).

We easily see from (2.6) that controllability will be lost when \(\sigma\) is a multiple of \(1.5,2,3\), or 6 . Let
\[
F_{I}=\left(\begin{array}{cccc}
0 & I & 0 & 0 \\
-\frac{\pi}{3} & 0 & 0 & 0 \\
0 & 0 & 0 & 1 \\
0 & 0 & -\frac{2 \pi}{3} & 0
\end{array}\right)
\]
correspond to a realization of the factors \(\left(s^{2}+\pi^{2} / 9\right)\) and \(\left(s^{2}+4 \pi^{2} / 9\right)\) in (3.1). Let \(e^{F t}=A(t)\). By examining \(\left[G, A G, A^{2} G, A^{3} G\right]\) for
\[
A=\left[\begin{array}{cccc}
\cos \frac{\pi}{3} t & \sin \frac{\pi}{3} t & 0 & 0 \\
-\sin \frac{\pi}{3} t & \cos \frac{\pi}{3} t & 0 & 0 \\
0 & 0 & \cos \frac{2 \pi}{3} t & \sin \frac{2 \pi}{3} t \\
0 & 0 & -\sin \frac{2 \pi}{3} t & \cos \frac{2 \pi}{3} t
\end{array}\right]
\]
for \(t=\sigma\), and appropriate \(G\) vectors, we conclude that the maximum controllability rank \(r\) is
\begin{tabular}{cc}
\(\sigma\) & \(r\) \\
\(3 / 2\) & 4 \\
2 & 3 \\
3 & 3 \\
4 & 3 \\
\(9 / 2\) & 4 \\
6 & 2
\end{tabular}

The two periods, 6 and 3 are commensurable so we might ask how the gains differ for \(\sigma\) and \(6+\sigma\). Since, except for the effect of the root \(-2, \Phi\) will be the same for \(\sigma\) and \(6+\sigma\) we might hypothesize that the gains will be the same after \(\sigma\) is large enough for \(e^{-12 \sigma}\) to be negligible.

We would also like to see the closed loop transients for \(\sigma\) and \(\sigma+\sigma\), and the transients and required control for \(\sigma\) in the vicinity of the poles.
4. Results: In Fig. 1 appears the program used to calculate the deadbeat control law
\[
\left[k_{1}, k_{2}, k_{3}, k_{4}, k_{5}\right]
\]
\(k_{1}, k_{2}, k_{3}\) and \(k_{5}\) are graphed in Fig. 2, 3, 4, and 5. Notice how sensitive they are to the sampling period. E.g.. \(k_{2}\) in neighborhoods of \(\sigma=2 q, q=1,2, \ldots\), goes from \(-\infty\) to \(+\infty\).

In Fig. 6 and 7 appear the graphs of \(k_{1}\) and \(k_{2}\) for \(\sigma\) in [6, 9.4]. These show very well how the gains differ between say . 3 and 6.4 but by the time we get to 1.4 and 7.4 the differences are less than \(10 \%\), by 2.5 and 8.5 the differences are less than \(1 \%\). When the differences are large, the small \(\sigma\) gains are larger of course, since the eigenvector associated with -2 must be taken to zero. After \(\sigma\) becomes large \(e^{-12 \sigma}\) is essentially zero without control.

Next we examine the rank of the matrices
\[
\left[G, \varphi G, \ldots, \varphi^{4} G\right]
\]
and
\[
\left[\Gamma, \varphi, \ldots, \varphi^{4} \Gamma\right] .
\]
this is done with the program appearing in Fig. 8. Notice that we compute the pseudo-inverse iteratively, thus giving us some idea of the numerical sensitivity of rank. The following table gives our results.

\begin{tabular}{|c|c|c|c|c|}
\hline \multirow[t]{3}{*}{2.95} & 3 & . \(3 \cdot 10^{-3}\) & & \\
\hline & 4 & . \(9 \cdot 10^{-5}\) & 4 & . \(18 \cdot 10^{-4}\) \\
\hline & 5 & . \(2 \cdot 10^{-5}\) & 5 & . \(22 \cdot 10^{-4}\) \\
\hline \multirow[t]{3}{*}{3.0} & 2 & . \(3 \cdot 10^{-6}\) & & \\
\hline & 3 & .2 \(\cdot 10^{1}\) & 3 & .1 \(\cdot 10^{-6}\) \\
\hline & & & 4 & . 2 \\
\hline \multirow[t]{3}{*}{3.05} & 3 & \(.2 \cdot 10^{-3}\) & & \\
\hline & 4 & . \(28 \cdot 10^{-4}\) & 4 & . \(26 \cdot 10^{-4}\) \\
\hline & 5 & \(.2 \cdot 10^{-2}\) & 5 & . \(5 \cdot 10^{-4}\) \\
\hline \multirow[t]{3}{*}{3.95} & & & 3 & . \(7 \cdot 10^{-3}\) \\
\hline & 4 & . \(2 \cdot 10^{-4}\) & 4 & . \(9 \cdot 10^{-5}\) \\
\hline & 5 & . \(1 \cdot 10^{-3}\) & , & . \(1 \cdot 10^{-3}\) \\
\hline \multirow[t]{2}{*}{4.} & 3 & .I \(\cdot 10^{-5}\) & 3 & . \(2 \cdot 10^{-6}\) \\
\hline & 4 & . \(2 \cdot 10^{1}\) & 4 & . \(1 \cdot 10^{2}\) \\
\hline \multirow[t]{3}{*}{4.05} & & & 3 & \(.4 \cdot 10^{-3}\) \\
\hline & 4 & . \(3 \cdot 10^{-4}\) & 4 & \(.4 \cdot 10^{-5}\) \\
\hline & 5 & . \(8 \cdot 10^{-4}\) & 5 & .2 \(\cdot 10^{-3}\) \\
\hline \multirow[t]{2}{*}{4.45} & 4 & .2 \(\cdot 10^{-3}\) & 4 & . \(6 \cdot 10^{-4}\) \\
\hline & 5 & . \(1.10^{-4}\) & 5 & .1. \(\cdot 10^{-4}\) \\
\hline \multirow[t]{2}{*}{4.5} & 4 & . \(2 \cdot 10^{-5}\) & 4 & .1 \(\cdot 10^{-6}\) \\
\hline & 5 & . \(2 \cdot 10^{1}\) & 5 & . \(2 \cdot 10^{3}\) \\
\hline \multirow[t]{2}{*}{4.55} & 4 & .1. \(10^{-3}\) & 4 & . \(4 \cdot 10^{-4}\) \\
\hline & 5 & \(.9 \cdot 10^{-5}\) & 5 & . \(2 \cdot 10^{-4}\) \\
\hline \multirow[t]{3}{*}{5.95} & 2 & . \(2 \cdot 10^{-3}\) & & \\
\hline & 3 & .1. \(10^{-4}\) & 3 & .1. \(10^{-5}\) \\
\hline & 4 & .1. \(10^{-1}\) & 4 & . \(2 \cdot 10^{-2}\) \\
\hline \multirow[t]{3}{*}{6.0} & 1 & . \(5 \cdot 10-7\) & & \\
\hline & 2 & . 7 & 2 & \(.7 \cdot 10^{-7}\) \\
\hline & & - 352 - & 3 & . \(3 \cdot 10^{2}\) \\
\hline
\end{tabular}
. In general this table speaks for itself, both \(\Gamma\) and \(G\) giving the correct answers except at 3 and 6 where the \(\Gamma\) rank is low. We must remember however that \(G\) was chosen to maximize the controllability; it is not necessarily true that \(\Gamma\) will give us the largest controllability rank. For instance if
\[
F=\left[\begin{array}{cc}
0 & 1 \\
-1 & 0
\end{array}\right] \quad G=\left[\begin{array}{l}
0 \\
1
\end{array}\right] \quad \sigma=2 \pi
\]
then
\[
\varphi=\left[\begin{array}{ll}
1 & 0 \\
0 & 1
\end{array}\right] \quad \Gamma=\left[\begin{array}{l}
0 \\
0
\end{array}\right]
\]
and
[G, MG] has rank one,
but
[ \(\Gamma, \Phi\) ] has rank zero.

Certain gain and sampling interval interchanges were made. For instance the gain \(K_{2.7}\) which is deadbeat for \(\sigma=2.7\) was run with \(\sigma=2.8\); the results were not as unstable as we might have expected considering the differences between the \(K\) values.

The following results were obtained:
\begin{tabular}{lll}
\(\sigma_{K}\) & \(\sigma_{\varphi}\) & stability \\
\hline 1.9 & 2.1 & apparently stable \\
2.1 & 1.9 & apparently stable \\
2.7 & 2.8 & questionable \\
2.8 & 2.7 & apparently unstable \\
2.9 & 3.1 & apparently unstable \\
3.1 & 2.9 & apparently unstable \\
3.3 & 3.4 & questionable \\
3.4 & 3.3 & questionable.
\end{tabular}

We were also interested in illustrating the lack of controllability by showing a vector which was ignored by the control. We noticed that \(K_{6}\) was orthogonal to \([1,-2,4,-8,26]\) to about six significant figures, so using this vector for initial condtion an uncontrolled run and a run using \(K_{6}\) were both made and were indeed the same to about four decimal places.

Using the program appearing in Fig. 9 we obtained transients for various sampling periods. In Fig. 10 and 11 appear the responses for \(\sigma=2.5\) and \(\sigma=8.5\). As we have seen, the gain matrices are nearly the same, but we may wonder what is the effect of holding the input over three times as long a period. The graph shows that the value of the output and the wave shape are the same at corresponding control points. The printed output shows that the entire state is the same.

The following table shows the number actually obtained
\begin{tabular}{ccccc} 
Control point & \(y_{2.5}\) & \(y_{8.5}\) & \(u_{2.5}\) & \(u_{8.5}\) \\
0 & 1. & 1. & 7.0253 & 7.0428 \\
1 & .5773 & .5800 & 5.1429 & 5.1557 \\
2 & .4971 & .4975 & 4.4603 & 4.4649 \\
3 & .6674 & .6662 & 2.5650 & 2.5778 \\
4 & .0260 & .0302 & -0.0175 & 0.0000
\end{tabular}
- When we tried to obtain the transient near a pole we encountered one of IRNSI's drawbacks. If \(X\) is large enough for significance, the control exceeds the print format. So we used the program in Fig. 12 and computed transients for \(\sigma=2.6,2.8\), and 2.9. The outputs are graphed in Fig. 13., 14, and 15 and illustrate beautifully how control energy and state excursions build up as an uncontrollable point is approached.


Fig. 1


Fig. 2
\(k_{2}\) vs. SAMPLING PERIOD \(\sigma\)


Fig. 3


Fig. 4


Fig. 5


Fig. 6


Fig. 7


Fig. 8


7
Fig. 9

\[
51.1
\]

Fig. 9


Fig. 10


Fig. 11


Fig. 12



Fig. 13

\section*{TRANSIENT RESPONSE for \(\sigma=2.8\)}


Fig. 14


Fig. 15

COMPUTATION OF A MINLMAL REALIZATION
1. Description of the Problem: Given a \(p \times m\) matrix \(Z(s)\) of transfer functions we wish to obtain a triple \([H, F, G]\) of matrices such that
\[
\mathrm{Z}(\mathrm{~s})=\mathrm{H}(\mathrm{sI}-\mathrm{F})^{-1} \mathrm{G} .
\]

Note that \(Z\) is then the formal Laplace transform of the impulse response matrix \(\mathrm{He}^{\mathrm{Ft}} \mathrm{G}\).

The method used in this chapter was developed by B. L. Ho and has the advantage of directly using experimental input-output data, when \(Z\) is interpreted as the z-transform of the sampled impulse-response function \(H \Phi^{k} G, \quad k=\) integer.

Furthermore, in the two examples which we have used, the method appears to be well suited to computation, although as usual, a large spread in the eigenvalues will occasion numerical scaling problems. Because of these two favorable aspects of the method, it appears to be much better adapted for practical application than the methods appearing in the references 2 and 3.
2. Theory and References:
[i] B. L. Ho, SIAM J. Control, 1966.
[2] R. E. Kalman, "Mathematical description of linear dynamical systems", SIAM J. Control, 1 (1963) 152-192.
[3] R. E. Kalman, "Irreducible realizations and the degree of a rational matrix", SIAM J. 1965.
[4] J.R. Ragazzini and G.F. Franklin, "Sampled-data control systems", (1958) McGraw Hill.

Briefly we can describe our particular variant of Ho's method as follows:

Let \(z_{i j}(s)\) denote the elements of \(z(s)\). Let \(s_{i j k}\) denote the coefficient of \(s^{-k}\) in the expansion of \(z_{i j}\) in powers of \(s^{-1}\). Let \(\delta_{i}\) denote the degree of the least common denominator of the \(i^{\text {th }}\) row of \(Z(s)\), \(\mu_{j}\) the degree of the l.c.d. of the \(j^{\text {th }}\) column, and \(a=\max _{i}\left(\max \left(\delta_{i}, \mu_{i}\right)\right.\) ). Then we form the matrices

\(\Sigma_{j i}=\left[\begin{array}{cccc}s_{i j 2} & s_{i j} 3 & \cdots & s_{i j a+1} \\ s_{i j 3} & s_{i j 4} & \cdots- & s_{i j a+1} \\ - & - & - & - \\ s_{i j a+1} & s_{i j a+2} & \cdots- & s_{i j 2 a}\end{array}\right]\)
\[
\begin{aligned}
& S=\left[S_{i j}\right], \text { and } \Sigma=\left[\Sigma_{i j}\right] \\
& \qquad \begin{array}{l}
i=1, \ldots, p \\
j=1, \ldots, m
\end{array} \\
& \tilde{G}=\left[c_{1}, c_{a+1}, c_{2 a+1}, \ldots, c_{(m-1) a+1}\right]
\end{aligned}
\]
\[
\tilde{H}=\left[\begin{array}{l}
r_{1} \\
r_{a+1} \\
r_{2 a+1} \\
- \\
- \\
r_{(p-1) a+1}
\end{array}\right]
\]
where \(c_{i}\) is the \(i^{\text {th }}\) column of \(S\) and \(r_{i}\) is the \(i^{\text {th }}\) row of \(S\).
At this point Ho proceeds by computing nonsingular matrices \(P\) and Q such that
\[
\mathrm{PSQ}=\left[\begin{array}{cc}
I_{n} & 0 \\
0 & 0
\end{array}\right]
\]

Then
\[
\begin{gathered}
P \Sigma Q=\left[\begin{array}{ccc}
F_{n} & \cdot & x \\
- & - & - \\
x & \cdot & - \\
& \cdot & x
\end{array}\right] \\
\tilde{P Q}=\left[\begin{array}{c}
G \\
--- \\
x
\end{array}\right]
\end{gathered}
\]
\[
\tilde{H} Q=[H: x]
\]

Then \(H, F\), and \(G\) (which are respectively \(p \times n, n \times n\), and \(n \times q\). matrices), constitute a minimal realization of \(Z(s)\). The \(x^{\prime}\) s represent terms for which no practical or theoretical use is known at present.

We proceed as follows.
Assuming that \(m \geqq p\), form the \(p \times p\) matrix \(S S^{\prime}=B\) and apply
DECOM. This will give us nonsingular matrices \(T\) and \(R\) such that
\[
\operatorname{RTSS}^{\prime} T^{\prime} R^{\prime}=\left[\begin{array}{ll}
I_{n} & 0 \\
0 & 0
\end{array}\right]
\]

However, this matrix is \(p \times p\), whereas \(P S Q\) is \(p \times q\). Hence we let \(P=R T\) and \(Q^{*}=S^{\mathbf{t}} T^{t} R^{\mathbf{t}}\). Then we claim that
\[
\mathrm{PSQ}^{*}=\left[\begin{array}{ll}
\mathrm{F} & \mathrm{x} \\
\mathrm{x} & \mathrm{x}
\end{array}\right] \quad \mathrm{PG}=\left[\begin{array}{l}
\mathrm{G} \\
\mathrm{x}
\end{array}\right]
\]
and
\[
H Q^{\prime}=\left[\begin{array}{ll}
H & x
\end{array}\right] .
\]

The reason for this is that \(Q^{*}\) may be made equal to \(Q\) by appending to \(Q^{*} m-p\) columns independent of the previous columns of \(Q^{*}\). This makes a nonsingular \(Q\), and therefore \(H H^{\prime}\) 's formulas for a realization may be applied.

For computational purposes, we may just as well use \(Q^{*}\) rather than \(Q\) because we are uninterested in the last \(m-p\) columns of PSQ anyway.

3A. The Specific Problem: We take
\[
Z(s)=\frac{1}{s^{4}}\left[\begin{array}{ccc}
s^{3}-s^{2}+1 & 1 & -s^{3}+s^{2}-2 \\
1.5 s+1 & s+1 & -1.5 s-2 \\
s^{3}-9 s^{2}-s+1 & -s^{2}+1 & s^{3}-s-2
\end{array}\right]
\]

See Reference [3]. Then
\[
\begin{aligned}
& S=\left[\begin{array}{cccccccccccc}
1 & -1 & 0 & 1 & 0 & 0 & 0 & 1 & -1 & 1 & 0 & -2 \\
-1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 1 & 0 & -2 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -2 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -2 & 0 & 0 & 0 \\
0 & 0 & 1.5 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & -1.5 & -2 \\
0 & 1.5 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & -1.5 & -2 & 0 \\
1.5 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & -1.5 & -2 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -2 & 0 & 0 & 0 \\
1 & -9 & -1 & 1 & 0 & -1 & 0 & 1 & 1 & 0 & -1 & -2 \\
-9 & -1 & 1 & 0 & -1 & 0 & 1 & 0 & 0 & -1 & -2 & 0 \\
-1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & -1 & -2 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -2 & 0 & 0 & 0
\end{array}\right] \\
& \Sigma=\left[\begin{array}{cccccccccccc}
-1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & I & 0 & -2 & 0 \\
0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -2 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -2 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1.5 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 1.5 & -2 & 0 \\
1.5 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & -1.5 & -2 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -2 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
-9 & -1 & 1 & 0 & -1 & 0 & 1 & 0 & 0 & -1 & -2 & 0 \\
-1 & 1 & 0 & 0 & 0 & 1 & 0 & 0 & -1 & -2 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & -2 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{array}\right]
\end{aligned}
\]
\[
\left.\begin{array}{l}
\tilde{\mathrm{G}}^{\prime}=\left[\begin{array}{cccccccccccc}
1 & -1 & 0 & 1 & 0 & 0 & 1.5 & 1 & 1 & -9 & -1 & 1 \\
0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & -1 & 0 & 1 \\
-1 & 1 & 0 & -2 & 0 & 0 & -1.5 & -2 & 1 & 0 & -1 & -2
\end{array}\right] \\
\tilde{H}=\left[\begin{array}{ccccccccccc}
1 & -1 & 0 & 1 & 0 & 0 & 0 & 1 & -1 & 1 & 0 \\
0 & 0 & 1.5 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 1.5 \\
1 & -9 & -1 & 1 & 0 & -1 & 0 & 1 & 1 & 0 & -1
\end{array}\right]-2
\end{array}\right] .
\]

4A. Results: Applying the program appearing in Fig. I, we obtained an F, G, and \(H\) and checked these by computing their impulse response. The results were excellent. At \(t=3\), the errors were less than four in the seventh significant digit.

The accuracy of the results was caused by the favorable circumstance of the zero eigenvalues. In the next problem we shall see how numerical problems can arise when nonzero eigenvalues are introduced.

3B. The Specific Problem: We consider
\[
z(s)=\left[\begin{array}{cccc}
\frac{3(s+3)(s+5)}{(s+1(s+2)(s+4)} & \frac{6(s+1)}{(s+2)(s+4)} & \frac{2(s+7)}{(s+3)(s+4)} & \frac{2 s+5}{(s+2)(s+3)} \\
\frac{2}{(s+3)(s+5)} & \frac{1}{s+2} & \frac{2(s-5)}{(s+1(s+2)(s+3)} & \frac{8(s+2)}{(s+1)(s+3)(s+5)} \\
\frac{2\left(s^{2}+75+18\right)}{(s+1)(s+3)(s+5)} & \frac{-2 s}{(s+1)(s+3)} & \frac{1}{s+3} & \frac{2\left(5 s^{2}+275+34\right)}{(s+1)(s+3)(s+5)}
\end{array}\right]
\]

We will delineate \(S_{i j}\) with solid brackets and \(\Sigma_{i j}\) with dashed brackets
\[
\left[s_{11}\right]=\left[\begin{array}{r:crrr}
3 & 1 & 3 & -18 & 60 \\
3 & & -18 & 60 & -192 \\
-18 & 60 & -192 & 648 & -2328 \\
60 & -192 & 648 & -2328 & 8760 \\
-192 & 648 & -2328 & 8760 & -33912
\end{array}\right] \begin{aligned}
648 & \vdots \\
-2328 & \vdots \\
8760 & \vdots \\
-33912 & \vdots \\
133368 & \vdots
\end{aligned}
\]
\[
S_{12}=\left[\begin{array}{rrrrrr}
6 & \Gamma & -30 . & 132 & -552 & 2256 \\
-30 & 1 & 132 & -552 & 2256 & -9120 . \\
132 & -552 & 2256 & -9120 & 36672 \\
-552 & 2256 & -9120 & 36672 & -147072 \\
2256 & -9120 & 36672 & -147072 & 589056
\end{array}\right] \begin{array}{r}
-9120 \\
36672
\end{array}
\]
\[
S_{13}=\left[\begin{array}{rrrrrr}
2 & 1 & -7 & 25 & -91 & 337 \\
-7 & 1 & 25 & -91 & 337 & -1267 \\
25 & 1 & -91 & 337 & -1267 & 4825 \\
-91 & 1 & 337 & -1267 & 4825 & -18571 \\
337 & -1257 & 4825 & -18571 & 72097
\end{array}\right] \begin{array}{rl}
-1267 & \vdots \\
4825 & 1 \\
-18571 & 1 \\
1 & 1
\end{array}
\]

Clearly these matrices are each determined by a ten-vector. We shall write these ten-vectors for the remaining \(S_{i j}\).
\[
\begin{aligned}
& 1,1 \simeq[3,3,-18,60,-192,648,-2328 \text {, } \\
& \text { 8760, -33912, 133368] } \\
& \text { I, } 2 \simeq[6,-30,132,-55,2256,-9120 \text {, } \\
& \text { 36673, -147072, 589056, -2357760.] } \\
& 1,3 \simeq[2,-7,25,-91,337,-1267,4835,-18571, \\
& \text { 72097, -281827] } \\
& 1,4 \simeq[2,-5,13,-35,97,-275,793,-2315 \\
& \text { 6917, -20195] } \\
& 2,1 \simeq[0,2,-16,98,-544,2882,-14896 \\
& 75938,-384064,1933442] \\
& 2,2 \simeq[1,-3,9,-27,81,-243,729,-2187,6561, \\
& \text {-19683] } \\
& \text { 2, } 3 \simeq[0,2,-22,110,430,1502,-4942,15710, \\
& \text {-48910, 150302] } \\
& 2,4 \simeq[0,8,-56,320,-1712,8888,-45416, \\
& \text { 230000, -1158752, 5820008] } \\
& \text { 3, } 1 \simeq[2,-4,26,-172,1010,-5524,29066, \\
& \text {-149692, 761570, -3847204] } \\
& 3,2 \simeq[-2,8,-26,80,-242,728,-2186,6560 \text {, } \\
& \text {-19682, 59048] } \\
& \text { 3, } 3 \simeq[1,-3,9,-27,81,-243,729,-2187,6561, \\
& \text {-19683] } \\
& 3,4 \simeq[10,-36,163,-780,3834,-18996,94482, \\
& \text {-470940, 2350314, -11738436] }
\end{aligned}
\]
\[
G=\left[\begin{array}{rrrr}
3 & 6 & 2 & 2 \\
3 & -30 & -7 & -5 \\
-18 & 132 & 25 & 13 \\
60 & -552 & -91 & -35 \\
-192 & 2256 & 337 & 97 \\
0 & 1 & 0 & 0 \\
2 & -3 & 2 & 8 \\
-16 & 9 & -22 & -56 \\
98 & -27 & 110 & 320 \\
-544 & 81 & -430 & -1712 \\
2 & -2 & 1 & 10 \\
-4 & 8 & -3 & -36 \\
26 & -26 & 9 & 162 \\
-172 & 80 & -27 & -780 \\
1010 & -242 & 81 & 3834
\end{array}\right]
\]


Rather than use the impulse response to check this decomposition, we shall use the following relation:
\[
H F^{k}=\left[s_{i j k}\right]
\]

4B. Results: Using the program appearing in Fig. 2 we found \(S\) to have rank four and computed HG and HFG to be the matrices in Fig. 3. These atrocious results were not unexpected considering that \(S\) has an element spread from two to eleven million and the spread in SS' would be even worse.

To obtain better conditioning some simple transformations were made. The rows of \(S\) were multiplied by
\[
[1,1, .1,1 ., .01,1,1, .1, .1, .01,1,1, .1, .1, .01]
\]
and the columns of \(S\) by
\[
[1,1, .1, .1, .01,1,1, .1, .1, .01,1,1, .1, .1, .01,1,1, .1, .1, .01] .
\]

Despite the lack of intensive analysis which went into this choice, the results as obtained by the program in Fig. 4 were tremendously improved. Fig. 5 displays \(H G\) and \(H F G\) which are accurate to about for significant digits, Fig 6 shows \(H F^{6}{ }_{G}\) and \(H F^{7}{ }_{G}\) in which the largest error is about \(2 \%\). These errors will increase as the power of \(F\) increases. Presumably more careful preconditioning could further improve the accuracy.


\section*{Fig. 1}


Fig. 1
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|}
\hline & \multicolumn{2}{|l|}{} & 0 & & -1.5 & & -2. & & 1. \\
\hline & \multicolumn{2}{|l|}{-9.} & \multicolumn{2}{|l|}{-1.} & \multicolumn{2}{|l|}{1.} & \multicolumn{2}{|l|}{0} & -1. \\
\hline & 0 & & \(1 \cdot\) & & 1. & & 0 & & -1. \\
\hline & \multicolumn{2}{|l|}{-2.} & & & & & & & \\
\hline \multirow[t]{2}{*}{P1} & \multicolumn{2}{|l|}{1} & & & & & & & \\
\hline & \multicolumn{2}{|l|}{1.E-6} & & & & & & & \\
\hline P2 & \multicolumn{2}{|l|}{\multirow[t]{2}{*}{\[
1_{1 .}
\]}} & & & & & & & \\
\hline & & & & & & & & & \\
\hline 11 & 8 & \multicolumn{2}{|l|}{\(80^{12}\)} & & & & & & \\
\hline 1. & & 0 & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|l|}{} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & 0 & & 1. & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{\(\bigcirc\)} & & 0 & & 0 & & 0 & \\
\hline \(\bigcirc\) & \multicolumn{2}{|r|}{\(\bigcirc\)} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{1.} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & & & 0 & & 1. & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{\(\bigcirc\)} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{\(\bigcirc\)} & & 1. & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & 0 & & 0 & & 0 & \\
\hline \(1 \cdot\) & \multicolumn{2}{|r|}{0} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & 0 & & 1. & & \(\bigcirc\) & \\
\hline 0 & \multicolumn{2}{|r|}{0} & & 0 & & 0 & & 0 & \\
\hline - & \multicolumn{2}{|r|}{0} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|r|}{1.} & & 0 & & 0 & & 0 & \\
\hline 0 & \multicolumn{2}{|l|}{\multirow[b]{2}{*}{11}} & & & & & & & \\
\hline T & & & & & & & & & \\
\hline \(\stackrel{-5}{+}\) & & & & & & & & & \\
\hline ND 2.5 & 1 & 1 & & & & & & & \\
\hline z1 & 1 & 1 & & & & & & & \\
\hline 0 & & & & & & & & & \\
\hline
\end{tabular}

Fig. 1


Fig. 2
\begin{tabular}{|c|c|c|c|}
\hline \[
\begin{array}{ccc}
\text { RINT } & 18 & \mathrm{~S} \\
\text { MULT } & \mathrm{F} & \mathrm{GX} \\
\hline
\end{array}
\] & GX & & \\
\hline MULT H GX & 18 & & \\
\hline RINT 18 S & & & \\
\hline MULT F GX & GX & & \\
\hline MULT H GX & 18 & & \\
\hline RINT 18 S & & & \\
\hline MULT F GX & \(6 \times\) & & \\
\hline MULT H GX & 18 & & \\
\hline RINT 18 S & & & \\
\hline MULT F GX & GX & & \\
\hline MULT H GX & 18 & & \\
\hline RINT 18 S & & & \\
\hline MULT E GX & GX & & \\
\hline Mult H GX & 18 & & \\
\hline RINT 1B S & & & \\
\hline MULT \(F\) GX & GX & & \\
\hline MULT H GX & 18 & & \\
\hline RINT 18 S & & & \\
\hline MULT F GX & 6 E & & \\
\hline MULT H GX & 18 & & \\
\hline RINT 18 S & & & \\
\hline MULT F GX & GX & & \\
\hline MULT H GX & 18 & & \\
\hline RINT 18 S & & & \\
\hline MULT FGX & GX & & \\
\hline MULT H GX & 18 & & \\
\hline RINT 18 S & & & \\
\hline MULT F GX & GX & & \\
\hline MULT HGX & 18 & & \\
\hline RINT 18 S & & & \\
\hline END & & & \\
\hline 15 5 & & & \\
\hline 3. & -18. & 60. & -192. \\
\hline -18. & 60. & -192. & 648. \\
\hline 60. & -192. & 648. & -2328. \\
\hline -192. & 648. & -2328. & 8760. \\
\hline 648. & -2328. & 8760. & -33912. \\
\hline 2. & -16. & 98. & -544. \\
\hline -16. & 98. & -544. & 2882. \\
\hline 98. & -544. & 2882. & -14896. \\
\hline -544. & 2882. & -14896 & 75938. \\
\hline 2882. & -14896. & 75938. & -384064. \\
\hline -4. & 26. & -172. & 1010. \\
\hline 26. & -172. & 1010. & -5524. \\
\hline -172. & 1010. & -5524. & 29066. \\
\hline 1010. & -5524. & 29066. & -149692. \\
\hline -5524. & 29066. & -14969 & 761570 . \\
\hline 15 5 & & & \\
\hline -30. & 132. & -552 . & 2256. \\
\hline 132. & -552. & 2256. & -9120. \\
\hline -552. & 2256. & \(-2120\). & 36672. \\
\hline 2256 & -9120. & 36672 - & -147072. \\
\hline
\end{tabular}

\footnotetext{
Fig. 2
}
\begin{tabular}{|c|c|c|c|c|}
\hline \[
\begin{aligned}
& 2256 \\
& 1 \\
& \hline
\end{aligned}
\] & \[
\begin{aligned}
& -9120 . \\
& -3 \\
& \hline
\end{aligned}
\] & \[
\begin{aligned}
& 36672 \\
& 9 .
\end{aligned}
\] & \[
\begin{aligned}
& -147072 . \\
& -27 .
\end{aligned}
\] & \[
\begin{aligned}
& 589056 \\
& 81
\end{aligned}
\] \\
\hline －3． & 9 。 & －27． & 81. & －243． \\
\hline 9. & －27． & 81. & －243 & 729. \\
\hline －27． & 81. & －243． & 729. & －2187． \\
\hline 81. & －243． & 729. & －2187 & 6561 \\
\hline －2． & 8. & －26． & 80. & －242． \\
\hline 8 & －26． & 88. & －242 & 728. \\
\hline －26． & 80. & －242． & 728. & －2186． \\
\hline 80. & －242． & 728. & －2186． & 6560. \\
\hline －242． & 728. & －2186． & 6560. & －19682． \\
\hline S3 & 5 & & & \\
\hline 2. & －7． & 25. & －91． & 337 。 \\
\hline －7． & 25. & －91． & 337. & －1267． \\
\hline 25. & －91． & 337 。 & －1267． & 4825. \\
\hline －91． & 337. & －1267． & 4825. & －18571． \\
\hline 337 ． & -1267 。 & 4825. & －18571． & 72097. \\
\hline 0 & 2. & －22． & 110. & －430． \\
\hline 2. & －22． & 110. & －430． & 1502. \\
\hline －22． & 110. & \(-430\). & 1502 & －49420 \\
\hline 110 & －430． & 1502. & －4942． & 15710 \\
\hline －430． & 1502. & －4942． & 15710 & －48910． \\
\hline 1. & －3． & 9. & －27． & 81. \\
\hline －3． & 9. & －27． & 81. & －243． \\
\hline 9. & －27． & 81. & －243． & 729. \\
\hline －27． & 81. & －243． & 729. & \(-2187\). \\
\hline 81. & －243． & 729. & －2187． & 6561 。 \\
\hline 54 & 5 & & & \\
\hline 2. & －5． & 13. & －35． & 97. \\
\hline －5． & 13. & －35． & 97. & －275． \\
\hline 13. & －35． & 97. & －275． & 793. \\
\hline －35． & 97. & －275． & 793. & －2315． \\
\hline 97 。 & －275． & 793. & －2315． & 6817. \\
\hline 0 & 8. & －56． & 320. & －1712． \\
\hline 8. & －56． & 320. & －1712． & 8888. \\
\hline －56． & 320. & －1712． & 8888. & －45416 \\
\hline 320. & －1712． & 8888． & －45416． & 230000. \\
\hline －1712． & 8888. & －45416． & 230000． & \(-1.158752\) \\
\hline 10. & －36． & 162. & －780． & 3834. \\
\hline －36． & 162. & \(-780\). & 3834. & \(-18996\). \\
\hline 162. & －780． & 3834. & －18996． & 94482. \\
\hline －780． & 3834. & －18996． & 94482. & －470940． \\
\hline 3834. & －18996． & 94482. & －470940． & 2350314 ． \\
\hline \(\times 1\) & 1 & & & \\
\hline 1. & & & & \\
\hline \(\times 2\) & 4 & & & \\
\hline 0 & & & & 1 ． \\
\hline 0 & & & & 1. \\
\hline 0 & & & & 1. \\
\hline 0 & & & & 1. \\
\hline \(\checkmark 1\) & 1 & & & \\
\hline 648. & －2328． & 8760. & －33912． & 133368 \\
\hline 2882. & －14896． & 75938. & －384064． & 1933442 。 \\
\hline
\end{tabular}
\(\qquad\)

Fig． 2

1.

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Fig. 2
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\section*{1.}
1.

Fig. 2


Fig. 2


Fig. 2


Fig. 2
\begin{tabular}{|c|c|c|c|}
\hline NUMBER OF ROWS 3 & NUMBER OF COLUMNS & 4 & \\
\hline -0.60633675E 05 & -0.82538218E 05 & -0.31000812E 05 & \(0.81135172 E 05\) \\
\hline \(0.48906875 E 05\) & \(0.52736579 E 05\) & \(0.61705748 E 05\) & -0.40652142E 05 \\
\hline -0.91309955E 05 & -0.12957074E 06 & -0.53789918E O5 & \(0.12663344 E 06\) \\
\hline MATRIX S & & & \\
\hline \multicolumn{4}{|l|}{NUMBER OF RUWS 3 NUMBER OF COLUMNS 4} \\
\hline -0.15341415E 11 & -0.25053193E 11 & -0.46605802E 09 & 0.25663784 E 11 \\
\hline 0.11584865 E 11 & \(0.19123507 E 11\) & -0.19607167E 09 & -0.19742244E 11 \\
\hline -0.24571605E 11 & -0.40141921E 11 & -0.69948262E 09 & 0.41134847 E 11 \\
\hline
\end{tabular}

Fig. 3
```

BEGIN
LOAD S1 S2 S3 S4 X1 X2 V1 V2 V3 V4-P1_R2 HR O1-02-01 LM
MULT S1.\times1, G1.
MUT S2X1 G2
MULT S3 <1 G3
MULT S4 X1 - <4
MUXTC G1 G2
UUXTC
MUTT SI X2 01
MULT S2 x2 Q2
MULT S3 x2 03
MULT S4 <2 Q4
NUTT SLOV1, 3
JUXTC 3 Q2
JUXTC 4
UXTC 6 V3 7
JUXTC 7 Q4 8
UXTE B VA SE
JUXTC S1.S2, 9
\#UxTC 0 53 10
JUXTC 10 S4 SR
MULT DISR SR
MULT SR LM SR
FRANP SR-ST
PIZER P1.P2,
MULT SR.ST...BO.
PSEUO BQ.+ 1BI,RJ,PRINT
DECOM_BO LS IER P ERK
RINT ER,ER SB,SB SR,SR G.GR HR HR
IRANP T. TT.
MULT P, T, T,
TRANP P P P
MULT ST.TT, 12
MULT 12.P. 0.
MULT T DI T
MULT LM O O
MULT T.SB, 13
MULT_13.0._14
MULT T. G 15
MULT HR, OE 16
RINT 14. F 15 G 16 H
MULT 14.E1. 17
MULT B2 17 F
MULT 16 81 % H
MULT B2 15 GX
RINT FEFH HGX G
MULT HGX 18
RINT 18 S,
MULT FGX GX
MULT H6X 18
RINT 18 S

```

Fig. 4

\(\qquad\)

Fig. 4
\begin{tabular}{|c|c|c|c|c|}
\hline \[
\begin{gathered}
10 \\
-3 .
\end{gathered}
\] & \[
\begin{array}{r}
-3 \\
0 \\
\hline
\end{array}
\] & \[
\begin{aligned}
& 9 . \\
& -27 .
\end{aligned}
\] & \[
\begin{aligned}
& -27 \\
& 81
\end{aligned}
\] & \[
\begin{aligned}
& 81 . \\
& -243 .
\end{aligned}
\] \\
\hline 9. & -27. & 81. & -243. & 729. \\
\hline -27. & 81. & -243. & 729. & -2187. \\
\hline 81. & -243. & 729. & -2187. & 6561. \\
\hline -2. & 8. & -26. & 80. & -242. \\
\hline 8. & -26. & 80. & -242. & 728. \\
\hline \(-26\). & 80. & -242. & 728. & -2106. \\
\hline 80. & -242. & 728. & -2186. & 6550. \\
\hline -242. & 728. & -2186. & 6560. & -19682. \\
\hline S3 & 5 & & & \\
\hline 2. & -7. & 25. & -91. & 337. \\
\hline -7. & 25. & -91. & 337. & -1267. \\
\hline 25. & -91. & 337. & -1267. & 4825. \\
\hline -91. & 337. & -1267. & 4825. & -18571. \\
\hline 337. & -1267. & 4825. & -18571. & 72097. \\
\hline 0 & 2. & -22. & 110. & -430. \\
\hline 2. & -22. & 110. & -430. & 1502. \\
\hline -22. & 110. & -430. & 1502. & -4942. \\
\hline 110. & -4.30. & 1502. & -4942. & 15710. \\
\hline -430. & 1502. & -4942. & 15710 . & -48910. \\
\hline 1. & -3. & 9. & -27. & 81. \\
\hline -3. & 9. & -27. & 81. & -243. \\
\hline 9. & -27. & 81. & -243. & 729. \\
\hline -27. & 81. & -243. & 729. & -2187. \\
\hline 81. & -24.3. & 729. & \(-2187\). & 6561. \\
\hline S4 & 5 & & & \\
\hline 2. & \(-5\). & 13. & -35. & 97. \\
\hline -5. & 13. & -35. & 97. & -275. \\
\hline 13. & \(-35\). & 97. & -275 & 793. \\
\hline -35. & 97. & -275. & 793. & -2315. \\
\hline 97. & -275. & 793. & -2315. & 6817. \\
\hline 0 & 8. & -56. & 320. & -1712. \\
\hline 8. & -56. & 320. & -1712 & -1712. \\
\hline -56. & 320. & -1712. & 8888. & -45416. \\
\hline 320. & \(-1712\). & 8888. & -454.16 & 230000. \\
\hline -1712. & 8888. & -45416. & 230000. & -1158752. \\
\hline 10. & -36. & 162. & -780. & \\
\hline -36. & 162. & -780. & 3834 . & -18996. \\
\hline 162. & -780. & 3834. & \(-18996\) & \\
\hline -780. & 3834 • & -18996. & 94482 . & -470940. \\
\hline 3834. & -18996. & 94482. & -470940 & -4350314. \\
\hline \(\times 1\) & 1 & & & 23503.4. \\
\hline 1. & & & & \\
\hline \(\times 2\) & 4 & & & \\
\hline 0 & & & & \\
\hline 0 & & & & 1. \\
\hline 0 & & & & 1. \\
\hline 0 & & & & \\
\hline \(\mathrm{V}_{1}\) & 1 & & & 1 。 \\
\hline 648. & -2328. & 8760. & -33912. & \\
\hline 2882. & -14896. & 75938. & -384064. & 1933442. \\
\hline -5524. & 29066. & -149692. & 761570. & -3847204. \\
\hline
\end{tabular}

Fig. 4
\begin{tabular}{|c|c|c|c|c|c|}
\hline \[
\begin{aligned}
& v 2 \\
& -2120 .
\end{aligned}
\] & 15 & \[
\begin{gathered}
1 \\
36672 .
\end{gathered}
\] & -147072. & 5890560 & \(-2357760\). \\
\hline -243. & & 729. & -2187. & 6561. & -19683. \\
\hline 728. & & -2186. & 6560. & -19682. & 59048. \\
\hline V3 & 15 & 1 & & & \\
\hline -1267. & & 4825. & -18571. & 72097. & -284827. \\
\hline 1502. & & -4942. & 15710. & -48910. & 150302. \\
\hline -243e & & 729. & -21870 & 6561. & -19683. \\
\hline V4 & 15 & 1 & & & \\
\hline -275. & & 793. & -2315. & 6817. & -20195. \\
\hline 8888. & & -45416. & 230000. & -1158752. & 5820008. \\
\hline -18996. & & 94482. & -470940. & 2350314. & - 12738436 . \\
\hline P1 & 1 & 1 & & & \\
\hline . 000001 & & & & & \\
\hline P2 & 1 & 1 & & & \\
\hline 1. & & & & & \\
\hline HR & 3 & 20 & & & \\
\hline 3. & & 3. & -18. & 60. & -192. \\
\hline 6. & & -30. & 132. & -552. & 2256. \\
\hline 2. & & -7. & 25. & -91. & 337. \\
\hline 2 。 & & -5. & 13. & -35. & 97. \\
\hline 0 & & 2. & -16. & 98. & -544. \\
\hline 1. & & -3. & 9. & -27. & 81. \\
\hline 0 & & 2. & -22. & 110. & -430. \\
\hline 0 & & 8. & -56. & 320. & -1712. \\
\hline 2. & & -4. & 26. & \(-172\). & 1010. \\
\hline -2. & & 8. & -26. & 80. & -242. \\
\hline 1. & & -3. & 9. & -27. & 81. \\
\hline 10. & & -36. & 162. & -780. & 3834 - \\
\hline 81 & 15 & 12 & & & \\
\hline 1. & & & & & \\
\hline
\end{tabular}
1.
1.

1 。

Fig. 4


1 •


FIg. 4



Fig. 4
- 402 -

\begin{tabular}{|c|c|c|c|}
\hline NUMBER OF ROWS 3 & number of columns & 4 & \\
\hline \(0.30000562 E 01\) & 0.60000406 E O1 & 0.19999760 E O1 & \(0.19999504 E 01\) \\
\hline \(0.56246562 E-05\) & 0.99998961 EO & -0.76427437E=04 & \(=0.24703038 \mathrm{E}-04\) \\
\hline D.19999890E O1 & -0.19999588E Or & 0.10003050 E O1 & 0.10000012 E 02 \\
\hline matrix \(S\) & & & \\
\hline \multicolumn{4}{|l|}{NUMBER OF ROWS 3 - NUMBER OF COLUMNS 4} \\
\hline \(0.29998252 \mathrm{E} \mathrm{O1}\) & -0.30000342E 02 & -0.69998919E 01 & -0.49996567E 01 \\
\hline 0.19999714 E 01 & -0.29999191E 01 & \(0.20003461 E 01\) & 0.79999965 E 01 \\
\hline \(-0.39999356 \mathrm{ECl}\) & 0.79998185 E 01 & -0.30008943E 01 & -0.36000139E 02 \\
\hline
\end{tabular}
\begin{tabular}{|c|c|c|c|}
\hline \multicolumn{4}{|l|}{MATRIX 5} \\
\hline NUMBER OF ROWS 3 & NUMBER OF COLUMNS & 4 & \\
\hline -0.23547876E 04 & \(0.36666603 E 05\) & 0.48401163 E 04 & \(0.69591645 \mathrm{E}^{03}\) \\
\hline -0.14896059E 05 & \(0.72841801 E 03\) & \[
-0.49452196 E 04
\] & \[
=0.45416312 E 05
\] \\
\hline -0.29066005E 05 & -0.21849774E-04 & \(0.73730381 E 03\) & \(0.94482138 \mathrm{E}-05\) \\
\hline MATRIX S & & & \\
\hline NUMBER OF ROWS 3 & NUMBER OF COLUMNS & & \\
\hline 0.88658751 E 04 & -0.14704803E O6 & -0.18653721E 05 & -0.19579727E 04 \\
\hline \(0.75938398 \mathrm{E} \quad 05\) & -0.21837629E 04 & 0.15728378 E 05 & \(0.23000103 E 06\) \\
\hline -0.14969205E 06 & \(0.65527389 \mathrm{E} \quad 04\) & -0.22299267E 04 & -0.47094142E 06 \\
\hline
\end{tabular}
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)

Fig. 6

\section*{APPROXIMATION OF AN IMPULSE RESPONSE}
1. Description of the Problem: Given a sampled signal (i.e. a sequence of scalars), we wish to approximate it in the least squares sense by the impulse response of some other system (preferably perhaps smaller), whose dynamics are specified. The approximation procedure is to be applied to signals on any finite interval; as the interval increases, we want our approximation to change accordingly. We will treat this problem in close analogy with the general statistical filtering problem.
2. Theory and References: See, in addition to Chapter VIII
[1] R. E. Kalman, "A New Approach to Linear Filtering and Prediction Problems", Journal of Basic Engineering, March, 1960.

Given the signal \(\left\{z_{k}\right\}, k=0,1, \ldots\), a vector \(h\), and a matrix \(F\), we wish to determine a vector \(\hat{G}_{N}\) such that
\[
\begin{aligned}
\sum_{k=0}^{N}\left(z_{k}-\hat{H} e^{k \hat{F}_{G_{N}}}\right)^{2} \quad \text { is minimum for each } \\
N=0,1, \ldots .
\end{aligned}
\]

This problem has a well-defined solution, which is readily derived by least-squares fitting techniques (see Section 5). We will approach the problem from a slightly different point of view and obtain a solution by using an optimal filter. This will not give us the true minimum because we cannot put in the correct initial covariance matrix, but from the practical point of view the results will be very satisfactory.
3. Specific Problem: we are given a sequence of scalars \(\left\{z_{k}\right\} k=0,1, \ldots\) where \(z_{k}\) is the response at \(t=0.5 \mathrm{k}\) of a dynamical system having impulse response


We will approximate this as the output of a system with
\[
\begin{equation*}
\hat{F}=\operatorname{diag}(-.8,-1.5,-3 .), \quad H=[1, \quad 1, \quad 1] \tag{3.1}
\end{equation*}
\]
by determining the optimal estimate \(\hat{x}_{N}\) of \(x(.05 N)\) with the aid of discrete filtering. Then we relate this back to
\(t=0\) via the transition matrix to obtain an estimate of \(\hat{x}(0)\). We may regard \(\hat{x}(0)\) as equivalent to the matrix \(G\) for the system (3.1). Thus we will estimate the given impulse of a known finite-dimensional linear dynamical system, in which \(\widehat{\mathrm{F}}\) and \(\hat{H}\) are fixed (the latter without loss in generality) and \(G\) is to be determined, optimally.
4. Preliminary Computations:
\[
\begin{aligned}
& F=\left[\begin{array}{cc}
0 & 0 \\
0 & -1
\end{array}\right], \quad G=\left[\begin{array}{c}
1 \\
-1 \\
\end{array}\right], \quad H=[1 \\
& I=I] \\
& T=I
\end{aligned}
\]

We generated a tape of the impulse response of (4.1) using the program in Fig. 1.

This specified the given signal. Then using \(\hat{H}=1, \hat{F}=.5\)
( \(R=1\) ), we ran the filtering program Fig. 2 , to obtain \(\hat{x}(0 \mid t)\). The initial variance was \(P_{0}=100\), initial estimate \(\hat{x}_{0}=\hat{x}(0 \mid-1)=0\). It follows that
\[
\begin{aligned}
P_{N+1} & =e^{-.1} \frac{P_{n}}{P_{N}+1} \\
K_{N} & =e^{-.05} \frac{P_{N}}{P_{N}+1} \\
\hat{x}_{N+1} & =e^{-.05 \hat{x}_{N}}+K_{N N}\left(y_{N}-H \hat{x}_{N}\right) \\
G_{N-1} & =e^{.05 \hat{N}_{\hat{x}_{N}}}=e^{.05 N \hat{x}}(0.5 N \mid .05(N-1))
\end{aligned}
\]

The exact values of \(\hat{\mathrm{g}}_{\mathrm{N}}\) are given by
\[
\begin{aligned}
& \hat{G}_{0}=0 \\
& \hat{G}_{1}=.04727 \\
& \hat{G}_{2}=.09311 \\
& \hat{G}_{3}=.13746
\end{aligned}
\]
compared with the machine results
\[
\begin{aligned}
& \hat{G}_{0}=0 \\
& \hat{G}_{1}=0.47273731 \\
& \hat{G}_{2}=.093116675 \\
& \hat{G}_{3}=.13746906 .
\end{aligned}
\]

The small loss in accuracy is apparently caused by the fact that \(P_{1}\) is only accurate to six decimal places.

A second check was made using
\[
\left.\begin{array}{c}
F=\left[\begin{array}{ccc}
0 & 1 & 0 \\
0 & 0 & 1 \\
-3.6 & -8.1 & -5.3
\end{array}\right], \\
G=\left[\begin{array}{l}
0 \\
0 \\
1
\end{array}\right], \quad H=[1
\end{array} 0 \begin{array}{l}
1
\end{array}\right],
\]
to specify the impulse response
\[
\frac{1}{(s+.8)(s+1.5)(s+3)}
\]

This was approximated with
\[
F=\left[\begin{array}{ccc}
-.8 & 0 & 0 \\
0 & -1.5 & 0 \\
0 & 0 & -3
\end{array}\right], \quad H=[1, \quad 1, \quad 1]
\]

The two systems have the same eigenvales. \(\hat{G}\) can be calculated to be
\[
\hat{G}=\left[\begin{array}{c}
.64935065 \\
-.95238095 \\
.30303030
\end{array}\right]
\]

Using \(P_{0}=1000 I(R=1)\), the approximation was run and converged to
\[
\hat{\mathrm{G}}=\left[\begin{array}{r}
.64159 \\
-.93345 \\
.29022
\end{array}\right]
\]
by \(t=7.1\).
5. Procedure and Results for Specific Problem: We computed the impulse response at intervals of .05 for the transfer function (3.1) by applying the transformation
\[
T=\operatorname{diag}\left(10^{4}, 10^{4}, 10^{4}, 10^{4}, 10^{4}, 10^{3}, 100,10\right)
\]
to the system
\[
\begin{aligned}
H & =\left[10^{4}, 0,0,0,0,0,0,0\right] \\
G^{\prime} & =\left[0,0,0,0,0,0,0,10^{2}\right] \\
F & =\text { companion }[-40,320 .,-109584 .,-118,124 .,-67,284 ., \\
& -22,449 .,-4536 .,-546 .,-36 .] .
\end{aligned}
\]

The corresponding signal is plotted in Fig. 3. It is obtained using the program in Fig. 4, which is essentially the same as in Fig. I, except that the response is printed.

Then we approximated the signal with the system
\[
\hat{F}=\left[\begin{array}{ccc}
-.8 & 0 & 0 \\
0 & -1.5 & 0 \\
0 & 0 & -3 .
\end{array}\right], \quad H=[1, \quad 1, \quad 1]
\]
using the program in Fig. 5, which gives us \(\hat{x}(t \mid t-1), \hat{G}\), and the cumulative square errors. This was done by obtaining a sequence \(\hat{x}(.05 N \mid .05(N-I))=\hat{x}_{N}\) which would be translated back to the origin as \(\hat{G}_{N}\) by using the transition matrix \(\Phi(0, .05 \mathrm{~N})\). The three components of \(\hat{G}\) are plotted in Figs. 6 and 7 .

It is of interest to have
\[
\sum_{k=0}^{N}(z(.05 k)-\hat{z}(.05 k \mid .05 k))^{2} . \text { This is }
\] is tabulated in Fig. 8, along with
\[
\sum_{k=0}^{N}\left(z(0.5 k)-\hat{z}\left(0.5 k \mid .05\left(k^{-1}\right)\right)\right)^{2}
\]
.It is really amazing how much better estimate is obtained by including an extra reading. The period of small increase around \(4.5-5.0\) seems to corres pond to the region where the optimally approximating curve crosses the signal curve, see Fig. 9.

There only remains the task of displaying the approximating impulse response computed in this manner and the square error given by it. For this we can choose any value of \(\hat{G}\). In Fig. 9 we have graphed the impulse response corresponding to \(\hat{G}(7 \cdot)\), a point where \(\hat{G}\) has attained steady state. The error is tabulated in Fig. 10. These results were obtained using the program in Fig. 12.

The response and error were also obtained for \(\hat{G}(2.0)\), which is approximately two-thirds the final value of \(\hat{G}\). The impulse reponse is graphed in Fig. 1l, the error tabulated in Fig. 10. These results were obtained using the program in Fig. 12.

As an experiment, we let the initial variance matrix vo be \(10^{17}\) I. This gave a run which differed drastically from the previous run with \(\mathrm{VO}=10^{3} \mathrm{I}\). The terminal value of \(\hat{G}\) (compare with Fig. 6 and 7) was
\[
\hat{G}(7)=\left[\begin{array}{r}
101.93869 \\
-235.47173 \\
196.84500
\end{array}\right] .
\]

Immediately we see that the curve generated by this \(\hat{G}(7)\) will have an enormous sum square error. The initial error \((63.311958)^{2}\) above is larger than the total error for the previous estimates (see Fig. 10); however the error given by \(\hat{z}(t \mid t\) ) is extremely small (see Fig. 13 and compare with Fig. 8). The response curve appears in Fig. 14; it has very good fit at the peak and rather poor fit at the ends.

In an attempt to improve the fit in the vicinity of the peak for the problem with \(V 0=10^{3} \mathrm{I}\), we let \(\mathrm{R}=0\) on the interval [1, 3], using the program in Fig. 15. This gave behavior very much like that with the large vo. The terminal value of \(\widehat{G}\) was
\[
\hat{G}(10)=\left[\begin{array}{r}
117.91459 \\
-299.13265 \\
315.48727
\end{array}\right]
\]

The errors are given in Fig. 16 and the curve plotted in Fig. 17.
This procedure was extremely successful in giving us good results, very good results, at the peak, but associated with this is a much poorer performance at each end. These results are quite reasonable considering that we have penalized errors on \([1,3]\) so heavily.
6. Least Square Procedure: We will now analyze the same problem from a strictly least square approach.

Define
\[
\hat{W}_{N}=\sum_{i=0}^{N} \hat{\Phi}^{i} \hat{H}^{\imath} \hat{H} \hat{\Phi}^{i}
\]

Then the problem stated in Sec. 2 has the solution
\[
\hat{G}_{\mathbb{N}}=\hat{W}_{\mathbb{N}}^{\#} \sum_{i=0}^{N} \hat{\Phi}^{i^{\prime}} \hat{H}^{\prime} z_{i}
\]

Observing that
\[
\begin{equation*}
\hat{W}_{\mathbb{N}+I}=\hat{H}^{\prime} \hat{H}+\hat{\Phi}^{\prime} \hat{W}_{N} \hat{\Phi}^{\Phi} \tag{6.1}
\end{equation*}
\]
or
\[
\begin{equation*}
\hat{W}_{N+1}=\hat{W}_{N}+\hat{\Phi}^{N+1} \hat{H}^{\prime} \hat{H}^{N+1} \tag{6.2}
\end{equation*}
\]
we will try to obtain a recursive definition of \(\hat{G}_{N}\).
\[
\begin{aligned}
\hat{G}_{N+1} & =\hat{W}_{N+1}^{\#} \sum_{i=0}^{N+1} \hat{\Phi}^{i^{\prime}} \hat{H}^{\prime} z_{i} \\
& =\hat{W}_{N+1}^{\#} \hat{W}_{N} \hat{G}_{N}+\hat{W}_{N+1}^{\#} \hat{\Phi}^{N+1} \hat{H}^{\prime} z_{N+1}
\end{aligned}
\]
because \(\hat{W_{N}} \hat{W}_{N}^{\#}\) is the identity operator on the range of \(\left[\hat{H}^{\prime}, \hat{\Phi}^{\prime} \hat{H}^{r}, \hat{\Phi}^{N^{\prime}} \hat{H}^{\mathbf{n}}, \ldots, \hat{\Phi}^{n^{\prime}} \hat{H}^{\prime}\right]\)
\[
\hat{G}_{N+1}=\hat{W}_{N+1}^{\#}\left(\hat{W}_{N+1}-\hat{\Phi}^{N+1} \hat{H}^{\prime} \hat{H}^{\prime}{ }^{N+1}\right) \hat{G}_{N}+\hat{W}_{N+1}^{\#} \hat{\Phi}^{N+1}{ }_{H}^{\prime} z_{n+1}
\]
from (6.2). Now \(\hat{W}_{N+1}^{\#}, \hat{W}_{N+1}\) is the identity operator on range \(\hat{W}_{N+1}\) ) range \(W_{N}\). But \(\hat{G}_{N} \in\) range \(\hat{W}_{N}^{\#}\), so we obtain the recursion formula
\[
\hat{G}_{N+1}=\hat{G}_{N}+\hat{W}_{N+1}^{\#} \hat{\underline{\Phi}}^{N+1} \hat{H}^{!} \cdot\left(z_{N+1}-\hat{H}^{N+1} \hat{G}_{N}\right)
\]
which holds at every step.
Unfortunately we will find no such formula for \(W_{\mathbb{N}+1}^{\#}\). A recursion formula exists for \(\hat{W}_{N+1}^{-1}\), but it requires that \(\hat{\Phi}^{-1}\) and \(\hat{W}_{\mathbb{N}}^{-1}\) exist. This will mean of course that before starting the recursion formula we must obtain \(n\) readings, find \(\hat{\mathrm{W}}_{\mathrm{N}}^{-1}\) and then proceed.
\[
\hat{W}_{N+1}^{-1}=\hat{\Phi}^{-1}\left[\hat{W}_{N}^{-1}-\hat{W}_{N}^{-1} \hat{\Phi}^{-1 '} \hat{H}^{\prime}\left(\hat{H}^{-1} \hat{W}_{N}^{-1} \hat{\Phi}^{-1 '} \hat{H}^{\prime}+I\right)^{-1} \hat{H}^{-1}-1 \hat{W}_{N}^{-1}\right]_{\Phi^{\prime}}^{-1 '} .
\]

The following example shows that the recursion formula need not hold, even if \(\hat{\mathrm{W}}_{\mathrm{N}-1}^{-1}\) exists.

Consider
\[
\hat{H}=\left[\begin{array}{ll}
1 & 0
\end{array}\right] \quad \hat{\Phi}=\left[\begin{array}{ll}
1 & 1 \\
0 & 1
\end{array}\right]
\]

This system is completely observable since \(\operatorname{det}\left[\begin{array}{c}\hat{H} \\ \hat{H} \hat{\widehat{\Phi}}\end{array}\right] \neq 0\).
\[
\begin{aligned}
& \hat{W}_{0}=\left[\begin{array}{ll}
1 & 0 \\
0 & 0
\end{array}\right], \quad \hat{W}_{0}^{\#}=\left[\begin{array}{ll}
1 & 0 \\
0 & 0
\end{array}\right], \quad \hat{\Phi}^{-1}=\left[\begin{array}{cc}
1 & -1 \\
0 & 1
\end{array}\right], \quad \hat{\Phi}^{-1}=\left[\begin{array}{cc}
1 & 0 \\
-1 & 1
\end{array}\right] \cdot \\
& \hat{W}_{1}=\left[\begin{array}{ll}
2 & 1 \\
1 & 1
\end{array}\right], \quad \hat{W}_{I}^{-1}=\left[\begin{array}{cc}
1 & -1 \\
-1 & 2
\end{array}\right] .
\end{aligned}
\]

But using the recursion formula, we obtain
\[
\hat{W}_{1}^{\#}=\left[\begin{array}{cc}
1 / 2 & 0 \\
0 & 0
\end{array}\right] .
\]

Not only is \(\hat{W}_{2}^{\#}\) incorrect, but it is singular, and in fact all the subsequent \(\hat{W}_{1}^{\#}\) will be singular (because \(\left[\hat{\Phi}^{-1}, \hat{H}\right]\) is not completely controllable).

Using this procedure and the programs appearing in Figs. 18 and 19 we computed
\[
\hat{G}(2 .)=[63.124303,-118.11554,58.159163]
\]
and
\[
\hat{G}(7 \cdot)=[79.965998,-153.58624,78.573582]
\]

These gave the response appearing in Fig. 20 and the errors tabulated in Fig. 2l. Notice that the filter gave results quite comparable to the true minimum.

In Fig. 18 we have used 9 steps before inverting the observability matrix \(\hat{W}_{\mathrm{N}}\) with inversion errors of about \(10^{-4}\). This was required because inverting at three steps gave inversion errors of \(10^{-1}\).

As a test we put the same system in companion form with \(\hat{H}=\left[\begin{array}{lll}1 & 0 & 0\end{array}\right]\) and were able to invert at three steps with errors less than \(10^{-4}\). Using \(F\) in companion form with \(\hat{H}=[1,1,1]\) we obtained inversion errors of \(10^{-2}\). The cumulative error was not significantly affected by these small errors. This is an interesting point which can perhaps be resolved as follows: If knowledge of the system had been perfect i.e. if we had used the \(\hat{F}=F\), then our use of \(10^{17}\) I as an initial covariance would probably not have affected the limit value of \(\hat{G}\). However by using an incorrect value of \(\hat{F}\) we were insensitive to small
errors in the sense that their contribution would be small to a total which, because of the mismatched dynamics, must be large.

On the other hand, because of the mismatched dynamics, information about the whole curve must be available. Theoretically if the dynamics are matched we need only any three points on the curve.
7. Digression: To the person interested in using digital computers to apply optimal system theory, one of the most frustrating and lingering problems is that of matrix inversion.

In discrete problems, many engineers have felt that the matrix \(P_{k+1}\) should be computed stepwise by using one column of \(\Gamma\) (row of \(H\) ) at a time, in order to guarantee that \(\left[\Gamma^{*} \mathrm{Pr}+\mathrm{R}\right]^{\#}\) can be accurately calculated. This procedure can be used if \(R\) is diagonal; we can prove this by remembering that \(\Gamma\) and \(\Phi\) need not be constant matrices. In the filtering problem this corresponds to treating the output vector one component at a time with no dynamics between, a procedure which is clearly feasible if the noise in the different components is uncorrelated, i.e. if \(R\) is diagonal.

If an inversion routine is used routinely then problems can arise (e.g. \(\left[\Gamma^{i} \mathrm{P} \Gamma+\mathrm{R}\right]\) is always nonnegative definite but an inversion routine may very well treat "noise" of the wrong sign as legitimate numbers, rendering the result \(\left[\Gamma^{\prime} P \Gamma+R\right]^{-1}\) indefinite). This particular problem can be avoided by using a pseudo-inversion routine for nonnegative definite symmetric matrices which will guarantee symmetry and nonnegativity of the output. More serious is the question of the subtraction occurring in
\[
P-\mathrm{PM}^{\prime}\left(\mathrm{MPM}^{\prime}+N\right)^{\#} \mathrm{MP}
\]

If \(P_{k} \rightarrow 0\) as \(k \rightarrow \infty\), it will be difficult computationally to preserve nonnegativity even with the use of PSEUO. Using a stepwise process it may well happen that
\[
\begin{equation*}
P-\frac{P M^{1} M P}{M P M^{1}+\mathbb{N}} \quad(M=\text { row vector }) \tag{7.1}
\end{equation*}
\]
will be numerically nonnegative. In particular if \(N \neq 0\), it seems that (7.1) should always be \(\geqq 0\).

It turns out that this process also uses less machine time and therefore appears from every viewpoint to be the desirable means of computation if \(N\) is diagonal.

In what follows we give a strictly algebraic proof that the two methods of computation are equivalent.

Let
\[
S=P-\mathrm{PM}^{\mathrm{s}}\left(\mathrm{MPM}^{1}+\mathrm{N}\right)^{\#} \mathrm{MP}^{( }
\]
where
\[
M=\left[\begin{array}{l}
H \\
h
\end{array}\right] \text { and } N=\operatorname{diag}(R, r)
\]

Let
\[
\begin{aligned}
& S_{1}=P-\mathrm{PH}^{\mathrm{t}}\left(\mathrm{H}^{\mathrm{t}} \mathrm{H}^{\mathrm{y}}+\mathrm{R}\right)^{\#}{ }^{\#} \mathrm{HP} \\
& \mathrm{~S}_{2}=\mathrm{S}_{1}-\mathrm{S}_{1} \mathrm{~h}^{\mathrm{l}}\left(\mathrm{hS}_{1} \mathrm{~h}^{\mathrm{y}}+\mathrm{r}\right)^{\#{ }_{h S_{1}} .}
\end{aligned}
\]

We want to show that \(S=S_{2}\). This reduces to proving that
\(\mathrm{PM}^{1}\left(\mathrm{MPM}^{1}+\mathrm{N}\right)^{\#} \mathrm{MP}^{2}=\mathrm{PH}^{1}\left(\mathrm{HPH}^{\mathbf{2}}+\mathrm{R}\right)^{\#} \mathrm{H}^{\mathbf{t}} \mathrm{P}\)

The psuedo-inverse of a matrix is, unfortunately, not a continuous function of the elements of the matirx, hence we will need to consider several cases
1) If \(r=0\) and \(h P h^{2}=0\), then \(h P=0\) and we prove quickly that
\[
\begin{aligned}
& ] M_{P M}{ }^{\mathbf{2}}+\mathrm{N}\right]^{\#}=\left[\begin{array}{cc}
\mathrm{HPH}^{2}+\mathrm{R} & \mathrm{HPh}^{2} \\
\mathrm{hPH}^{\mathrm{t}} & \mathrm{hPH}^{\mathrm{t}}+\mathrm{r}
\end{array}\right]_{-}^{\#}=\left[\begin{array}{cc}
\mathrm{HPH}^{\prime}+\mathrm{R} & 0 \\
0 & 0
\end{array}\right]^{\#} \\
& =\left[\begin{array}{cc}
\left(H P H^{2}+R\right)^{\#} & 0 \\
0 & 0
\end{array}\right]
\end{aligned}
\]
2) In the most important case, when \(h S_{1} h^{2}+r \neq 0\), we can still prove that \(\left(M P M^{2}+R\right)=\theta\), where


We do this by recourse to the pseudo-inverse axioms:
\[
\begin{gathered}
M P M^{\prime}+R=\left[\begin{array}{cc}
H P H^{\prime}+R & H P h^{\prime} \\
h P H^{\prime} & h P h^{\prime}+r
\end{array}\right] \\
\theta=\left[\begin{array}{cc}
\left(H P H^{\prime}+R\right)\left(H P H^{\prime}+R\right)^{\#} & 0 \\
0 & 0
\end{array}\right] .
\end{gathered}
\]

This is symmetric, which proves that axiom 4 holds.
In order to obtain this form it is necessary to know that
\[
\begin{equation*}
\left(\mathrm{HPH}^{\prime}+\mathrm{R}\right)\left(\mathrm{HPH}^{\prime}+\mathrm{R}\right)^{\#} \mathrm{H}=\mathrm{H} \tag{6.2}
\end{equation*}
\]

This follows from Lenna (2.14), Chapter IV.

It is clear now that \(\theta\left(M_{P M}{ }^{2}+N\right) \theta=\theta\), which proves that axiom 2 holds. Using (2.1) we see that \(\left(M P M^{\prime}+R\right) \theta\left(M P M^{\prime}+N\right)=\left(M^{\prime}+N\right)\), which proves that axiom 1 holds.

There remains to show that \(\theta\left(\mathrm{MPM}^{\prime}+\mathbb{N}\right)\) is symmetric
\[
\theta\left(M P M^{2}+N\right)=\left[\begin{array}{cc}
\left(H P H^{\prime}+R\right)^{\#}\left(H^{2} H^{\prime}+R\right) & 0 \\
0 & 1
\end{array}\right]
\]
3) The final case is considerably less important. We have \(h S_{1} h^{\prime}+r=0\) and \(h P h^{\prime} \neq 0\). Unfortunately it is no longer true that
\[
\left(\mathrm{MPM}^{\mathrm{y}}+\mathrm{N}\right)=\left[\begin{array}{cc}
\left(\mathrm{HPH}^{2}+\mathrm{R}\right)^{\#} & 0 \\
0 & 0
\end{array}\right]
\]
so we will have to prove that
\[
\mathrm{PM}^{\mathbf{2}}\left(\mathrm{MPM}^{1}+\mathrm{N}\right)^{\#} \mathrm{MP}=\mathrm{PH}^{2}\left(\mathrm{HPH}^{\prime}+\mathrm{R}\right)^{\#} \mathrm{HP}
\]

There seems to be no royal way of doing this, so we will compute (MPM' \(+\mathbb{N}\) )
\[
\left[\begin{array}{c}
\mathrm{HPH}^{\prime}+\mathrm{R} \\
\mathrm{hPH}
\end{array}\right]=\left[\begin{array}{c}
{\left[1-\frac{\left(H P H^{\prime}+R\right)^{\# 2} \mathrm{HPh}^{\prime} h \mathrm{hPH}^{\prime}}{1+\mathrm{HPH}^{\prime}\left(H P H^{2}+R\right)^{Z_{H P H}}}\right]\left(H P H^{\prime}+R\right)^{\#}\left|\frac{\left(\mathrm{HPH}^{\prime}+R\right)^{\# 2} \mathrm{HPH}^{\prime}}{1+\sim}\right|}
\end{array}\right]
\]

This follows from the fact that
\[
\left(H P H^{\prime}+R\right)\left(H P H^{\prime}+R\right)^{H^{-}}=\left(H P H^{\prime}+R\right)
\]
(An interesting result obtained in this investigation is that \(S^{\# 2}=S^{2 \#}\) and \(S H_{S}=S S^{\#}\) for any symmetric \(S\) ). We wish to compute
\[
\left[\begin{array}{cc}
\mathrm{HPH}^{\prime}+\mathrm{R} & \mathrm{HPh} \\
\mathrm{hPH}^{\prime} & \mathrm{hPh}
\end{array}\right]^{\#}
\]
and before we can do so, we must determine if
\(=\left[\begin{array}{c}\mathrm{HPH}^{\prime}+\mathrm{R} \\ \mathrm{hPH}\end{array}\right]\left[\begin{array}{ll} \\ & {\left[\mathrm{I}-\frac{\left(\mathrm{HPH}^{\prime}+\mathrm{R}\right)^{\# 2} \mathrm{HPH}^{\prime} \mathrm{hPH}^{\prime}}{1+\sim}\right]\left(\mathrm{HPH}^{\prime}+\mathrm{R}\right) \mathrm{HPh}^{\prime}+\frac{(\mathrm{HPH}+\mathrm{R})^{\# 2} \mathrm{HPh}^{\prime} \mathrm{hPH}}{}{ }^{\prime}} \\ 1+\sim\end{array}\right]\)

If we now remember that \(h S_{1} h^{\prime}=h\left(P-P H^{\prime}\left(H P H^{\prime}+R\right)^{\#} H P\right) h^{\prime}=0\) we obtain
\[
\left[\begin{array}{c}
\mathrm{HPh}^{\prime} \\
\mathrm{hPH}^{\prime}(\mathrm{HPH} \\
\mathrm{t} \\
\mathrm{tR})^{\#} \mathrm{HPh}^{\prime}
\end{array}\right]=\left[\begin{array}{l}
\mathrm{HPh} \\
\\
\mathrm{hPh}
\end{array}\right] .
\]

This shows why the condition \(h S_{1} h^{1}+r=0\) is a natural one though it does not appear to be at first; it is important to the choice of which formula can be used in the iterative definition of the pseudo-inverse.
\[
\begin{aligned}
& \frac{\left[\mathrm{hPH}^{\prime} \mathrm{hPh}^{\prime}\right]}{\alpha}\left[\begin{array}{c}
\mathrm{HPH}^{\prime}+\mathrm{R} \\
\mathrm{hPH}
\end{array}\right]^{\text {' }^{\prime}}\left[\begin{array}{c}
\mathrm{HPH}^{\mathrm{t}}+\mathrm{R} \\
\mathrm{hPH}
\end{array}\right]
\end{aligned}
\]
where
\[
\alpha=1+\left[\begin{array}{ll}
\mathrm{hPH}^{\prime} & \mathrm{hPh}
\end{array}\right]\left[\begin{array}{c}
\mathrm{HPH}^{\prime}+\mathrm{R} \\
\mathrm{hPH}
\end{array}\right]^{\#^{\prime}}\left[\begin{array}{l}
\mathrm{HPH} \\
\mathrm{hPH}
\end{array}\right]\left[\begin{array}{l}
\mathrm{HPh} \\
\mathrm{hPh}^{\prime}
\end{array}\right]
\]
but

So \(\alpha=I+\sim\), and

Now consider \(h\left[P-H^{\prime}\left(H P H^{\prime}+R\right)^{\#} H P\right]=h \theta\).
We know that h \(\theta\) ' \(=0\) but since \(\theta\) is nonnegative definite, it must be that \(h \theta=0\).

Therefore
\[
P\left[H^{\prime} \quad h^{\prime}\right](\mathrm{MPM}+N)^{\#}\left[\begin{array}{l}
\mathrm{H} \\
\mathrm{~h}
\end{array}\right] \mathrm{P}=\mathrm{PH}^{\prime}(\mathrm{HPH}+\mathrm{R})^{\#} \mathrm{HP} .
\]
7. Adaptation by Error Minimization: This technique may be used to determine the parameters \(\widehat{F}\) by trial and error to minimize the least-squares fitting. As seen in Fig. 21 we had an exror of 221.4 when using \(\lambda(F)=-.8,-1.5,-3\). The folluwing table shows the cvolution of the system as this error is decreased.
\begin{tabular}{rccl}
\(-\lambda_{1}\) & \(-\lambda_{2}\) & \(-\lambda_{3}\) & ERR \\
.8 & 1.5 & 3. & 221.4 \\
.7 & 1.4 & 2.9 & 148.9 \\
.6 & 1.3 & 2.8 & 147.2 \\
.7 & 1.2 & 2.7 & 121.2 \\
.7 & 1.2 & 2.5 & 115.5 \\
.71 & 1.25 & 2.4 & 109.5 \\
.73 & 1.25 & 2.3 & 103.4 \\
.75 & 1.25 & 2.1 & 95.9 \\
.77 & 1.27 & 1.9 & 90.0 \\
.88 & 1.27 & 1.9 & 78.7
\end{tabular}

If we allow \(\hat{F}\) to have one more eigenvalue, we obtain the following results:
\begin{tabular}{ccccc}
\(-\lambda_{1}\) & \(-\lambda_{2}\) & \(-\lambda_{3}\) & \(-\lambda_{4}\) & \\
.6 & 1. & 2. & 2.9 & 176.2 \\
.8 & 1.1 & 1.9 & 2.9 & 102.3 \\
1. & 1.2 & 2. & 3. & 41.4 \\
1.1 & 1.4 & 2. & 3. & 13.2 \\
1.2 & 1.4 & 2. & 3. & 8.45 \\
1.3 & 1.4 & 2. & 3. & 7.78 \\
1.28 & 1.4 & 2. & 3. & 7.63
\end{tabular}

Like other adaptive schemes, this parameter search procedure is not as easy as the table above makes it appear. Nevertheless the search procedure can be mechanized to obtain an optimal fit over some chosen interval of the impulse response. This sequence of systems can then be patched together to provide an approximating time varying linear system.

The impulse responses of the "optimized" approximating systems appear in Fig. 22 and 23.

The following is a very rough estimate of the arithmetic operation required to compute \(P_{k+1}\). First by treating \(m\) outputs and then by treating 1 output \(m\) times. Floating addition, multiplication and division are considered equally time consuming.

The inner product of two \(n\) vectors is assumed to required \(2 n\) operations, actually \(n\) multiplication and \(n-1\) addition. Matrix inversion is assuned to require \(n^{3}\) operations.
\[
\begin{aligned}
& \text { (i) Inversion (ii) Single output } \\
& \text { MP } \\
& 2 m n^{2} \\
& 2 n^{2} \\
& \text { pPM }{ }^{1} \\
& M^{\prime} M^{1}+N \\
& \left(\text { pPM }^{\prime}+N\right)^{-1} \\
& \left(M P M^{\prime}+N\right)^{-1}{ }^{-1} \\
& P M^{\prime}\left(M P M^{\prime}+N\right)^{-1} M P \\
& P-\mathrm{PM}^{\mathrm{I}}\left(\mathrm{MPM}^{\mathrm{P}}+\mathrm{N}\right)^{-1} \mathrm{MP} \\
& 2 m n^{2} \\
& 2 n^{2}+2 n \\
& 2 n^{2}+2 n+1 \\
& 2 m n^{2}+2 m^{2} n+m \\
& 2 n^{2}+2 n+2 \\
& 2 m n^{2}+4 m^{2} n+m+m^{3} \\
& 2 n^{2}+3 n+2 \\
& 4 m n^{2}+4 m^{2} n+m+m^{3} \\
& 3 n^{2}+3 n+2 \\
& 4 m n^{2}+4 m^{2} n+m+m^{3}+n^{2} \\
& 4 n^{2}+3 n+2
\end{aligned}
\]

Now multiply the operations in the single stage process by \(m\) and subtract, the difference is
\[
4 m^{2} n-3 m n-m+m^{3}+n^{2}>0
\]

BEGIN
LOAD He F, Ge TeNDeZle 1,
\(\begin{array}{ll}\text { REW } & 5 \\ \text { WFF } & 5\end{array}\)
ETPHI F. T.PH
MULT I. Gi 1.
REW 5
HEAD IMULT He Le \(Y\).
Save \(\quad 5 \mathrm{Y}, \mathrm{Y}, \mathrm{Zl}, \mathrm{T}\) 。
\(A D D \quad 71 . T e \quad Z 1\)
MULT PH, 1. 1 ,
IF ND,Z1.HEAD 1
END

0
0
1.

Fig. 1
- 424 -

BEGIN
REW 5
LOAD Z1. D.PC.TI.LF,VO.LH, R, \(Q, 1, X C, N D\).
EQUAT I. 3,
ETPHI LF,T1,PH
SUBT Z1.T1, MT,
ETPHI LF,MT.HP.
HEAD 1BRING \(5 \mathrm{Y}, \mathrm{Y}\).
SAMPL PH,VO.LH, R. Q. D,PC. VO, K.AL.
\(\begin{array}{lcc}\text { MULT } & L H_{0} X C, & Y C \\ \text { SUBT } & Y, Y C, & Y T\end{array}\)
\(\begin{array}{lll}\text { MULT } & K_{0} Y T_{9} & 1 . \\ \text { MULT } & \text { PHoXC. } & 2,\end{array}\)
ADO 1.2. XC,
MULT HP. 3. 3.
MULT \(3 . X C\). GC.
RINT Z1. GC.GC
ADD Z1.T1. Z1
IF ND.Z1,HEAD 1

21
\begin{tabular}{lllll} 
& 0 & & \\
0 & 1 & 0 & 2 & 01 \\
& & 0 & & \\
\hline
\end{tabular}


Fig. 2


Fig. 3

BEGIN
LOAD HeF. Ge T.ND:Z1. Ie JeK. ReGM.TI
\(\begin{array}{ll}\text { REW } & 5 \\ \text { WEF } & 5\end{array}\)
ETPHI F, T.PH
MULT 1. Ge de
TRNSI J, K, R, G,PH,GM, H,TT
REW \(\quad H_{0} \quad 5\)
SAVE \(\quad 5 \mathrm{Y}, \mathrm{Y}, \mathrm{ZL}\). T.
ADD \(\quad \mathrm{Zi}, \mathrm{T}, \mathrm{Zl}\)
MULT PH, 1. 1.
IF ND,Z1.HEAD 1
END



Fig. 4


JAN. 22. 1965
BEGIN
REW 5

EQUAT 1, 3.Z1.Z2.
ETPHI LF.T1.PH
SUBT Z1.T1, MT.
ETPHI LEAMT.HP.
HEAD 1BRING \(5 \mathrm{Y} . \mathrm{Y}\).

\(\begin{array}{ccc}\text { MULT } & \text { LH, XC, } & \text { YC } \\ \text { SUBT } & Y, Y C, & Y T, \\ \text { MULT } & \text { K.YT, } & 1 . \\ \text { MULT } & \text { PHeXC, } & 2 . \\ \text { ADD } & 1.2 . & X C\end{array}\)
MULT HP. \(3 . \quad 3\).
MULT 3.XC. GC.
MULT HP XC \(\quad 7\)
\(\begin{array}{lrr}\text { MULT } & \text { LH } & 7 \\ \text { SUBT } & Y Y C & Y T\end{array}\)
MULT YT,YT. YZ
ADD Z2.YZ. Z2.
TRANP GC. GT,
TRANP \(X C, \quad X T\),
JUXTC GT.XT. 4 .
JUXTC \(4.22,5\).
RINT Z1. 5. X
\(A D D\) Z1,T1. Z1
IF ND.Z1.HEAD 1
END
Z1
D
1
\(\begin{array}{ll}1 \\ 0 & 2\end{array}\)


Fig. 5


Fig. 6


Fig. 7
\[
.05 \mathrm{~N}=\mathrm{T}
\]
\[
\sum_{k=0}^{N}(z(.05 k)-\hat{z}(.05 k \mid(k-1)))^{2}
\]
\[
\sum_{k=0}^{N}(z(.05 k)-\hat{z}(.05 k \mid .05 k))^{2}
\]
\begin{tabular}{lrr}
.5 & .02 & .01 \\
1.0 & 5.37 & 3.42 \\
1.5 & 48.59 & 36.93 \\
2.0 & 134.88 & 112.23 \\
2.5 & 212.03 & 184.01 \\
3.0 & 253.13 & 223.59 \\
3.5 & 267.85 & 238.03 \\
4.0 & 271.32 & 241.47 \\
4.5 & 271.72 & 241.86 \\
5.0 & 271.89 & 241.89 \\
5.5 & 272.10 & 242.03 \\
6.0 & 272.29 & 242.25 \\
6.5 & 272.43 & 242.44 \\
7.0 & 272.52 & 242.58 \\
7.5 & & 242.66
\end{tabular}

Fig. 8

OPTIMAL APPROXIMATION


Fig. 9
\[
.05 N=T \quad \sum_{k=0}(z(.05 k)-\hat{z}(.05 k \mid 7 .))^{2} \quad \sum_{k=0}^{N}(z(.05 k)-\hat{z}(.05 k \mid 2))^{2}
\]
\begin{tabular}{lll}
.5 & 68.59 & 26.43 \\
1.0 & 93.42 & 48.18 \\
1.5 & 146.19 & 60.57 \\
2.0 & 150.75 & 103.18 \\
2.5 & 175.06 & 208.78 \\
3.0 & 203.22 & 297.47 \\
3.5 & 217.07 & 342.65 \\
4.0 & 220.94 & 359.62 \\
4.5 & 221.46 & 364.64 \\
5.0 & 221.49 & 365.80 \\
5.5 & 221.62 & 365.97 \\
6.0 & 222.02 & 365.98 \\
6.5 & 222.17 & 365.99 \\
7.0 & 222.26 & 366.02
\end{tabular}

Fig. 10

OPTIMAL APPROXIMATION


Fig. 11

BEGIN
REW 5
LOAD Z1, T.ND, F. H.XC,
ETPHI F, I,PH,
EQUAT Z1.Z2.
HEAD IBRING \(5 \mathrm{Y} . \mathrm{Y}\).
MULT \(\mathrm{H}, \mathrm{XC}\). YC.
SUBT Y.YC. YI.
MULT YT.YT. YZ.
ADD Z2.YZ. \(Z 2\).
JUXTC YC Z2 23
RINT. \(\mathrm{Zl} \quad 23\) ERR
MULT \(\mathrm{PH} \times \mathrm{C} \quad \times \mathrm{C}\)
ADD Z1. T. Z1.
IF ND.Z1.HEAD 1
END
\(\begin{array}{lll}1 & & 1 \\ 1 & 0 & 1\end{array}\)
7.5
\begin{tabular}{|c|c|c|c|c|c|c|}
\hline \multirow[t]{2}{*}{\(F\)} & \multicolumn{2}{|l|}{\multirow[t]{2}{*}{\(\begin{array}{ll}3 & 3 \\ -.8 & \end{array}\)}} & \multicolumn{4}{|l|}{} \\
\hline & & & 0 & 0 & 0 & \(-1.5\) \\
\hline & 0 & & 0 & 0 & -3. & \\
\hline H & 1 & 3 & & & & \\
\hline XC & \[
3^{10}
\] & 1 & 1. & 1. & & \\
\hline & & 13 & & & & \\
\hline
\end{tabular}

Fig. 12
\[
.05 \mathrm{~N}=\mathrm{T}
\]
\[
\Sigma \tilde{z}^{2}(t \mid t)
\]
\[
\Sigma \tilde{\mathrm{z}}^{2}(\mathrm{t} \mid 7)
\]
\begin{tabular}{|c|c|c|}
\hline . 5 & .2.10 \(0^{-5}\) & 9365. \\
\hline 1.0 & . 18 & 9368. \\
\hline 1.5 & 1.20 & 9371. \\
\hline 2.0 & 5.45 & 9372. \\
\hline 2.5 & 9.10 & 9375. \\
\hline 3.0 & 9.86 & 9377. \\
\hline 3.5 & 10.1 & 9377. \\
\hline 4.0 & 11.5 & 9378. \\
\hline 4.5 & 13.9 & 9380. \\
\hline 5.0 & 16.3 & 9382. \\
\hline 5.5 & 18.2 & 9384. \\
\hline 6.0 & 19.5 & 9385. \\
\hline 6.5 & 20.3 & 9386. \\
\hline 7.0 & 20.8 & 9387. \\
\hline 7.5 & 21.1 & 9387. \\
\hline
\end{tabular}

Fig. 13

OPTIMAL APPROXIMATION


Fig. 14

BEGIN
REW 5
LOAD Z1, D,PC,T1,LF,VO,LH, R, Q. 1,XC,ND,N2,N3,R1,R2
EQUAT Le 3,21,22.21,23.
ETPHI LF,T1,PH
SUBT Z1,T1, MT.
ETPHI LF,MT•HP.
HEAD 1 BRING \(5 \mathrm{Y}, \mathrm{Y}\),
SAMPL PH,VO,LH, R, Q, D,PC, VO, K,AL,
MULT LH,XC, YC
\(\begin{array}{lcc}\text { SUBT } & Y, Y C, & Y T \\ \text { MULT } & Y T, Y T, & Y Z \\ A D D & Z 3 Y Z & Z 3\end{array}\)
MULT K,YT, 1.
MULT \(\mathrm{PH}, \times \mathrm{C}, ~ 2 \cdot\)
ADD \(\quad 1,2, \quad \times \mathrm{C}\),
\(\begin{array}{ccc}\text { MULT } & 3, \times C, & G C, \\ \text { MULT } & H P \times C & 7\end{array}\)
\(\begin{array}{llrl}\text { MULT } & \text { LH } & 7 & Y C \\ \text { SUBT } & Y & Y C & Y T\end{array}\)
MULT YT.YT, YZ
ADD Z2,Y2, Z2,
TRANP GC, GT,
TRANP \(X C, \quad X T\),
JUXTC GT, \(\times\) T, 4 ,
JUXTC 4,Z2. 5.

ADD \(\quad \mathrm{Z} 1, \mathrm{Tl}, \mathrm{Z}\)
IF ND,Z1.HEAD 1
IF ND,N2.HEAD 2
EQUAT N2,ND,R1, R,
IF Z1, Z1,HEAD 1
HEAD PIF ND.N3.HEAD 3
\(\frac{\text { EQUAT N3.ND R2. R }}{\text { IF }}\)
HEAD 3END


Fig. 15

\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)

Fig. 15
\begin{tabular}{|c|c|c|}
\hline \(.05 \mathrm{~N}=\mathrm{T}\) & \(\Sigma \tilde{z}^{2}(t \mid t)\) & \(\Sigma \tilde{z}^{2}(t \mid 10)\) \\
\hline . 5 & . 017 & 47457. \\
\hline 1.0 & 3.42 & 47501. \\
\hline 1.5 & 3.42 & 47503. \\
\hline 2.0 & 3.42 & 47503. \\
\hline 2.5 & 3.48 & 47503. \\
\hline 3.0 & 4.77 & 47504. \\
\hline 3.5 & 9.26 & 47509. \\
\hline 4.0 & 16.4 & 47516. \\
\hline 4.5 & 23.8 & 47524. \\
\hline 5.0 & 29.8 & 47530. \\
\hline 5.5 & 34.0 & 47534. \\
\hline 6.0 & 36.6 & 47536. \\
\hline 6.5 & 38.1 & 47538. \\
\hline 7.0 & 38.9 & 47539. \\
\hline \(7 \cdot 5\) & 39.3 & 47539. \\
\hline & \(=1000\) & \(3]\) \\
\hline
\end{tabular}
\[
\mathrm{VO}=1000 \quad \mathrm{R}=0 \text { on }[1,3]
\]

Fig. 16

\section*{OPTIMAL APPROXIMATION}


Fig. 17


Fig. 18


Fig. 18


Fig. 19


Fig. 20
\begin{tabular}{lll}
.5 & 31.8 & 78.5 \\
1.0 & 52.6 & 107.0 \\
1.5 & 66.2 & 155.4 \\
2.0 & 102.4 & 159.5 \\
2.5 & 197.4 & 182.5 \\
3.0 & 278.0 & 206.6 \\
3.5 & 318.7 & 217.6 \\
4.0 & 333.7 & 220.3 \\
4.5 & 337.9 & 220.6 \\
5.0 & 338.9 & 220.6 \\
5.5 & 338.9 & 220.8 \\
6.0 & 339.0 & 221.1 \\
6.5 & 339.0 & 221.4
\end{tabular}

Fig. 21


Fig. 22


Fig. 23

\section*{CHAPIER XVII}

\section*{MULII-RATE SAMPLING}
1. Description of the Problem: Frequently information about the state of a dynamical system is available only at a discrete set of points in time. This fact has given rise to the study of discretized systems. To complicate matters, however, there are times when sample and hold elements in a system operate at two or more different frequencies.

In this chapter we will examine how we may produce an optimal control for a system having an internal sampling period distinct from the period at which control can be changed.

Parenthetically, we will examine the relation of the continuous performance index to sampled ones, with and without the additional (internal) sampler.
2. Theory and references: In addition to Chapter VIII, see R. E. Kalman and J. E. Bertram, "A Unified Approach to the Theory of Sampling Systems", Jour. Franklin Institute, vol. 267, May 1959.
3. The Specific Problem: We take the flow diagram of Fig. 1, where
\[
\begin{aligned}
& S_{1}=\frac{-10(s-1)}{s\left(s^{2}+2 s+8\right)} \\
& S_{2}=\frac{10}{2} \\
& S_{3}=\frac{1}{(s+3)(s+4)}
\end{aligned}
\]
and synthesize it by the flow diagram of Fig. 2, having
\[
\begin{aligned}
F & =\left[\begin{array}{ccccccc}
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & -8 & 0 & 0 & 0 & 0 \\
0 & 1 & -2 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & -12 & 0 & 1 \\
0 & 0 & 0 & 1 & -7 & 0 & 0 \\
0 & 0 & 1 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 10 & 0 \\
G & 10 \\
-10 \\
0 \\
0 \\
0 \\
0 \\
0
\end{array}\right]
\end{aligned}
\]

We wish to optimize this continuous system with respect to the performance index
\[
x^{2}(0) \operatorname{Px}(0)=\int_{0}^{\infty}\left[(y+2 \dot{y})^{2}+.01 u^{2}\right] d t
\]
having
\[
\begin{aligned}
& Q=\operatorname{diag}\left(0,0,0,0,0,\left[\begin{array}{cc}
1 & .2 \\
.2 & .04
\end{array}\right]\right) \\
& R=.01 . \\
& \\
& \quad-451-
\end{aligned}
\]

Having done this we will introduce a sampler on the control with period \(\tau\) and examine the performance index matrix \(P_{\tau}\),
\[
x^{\prime}(0) P_{\tau} x(0)=\sum_{i=1}^{\infty} x^{\prime}(i \tau) \tau Q x(i \tau)+u^{\prime}((i-1) \tau) \tau \operatorname{Ru}((i-1) \tau)
\]
as t goes from \(\frac{2}{e}=.73575888\), to zero. By the reasoning given in Chapter XI we realize that in the continuous control problem we may replace \(Q\) by \(Q=\operatorname{diag}\left(0,0,0,0,0,\left[\begin{array}{cc}1 & 0 \\ 0 & .04\end{array}\right]\right.\) ); we will see if this can be done in the discrete case as well.

We will then, using our multi-rate program introduce a new state variable \(x_{8}\) to describe a sample and hold element operating at a period of 2 . between \(x_{7}\) and \(x_{4}\). Because the two sampling periods are incommensurable, the transition matrix between control points is neither convergent nor periodic, so the optimal gains do not converge. We will take a total interval of 25 over which to optimize.

The open loop transfer function is
\[
\frac{x_{7}(s)}{u(a)}=-\frac{100(s-1)(s+3)(s+4)}{s\left(s^{2}+2 s+8\right)\left(s^{4}+7 s^{3}+125^{2}-10\right)}
\]
having poles at \(0,-1 \pm \sqrt{-7}, \sim .75, \sim-4.75\).
We will assume that both sample and hold elements operate at \(t=0\).
4. Results: Using the program appearing in Fig. 3, we ran the free motion which gave, as expected, stable behavior in \(x_{1}, x_{2}\), and \(x_{3}\) and instability in the other components.

We then computed the optimal control for the continuous system, using the program in Fig. 4. This converged in 9.47 seconds to a performance index with diagonal elements:
\[
\begin{aligned}
& p_{11}=16.233963 \\
& p_{22}=16.121959 \\
& p_{33}=14.866118 \\
& p_{44}=4.857859 \\
& p_{55}=4.407092 \\
& p_{66}=1822.1928 \\
& p_{77}=12.586129 .
\end{aligned}
\]

Using the program in Fig. 5 we computed sampled control for various values of \(\tau\). This generated the following table illustrating how the sampled performance index converges to the continuous one
\begin{tabular}{ccccc}
\(\tau\) & \(p_{11}\) & \(p_{66}\) & \(p_{77}\) & Time for convergence \\
.7257588 & 39.500149 & 3872.7168 & 24.452950 & 12.51 \\
.3678944 & 20.613631 & 2244.5554 & 15.730421 & 11.40 \\
.18393972 & 17.365082 & 1935.2903 & 14.137003 & 11.04 \\
.09196986 & 16.639765 & 1864.3951 & 13.795817 & 10.66 \\
.04598493 & 16.454767 & 1846.0598 & 13.716736 & 10.19 \\
.022992414 & 16.384925 & 1838.8439 & 13.683984 & 9.78 \\
.011496207 & 16.340233 & 1833.9453 & 13.655727 & 9.46
\end{tabular}

It appears from the experimental results in this case, that the sampled control is also independent of whether the error is \((y+2 \dot{y})^{2}\) or \(y^{2}+4 \dot{y}^{2}\).

Our multi-rate program appears in Fig. 6, three runs were made with this and checked by using the ordinary sampled program.

The first, with \(T 1=T 2=.73575888\) was checked with Fig. 7 and. showed agreement to five decimal places. This simulates operation of the intermal sampler infinitesimally prior to the control sampler.

The diagonal terms of \(P\) for this system were,
\[
\begin{aligned}
& p_{11}=23.758 \\
& p_{22}=22.105 \\
& p_{33}=14.325 \\
& p_{44}=6.5906 \\
& p_{55}=4.3283 \\
& p_{66}=2103.97 \\
& p_{77}=7.9393 \\
& p_{88}=1.9325
\end{aligned}
\]

The remarkable point here is the decrease in the performance index caused merely by providing an extra, constant state variable prior to \(x_{4}\). Here the diagonal terms of \(P\) were much smaller, probably because, once the loop is broken, the system is asymptotically stable.
\[
\begin{aligned}
& p_{11}=9.9194 \\
& p_{22}=8.8411 \\
& p_{33}=4.7264 \\
& p_{44}=2.6170 \\
& p_{55}=1.4585 \\
& p_{66}=776.93 \\
& p_{77}=2.5821 \\
& p_{88}=2.9742
\end{aligned}
\]

The second with \(T 1=.73575888\) and \(T 2=50\) was checked with Fig. \(\dot{8}\) and showed agreement to four decimal places. This simulates failure of the internal sampler even to operate. Notice that even though the state of the system will not go to zero (if \(\mathrm{x}_{8}(0) \neq 0\) ), the performance index is finite.

The third case is that of our problem, \(T 1=.73575888, T 2=2\). This gave a performance index of
\[
\begin{aligned}
& p_{11}=12.631 \\
& p_{12}=11.175 \\
& p_{33}=5.6149 \\
& p_{44}=3.3069 \\
& p_{55}=1.7685 \\
& p_{66}=971.03 \\
& p_{77}=3.0681 \\
& p_{88}=2.8250
\end{aligned}
\]

In Fig. 9 appear the transients, from unit initial condition on \(\mathrm{x}_{7}\), of the output as given by the free system, the controlled continuous system, the controlled discrete system, and the controlled multi-rate system.

In Fig. 10 appear the optimal control function required for continuous control and ordinary discrete control of the transients in Fig. 9, with the given performance index.
\begin{tabular}{ccc}
\(t\) & Ordinary & Multi-rate \\
0 & -1.091 & -.219 \\
\(\frac{2}{e}\) & 1.610 & .475 \\
\(\frac{4}{e}\) & -1.110 & -.514 \\
\(\frac{6}{e}\) &. .954 & .421 \\
\(\frac{8}{e}\) & -.622 & -.304 \\
\(\frac{10}{e}\) & .404 & .221 \\
\(\frac{12}{e}\) & -.237 & -.123 \\
\(\frac{14}{e}\) & .146 & .071 \\
\(\frac{16}{e}\) & -.085 & -.045 \\
\(\frac{18}{e}\) & .052 & .025 \\
\(\frac{20}{e}=7.358\) & -.030 & -.015.
\end{tabular}

Surprisingly enough, the gains for the multi-rate did not converge, to the extent that variations were only about \(10 \%\) of some average value. It is possible therefore to compare the steady-state gains for the three controlled runs.
\begin{tabular}{lccc} 
& Continuous & Sampled & Multi-rate \\
\(\mathrm{k}_{1}\) & 56.65 & 1.727 & .9915 \\
\(\mathrm{k}_{2}\) & 55.36 & 1.464 & .7168 \\
\(\mathrm{k}_{3}\) & 46.99 & 1.054 & .2558 \\
\(\mathrm{k}_{4}\) & 30.26 & .8225 & .4106 \\
\(\mathrm{k}_{5}\) & 25.58 & .6168 & .1835 \\
\(\mathrm{k}_{6}\) & 555.1 & 14.63 & 6.209 \\
\(\mathrm{k}_{7}\) & 40.95 & 1.091 & .2186 \\
\(\mathrm{k}_{8}\) & & & .4637.
\end{tabular}


Fig. 1



Fig. 3

BEGIN

SUBT ZR, F. 1 ,
TRANP F. FT,
TRANP G. GT.
MULT RL.GT: C.
MULT G. C. 5,
NORM Q. NO.
NORM 5. N5,
PSEUO NO, PQ.RK
MULT PQ.N5, M1,
DECOM M1.- S.S.ER.ERE.E.RK.
MULT S. \(Q\). \(Q_{\text {, }}\)
MUI T SUR 50 5.
MULT SJ, C, C.
BLOT NQe.
JuxTC 1.5, 2,
JUXIC Q.FI. 3.
JUXTR 2, 3. PH,
NORM PH. NP.
PSEUO NP, NP.RK
MULT T NP,TI, T...T
RINT PH,PH

RICAT Q.PH, C, D,PC•XX, P, K.AL.
RINT P,PERK,K
WRITE THE PRECEDING MATRICES WERE THE MATRIX P OF THE
WRITE - PERFORMANCE INDEX AND THE FEEDBACK GAIN. MATRIX K.
MULT G. K, GK.
SUBT FAGK, CF,
ETPHI CF,T1,P1.
HEAD IMULT K.XO. KXe
JUXTR \(\times 0 . R Z: \quad 6\),

JUXTR GUKXe_7.
FINT R1, 7. \(x\)
MULT PIexo XO,
ADD R1.T1. R1.
IF NDeRIOHEAD !
IF TT.TT.HEAD 2
WRITE RICAT CONVERGENCE TEST REMOVED. RECAUSE WITH \(Q=4.1\)
WRITE RI = 100. CONVERGENCE WAS NOT ACHIEVED.
HEAD 2END

\(\qquad\)

Fig. 4


Fig. 4


Fig. 4

JULY 10. 1965

\(\qquad\)

Fig. 5


Fig. 5



\footnotetext{
Fig. 6
}
\begin{tabular}{|c|c|c|}
\hline \[
\begin{aligned}
& \text { IF } \\
& \text { SAVE }
\end{aligned}
\] & D S1, HEAD 9 5 KO .K & \\
\hline IF & .5..5.0UT 1 & TRANSFER TO TRANSIENT. \\
\hline \multicolumn{3}{|l|}{HEADAIEQUAT TO. 1.} \\
\hline IF & D S2.HEAD42HEAD 10 & \\
\hline \multicolumn{3}{|l|}{HEAD42MULT . 5 T2. T3.} \\
\hline MULT EP & EP T2 S & \\
\hline SURT & TO. 5 S & \\
\hline \multicolumn{2}{|l|}{HEAD 44 SUBT 2 S T4} & \\
\hline \multicolumn{2}{|r|}{IF T3.T4.HEAD43} & \\
\hline ADD & T2 S S & \\
\hline IF & . 5.5 HEAD44 & \\
\hline \multicolumn{3}{|l|}{\multirow[t]{2}{*}{\begin{tabular}{ccc} 
HEAD 4 3EQUAT & 5 & 2 \\
IF & 5 & 5 .HEAD 10
\end{tabular}}} \\
\hline & & \\
\hline \multirow[t]{2}{*}{heAd gMULT
SUBT} & .5 T1 T3 & \\
\hline & I TO. T4 & \\
\hline \multicolumn{2}{|l|}{\multirow[t]{2}{*}{\(\begin{array}{ccc}\text { IF } & \text { T4 T3 HEAD4 } \\ \text { OUT IF } \\ \text { IF }\end{array}\)}} & \\
\hline & & BEGIN TRANSIENT. \\
\hline \multicolumn{2}{|l|}{EQUAT S1, 1} & \\
\hline \multicolumn{2}{|r|}{IF .5.5.HEAD 12} & \\
\hline \multicolumn{2}{|l|}{HEAD 1 1EQUAT T1, 1.} & \\
\hline \multicolumn{2}{|l|}{HEAD12IF D S2.HEAD13} & \\
\hline \multicolumn{2}{|l|}{EQUAT S2 2} & \\
\hline \multicolumn{2}{|r|}{IF -5.5 HEAD 14} & \\
\hline \multicolumn{3}{|l|}{\multirow[t]{2}{*}{HEAD 13 EQUAT T2, 2}} \\
\hline & & \\
\hline \multicolumn{2}{|l|}{HEAD148SR \(\frac{1}{\text { EQUAT TO, T.TO,PT. }}\)} & \\
\hline \multicolumn{2}{|r|}{BRING \(5 \mathrm{~K} . \mathrm{K}\).} & \\
\hline \multirow[t]{2}{*}{ADD P} & PTPI PT & \\
\hline & \(K \times 0 . \quad U\) & \\
\hline \multirow[t]{2}{*}{SUBT R} & \(R Z \cup \cup\) & \\
\hline & 25 & \\
\hline HEAD \(19 J U X T R\) & \(K \mathrm{RZ}\) K1 & \\
\hline \multicolumn{2}{|r|}{JUxTR \(\times 1 \times 0\) xo \(\times 2\)} & \\
\hline \multicolumn{2}{|r|}{JUXTR X2 RZ \(\times 3\)} & \\
\hline JUXTR \(\times\) & \(\times 3 \cup 1\) & \\
\hline \multicolumn{2}{|r|}{RINT T, \(\times 4\). MAT} & \\
\hline HEADIBLF P & PT, 1,HEAD15 & \\
\hline IF P & PT, 2.HEAD16 & \\
\hline IF P & PT,ND HEAD 17 & \\
\hline \multirow[t]{2}{*}{\begin{tabular}{l}
SUBT \\
EQUAI
\end{tabular}} & PT T, T3, & \\
\hline & PT T & \\
\hline \multirow[t]{2}{*}{\[
\begin{aligned}
& \text { ADD } \\
& \text { EAT }
\end{aligned}
\]} & PI,PT, PT, & \\
\hline & F.T3.PH.IN & \\
\hline EAT & IN G G3 & \\
\hline MULT G & G3 U GU & \\
\hline MULT P & \(\mathrm{PH} \times 0 \times \mathrm{T}\) & \\
\hline \(A D D\) & \(X T\) GU XO & \\
\hline \multirow[t]{2}{*}{\[
\begin{array}{r}
\text { IF } \\
\text { HEADIGIF }
\end{array}
\]} & -5 . 5 HEAD19 & \\
\hline & 2 ND HEAD 17 & \\
\hline \multirow[t]{2}{*}{\begin{tabular}{l}
SUBT \\
EQUAT
\end{tabular}} & 2 T T3 & \\
\hline & 2 T & \\
\hline EAT & F T3 PH IN & \\
\hline
\end{tabular}

Fig. 6


Fig. 6


Fig. 6

\(\qquad\)
\(\qquad\)
\(\qquad\)
\(\qquad\)

Fig. 6


Fig. 7


Fig. 7

BEGIN

HEAD 2MULT T.R1. R
MULT T.OLE O
EAT F. T.PH,IN
MULT_IN_G_GM
MULT D2 PH PH
MULT D2 GM GM
TRANP PH, FT
TRANP GM GT
EQUAT \(Q \quad P\)
SAMPL FT. P.GT. R. Q. D.PC. PE,KT,AL
TRANP KT K
\(\begin{array}{llll}\text { SUET PE } & \text { RINT } & \text { P PERK } K & K\end{array}\)
LOAD T
IF T. TIHEAD 2
END
\begin{tabular}{ccc}
\hline\(T\) & 1 & 1 \\
\hline\(F 3575888\) & 8 & 8
\end{tabular}


Fig. 8
\begin{tabular}{|c|c|c|c|}
\hline \multicolumn{4}{|l|}{. 04} \\
\hline \multicolumn{4}{|l|}{\[
0
\]} \\
\hline \multicolumn{4}{|l|}{\(\begin{array}{lll}0 \\ \text { RZ } & \\ 0\end{array}\)} \\
\hline \multicolumn{4}{|l|}{0} \\
\hline \multicolumn{4}{|l|}{0} \\
\hline Z1 & 1 & & \\
\hline \multicolumn{4}{|l|}{0} \\
\hline \multicolumn{4}{|l|}{ND 1} \\
\hline \multicolumn{4}{|l|}{26.} \\
\hline & 8 & & \\
\hline \multicolumn{4}{|l|}{1.0} \\
\hline \multicolumn{4}{|l|}{0} \\
\hline \multicolumn{4}{|l|}{} \\
\hline \multicolumn{4}{|l|}{0} \\
\hline \multicolumn{4}{|l|}{0 O_ 1 .} \\
\hline \multicolumn{4}{|l|}{0} \\
\hline \multicolumn{4}{|l|}{0 1.} \\
\hline \multicolumn{4}{|l|}{0} \\
\hline \multicolumn{4}{|l|}{1.} \\
\hline & & & \\
\hline \multicolumn{4}{|l|}{0} \\
\hline 0 & & 1. & \\
\hline D2 & \(\beta\) & & \\
\hline \multicolumn{4}{|l|}{1.} \\
\hline \multicolumn{4}{|l|}{0 _} \\
\hline \multicolumn{4}{|l|}{0} \\
\hline 0 & & 1. & \\
\hline \multicolumn{4}{|l|}{0} \\
\hline \multicolumn{4}{|l|}{0 Le} \\
\hline \multicolumn{4}{|l|}{0} \\
\hline 0 & . & & \\
\hline \multicolumn{4}{|l|}{\(\bigcirc\)} \\
\hline \multicolumn{4}{|l|}{1.} \\
\hline 0 & & & 1 \\
\hline 0 & & & \\
\hline 0 & & 1 & \\
\hline
\end{tabular}

Fig. 8


Fig. 9


Fig. 10

\section*{CHAPIER XVIII}

\section*{MODEL-FOLLOWER CONIROL}
1. Description of the Problem: Given a system
\[
\dot{\mathrm{x}}=\mathrm{Fx}+G u
\]
(1.1)
\[
y=H x
\]
and another, homogeneous system
(1.2)
\[
z=\mathrm{Lz}
\]
we wish to obtain a control \(u(t)\) which minimizes the performance index
\[
\int_{0}^{T}\left[\|y-z\|_{Q}^{2}+\|u\|_{R}^{2}\right] d t
\]
2. Theory and References: Our method will be to augment the system matrix by \(I\), then \(\|y-z\|_{Q}^{2}\) can be represented as \(\|\hat{x}\|_{\hat{Q}}^{2}\) where
\[
\begin{gathered}
\hat{x}=\left[\begin{array}{l}
x \\
z
\end{array}\right], \quad \hat{x}=\left[\begin{array}{ll}
F & 0 \\
0 & L
\end{array}\right] \hat{x}+\left[\begin{array}{l}
G \\
0
\end{array}\right] u \\
\hat{Q}=\left[\begin{array}{cc}
H^{\prime} Q H & -H^{\prime} Q \\
-Q H & Q
\end{array}\right] \cdot
\end{gathered}
\]

Notice that this augmented system is not completely controllable and we may expect problems with the behavior of the performance index because of this. Fortunately, in this application \(L\) is a stable matrix which will mitigate the problem.

3A. The Specific Problem: This problem is taken from the paper "Synthesis of Feedback Controls Using Optimization Theory" by F. J. Ellert and C. M. Merriam III.

Examination of the aircraft system leads us to
\[
F=\left[\begin{array}{cccc}
-.6 & -.76 & .00296875 & 0 \\
1 . & 0 & 0 & 0 \\
0 & 102.4 & -.4 & 0 \\
0 & 6 & 1 & 0
\end{array}\right] \quad G=\left[\begin{array}{c}
-2.375 \\
0 \\
0 \\
0
\end{array}\right]
\]
where \(\dot{\mathrm{x}}=\mathrm{Fx}+\mathrm{Gu}\).
In addition we have a time-varying model to follow which necessitates enlarging the system by the direct sum with
\[
\left[\begin{array}{l}
\dot{x}_{5} \\
\dot{x}_{6}
\end{array}\right]=\left[\begin{array}{rr}
-.2 & 0 \\
0 & -.2
\end{array}\right]\left[\begin{array}{l}
x_{5} \\
\\
x_{6}
\end{array}\right] \quad \begin{aligned}
& 0 \leqq t \leqq 15 \\
& x_{5}(0)=100 \\
& x_{6}(0)=-20
\end{aligned}
\]
and
\[
\left[\begin{array}{l}
\dot{x}_{5} \\
\dot{x}_{6}
\end{array}\right]=\left[\begin{array}{ll}
0 & 1 \\
0 & 0
\end{array}\right]\left[\begin{array}{l}
x_{5} \\
x_{6}
\end{array}\right] . \quad 15 \leqq t \leqq 20
\]

The requirement that a second order system be used after \(t=15\)
is the only reason for using one prior to that time. It may appear that this does not satisfy the altitude requirements as specified in the paper. However a small amount of analysis shows that the differences are less than one percent since
\[
100 \mathrm{e}^{-\cdot .3}=4.9787071
\]
and
\[
-20 e^{-.3}=-.99574141
\]
compared with the stated desiderata of 5 and - I. Furthermore the system as we simulate it does have \(x_{5}(20)=0\).

The error function may be written as
\[
L=\varphi_{4}\left(x_{5}-x_{4}\right)^{2}+\varphi_{3}\left(x_{3}-x_{6}\right)^{2}+\varphi x_{1}^{2}+u^{2}=\frac{1}{2}\left[\|x\|_{Q}^{2}+u^{2}\right]
\]
with a terminal weighting of
\[
\frac{1}{2}\|x\|_{S}^{2}=\frac{1}{2}\left(\varphi_{4 T}\left(x_{5}-x_{4}\right)^{2}+\varphi_{3 T}\left(x_{r}-x_{6}\right)^{2}+\varphi_{2 T}\left(x_{2}-2^{0}\right)^{2}\right)
\]
where \(2^{0}\) can be written as \(\frac{2}{57.2957795}\) radians and hence we may write the
term as
\[
\varphi_{2 T}\left(x_{2}+.034906586 x_{6}\right)^{2}
\]

Using \(\mathrm{x}_{6}\) to specify the \(2^{0}\) terminal value of \(\mathrm{x}_{2}\) is of course purely coincidental, we can do this because \(x_{6}(20)\) is a known constant.

Considering Case III in the paper, we define
\(Q=\left[\begin{array}{cccccc}99 . & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & .0001 & 0 & 0 & \mathbf{- . 0 0 0 1} \\ 0 & 0 & 0 & .00005 & \mathbf{- . 0 0 0 0 5} & 0 \\ 0 & 0 & 0 & \mathbf{- . 0 0 0 0 5} & \mathbf{. 0 0 0 0 5} & 0 \\ 0 & 0 & \mathbf{- . 0 0 0 1} & 0 & 0 & \mathbf{. 0 0 0 1}\end{array}\right]\)
for \(15 \leqq t \leqq 20\),
\(Q=\left[\begin{array}{cccccc}99 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & .00005 & -.00005 & 0 \\ 0 & 0 & 0 & -.00005 & .00005 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0\end{array}\right]\)
for \(0 \leqq t \leqq 15\),
and
\[
S=\left[\begin{array}{cccccc}
0 & 0 & 0 & 0 & 0 & 0 \\
0 & 10 . & 0 & 0 & 0 & .34906586 \\
0 & 0 & .01 & 0 & 0 & \mathbf{- . 0 1} \\
0 & 0 & 0 & .001 & -.001 & 0 \\
0 & 0 & 0 & -.001 & .001 & 0 \\
0 & .34906586 & -.01 & 0 & 0 & .022184688
\end{array}\right]
\]

4A. Results: Running this on the program appearing in Fig. 1, we achieved results agreeing with those appearing in the paper. For instance
\[
\begin{array}{ll}
\mathrm{k}_{11}(0)=4.18 & \mathrm{k}_{11}(16)=4.22 \\
\mathrm{k}_{12}(0)=2.20 & \mathrm{k}_{12}(16)=3.25 \\
\mathrm{k}_{13}(0)=.00675 & \mathrm{k}_{13}(16)=.0136 \\
\mathrm{k}_{14}(0)=.00298 & \mathrm{k}_{14}(16)=.00642
\end{array}
\]

The graph of altitude for the high, nominal, and low initial condition is in Fig. 2. As would be expected with a relatively inaccurate integration tool such as ASP, we do not get the same pitch angles at termination as the paper. However, the errors are less than .003 \({ }^{\circ}\).
\begin{tabular}{cccccc} 
I.C. & \(|u|_{\max }^{\text {deg. }}\) & \(\theta(20\).\() deg.\) & \(h(20)\) ft. & \(h(20) \mathrm{ft} / \mathrm{sec}\). & \(|\alpha|_{\max }\) deg. \\
1 & .4 & -.033 & -.103 & -.76 & 1.0 \\
2 & 16.3 & .003 & -.025 & -.82 & 1.8 \\
3 & 32.8 & .038 & .053 & -.87 & 3.
\end{tabular}

Having obtained these results, we attempted to improve upon them. There were two points at which improvement was possible. One was at the beginning of the approach where the initial (. 5 sec ) transient gave extremely large control values compared with the remainder of the trajectory. The other was at the terminal time, when it appeared that state variables could be closer to the desired values. We felt that these desiderata could be accomplished because of the extremely low magnitude of control used everywhere except initially.

We mention here one confusing point in the article. Initial angle of attack, \(\alpha\), is supposed to be \(14^{\circ}\), yet in each of the three initial conditions given, \(\theta=r\), hence \(\alpha=0\).

In fact the condition that
\[
\ddot{h}(0)=\frac{V}{T_{S}}\left(\theta(0)-\frac{\dot{h}(0)}{V}\right)
\]
be zero requires that
\[
\alpha(0)=\theta(0)-\gamma(0)=\theta(0)-\frac{\dot{h}(0)}{V}=0
\]

Under these circumstances we deleted any consideration of \(\alpha\), though it will be found that if \(\alpha(\).\() is satisfactorily bounded in the article,\) it is also satisfactory in our runs.

To attack these problems, we needed a more flexible program; one capable of modifying the index weighting and the control gains. In addition we wanted more printout at the critical initial and terminal times. Using some hindsight we reran the problem with the program in Fig. 3, to check agreement with results using Fig. 1.

We then increased \(S\) (terminal weighting) by a factor of 100 by removing the two \(M U L T O T, S, S\) instructions, to improve terminal conditions. This affected the initial transient very little but gave the following terminal values.
\begin{tabular}{cccccc} 
I.C. & \(|u|_{\max }\) & \(\theta(20)\) & \(\mathrm{h}(20)\) & \(\dot{h}(20)\) & \(|\alpha|_{\max }\) \\
1 & .4 & 1.72 & -.007 & -.93 & 1.1 \\
2 & 16.1 & 1.73 & -.005 & -.93 & 1.8 \\
3 & 32.5 & 1.74 & -.003 & -.94 & 3.
\end{tabular}

This now looks very satisfactory except for the large control excursions. Notice that with increased weighting terminal conditions appear independent of initial conditions.

We then attempted to reduce the control requirement by reducing \(Q\) in the early part of the run, using the program in Fig. 4. This reduced \(Q\) by a factor of \(10^{-3}\) on \([1,2]\) and by an additional \(10^{-3}\) on \([0,1]\), and gave the following results:
\begin{tabular}{cccccc} 
I.C. & \(|u|_{\max }\) & \(\theta(20)\) & \(h(20)\) & \(\dot{h}(20)\) & \(|\alpha|_{\max }\) \\
1 & -13.0 & 1.73 & -.006 & -.93 & -4.8 \\
2 & 3.3 & 1.73 & -.007 & -.93 & 2.5 \\
3 & 19.1 & 1.73 & -.007 & -.93 & 6.2
\end{tabular}

Since we have lowered \(Q\) by a factor of \(10^{-6}\) and still have a fairly significant gain matrix, we infer that \(F\) has at least one unstable eigenvalue and therefore \(K\) cannot be indefinitely reduced by reducing Q. Despite the fact that \(u\) is within the bounds, - \(35^{\circ} \leqq u \leqq 15\), prescribed, we would like to show what can be done in such a case if the bounds were, e.g. \(-8^{\circ} \leqq u \leqq 8^{\circ}\).

An optimal system cannot be made to satisfy because \(K\) cannot be sufficiently reduced, but an ad hoc procedure of reducing \(u\) to the bound may very well provide the answer. This is particularly true in a case such as this where most of the control magnitude is used in the initial surge. To approwimate the effect of control stops we used the program in Fig. 5, multiplying \(K\) by \(\lambda(t)(\lambda(0)=.37, \lambda(.7)=1)\) before computing control. This gave the following results:
\begin{tabular}{cccccc} 
I.C. & \(|\mathrm{u}|_{\max }\) & \(\theta(20)\) & \(\mathrm{h}(20)\) & \(\dot{\mathrm{h}}(20)\) & \(|\alpha|_{\max }\) \\
1 & -4.6 & 1.73 & -.006 & -.933 & -2.2 \\
2 & 2.8 & 1.73 & -.007 & -.933 & 2.6 \\
3 & 7.8 & 1.74 & -.007 & -.934 & 5.4
\end{tabular}

The altitude profiles for this run appear in Fig. 6, in Fig. 7 and 8 we give plots of \(k_{3}\) and \(k_{4}\) as we computed them from Fig. 1 and for the final run (K modified) as computed from Fig. 5.

3B. The Specific Problem: This is an aircraft problem received in a private communication from J. S. Tyler, Jr. It is very similar to the one described in J. S. Tyler, Jr., "The Characteristics of Model-Following Systems as Synthesized by Optimal Control," IEEE Trans. on Automatic Control, vol. AC-9, No. 4, October, 1964.

The plant is specified by
\[
F=\left[\begin{array}{cccc}
0 & 1 & 0 & 0 \\
0 & -2.93 & -4.75 & .78 \\
.086 & 0 & -.11 & -1 . \\
0 & -. .049 & 2.59 & -.39
\end{array}\right]
\]
\[
G=\left[\begin{array}{cc}
0 & 0 \\
0 & -3.91 \\
.035 & 0 \\
-2.53 & .31
\end{array}\right]
\]
and the model by
\[
L=\left[\begin{array}{cccc}
0 & 1 & 0 & 0 \\
0 & -1 . & -73.14 & 3.18 \\
.086 & 0 & -.11 & -1 . \\
.0086 & .086 & 8.95 & -.49
\end{array}\right]
\]

We define the performance index by
\[
\int_{0}^{\infty}\left[\|y\|_{a}^{2}+\|u\|^{2}\right] d t
\]
where \(y=H x\),
\[
H=\left[I_{4},-I_{4}\right] \text { and }
\]
\[
Q=5 I_{4}
\]
4.B Results: Let \(K_{f b}, K_{f f}\) denote respectively the gain matrices from the plant and from the model. Then tyler gives the values
\[
\begin{aligned}
& K_{f b}=\left[\begin{array}{cccc}
.253 & -.185 & 1.58 & -2.34 \\
-2.21 & -1.83 & .7 & .01
\end{array}\right] \\
& K_{f f}=\left[\begin{array}{rrrr}
.104 & .377 & -3.63 & 4.16 \\
2.035 & 2.211 & -15.3 & 2.59
\end{array}\right]
\end{aligned}
\]

Using the program appearing in Fig. 9, we calculate the matrices
\[
\begin{aligned}
& K_{f b}=\left[\begin{array}{rrrr}
-.253 & -.185 & 1.584 & -2.342 \\
-2.214 & -1.827 & .700 & .010
\end{array}\right] \\
& K_{f f}=\left[\begin{array}{rrrr}
.104 & .377 & -3.630 & 4.161 \\
2.035 & 2.211 & -15.309 & 2.589
\end{array}\right]
\end{aligned}
\]


Fig. 1


Fig. 1


Fig. 1

MULT PR.XO. 32.
\(\begin{array}{lrr}\text { MULT } & \text { TI } 32 & \times \\ \text { MULT } & \text { K.32 } & -U\end{array}\)
MULT K,TR, TKR
RINT T2, KR, K \(X, X-U,-U\)
WRITE THE PRECEDING WERE \(K, X\), AND \(-U\) AT FINAL TIME.


Fig. 1


Fig. 1

\(\qquad\)
\(\qquad\)
\(\qquad\)

\(\qquad\)


\(\qquad\)

Fig. 1



Fig. 3


Fig. 3


\section*{Fig. 3}


Fig. 3


Fig. 3


Fig. 3


Fig. 3


Fig. 3
\begin{tabular}{|c|c|c|}
\hline \multicolumn{3}{|l|}{1.} \\
\hline LM & 1 & 1 \\
\hline \multicolumn{3}{|l|}{1.} \\
\hline L.M & 1 & 1 \\
\hline \multicolumn{3}{|l|}{1.} \\
\hline LM & 1 & 1 \\
\hline \multicolumn{3}{|l|}{1.} \\
\hline LM & 1 & 1 \\
\hline \multicolumn{3}{|l|}{1.} \\
\hline LM & 1 & 1 \\
\hline \multicolumn{3}{|l|}{1.} \\
\hline LM & 1 & 1 \\
\hline
\end{tabular}

Fig. 3


Fig. 4



Fig. 4



Fig. 4

RINT T, *7.INF
ADD T1.T2 T3
MULT \(.5 . T 3 \mathrm{HT}\)
SUBT HI. T TU
ETPHI CF.TU.PH.
MULT PH: XO XO.
EGUAT HT, T.
IF TleTL CHEAD 2 HEAD 7
HEAD 9SUBT T1. T. TU.
ETPHI CF.TU.PH.
MULT PH, XO, XO,
EQUAT T1. T.
BRING 7 T,T1,CF,CF, K. K, T,T2,
IF T.TM,HEAO23
LOAD LM
MULT LM.K.K.K
MULT G K GK

SUBT E GK CF
HEAD23BSR 77
\(A D D\) T1.T2. T3
MULT .5.T3. HT
SUBT HT. Te TU.
ETPHI CF,TU,PH,
MULT PHEXO. XO.
EQUAT HT, T,
IF T1,TL,HEAD 12HEAD 7
HEAD12BRING 7CF,CF.K. K, T,T2,
SUBT T2. T, TU.
ETPHI CF,TU,PH.
MULT PHEXO: 32.
MULT TI \(32 \times\)
MULT K. \(32 \ldots-U\)
MULT K,TR. KR
MULT \(H \quad X \quad H X\)
RINT T2, KR, \(K X, X-U,-U H X A L\)
WRITE THE PRECEDING WERE K. \(X_{C}\) AND \(-U\) AT FINAL TIME.
END

\(\begin{array}{rrr}11 & 1 & 1 \\ & 17.5 & \\ T 2 & 1 & 1\end{array}\)
12.5

Fig. 4




Fig. 4
\begin{tabular}{|c|c|c|}
\hline \[
\begin{gathered}
1 \\
ـ
\end{gathered}
\] & 1 & 1 \\
\hline \[
\begin{aligned}
& 1 . \\
& L M
\end{aligned}
\] & 1 & 1 \\
\hline \[
\begin{gathered}
1 . \\
ـ 1 \\
\hline
\end{gathered}
\] & 1 & 1 \\
\hline \[
\begin{gathered}
10 \\
\text { b. } M
\end{gathered}
\] & 1 & 1 \\
\hline \[
\begin{aligned}
& 10 \\
& L M
\end{aligned}
\] & 1 & 1 \\
\hline \[
\begin{aligned}
& 1 . \\
& \mathrm{L}
\end{aligned}
\] & 1 & 1 \\
\hline \[
\begin{gathered}
1 \\
\mathrm{~L}
\end{gathered}
\] & 1 & 1 \\
\hline 1. & & \\
\hline
\end{tabular}

Fig. 4

JUNE 28. 1965
begin
\(\begin{array}{ll}\text { REW } & 5 \\ \text { REW } & 6 \\ \text { WEF } & 5\end{array}\)
LOAD F. G.T1.T2.F1.G1.T3.20.DT.IS. Q.O1.TO.DS.ON
\(\begin{array}{ll}\text { REW } & 5 \\ \text { WFF } & 6\end{array}\)
SAVE ST1. T, F, F, G. G. Q. Q.TZ, T.Fi. F.G1, G.Q1, Q,T3. T.
REW \(\quad 6\)
SUBT 20.TQ 20
SAVE 620 T
SUBT 20.TQ 20
SAVE 620 T
SUBT 20,TQ 20
SAVE 620 T
SUBT 20.TQ 20
SAVE G20 T
SUBT 20,TQ 20
SAVE 620 T
HEAD2ISUBT 20.DT. 20
SAVE 620. T.
IF 20.TS.HEAD21
HEAD22SUBT 20.0S. 20
SAVE 620. T.
IF 20.ONTHEAD22
SUBT 20.TQ 20
SAVE 620, T
SAVE 620, T
SUBT 20.TQ 20
SAVE 620, T
SUBT 20.TQ 20
SAVE 620. T
SUBT 20.TQ 20
SAVE 620.I
SUBT 20,TQ 20
SAVE 620. T
SAVE 620. T
SUBT 20.TQ 20
SAVE 620. T
SUBT 20.TQ 20
SAVE 620. T
SAVE 620. T
SUBT 20,TQ. 20.
SAVE 620, T
SUBT 20.TQ, 20,
SAVE 620. T
SUBT 20.TQ, 20,
SAVE 620, T
SUBT 20.TQ. 20 .

Fig. 5


Fig. 5

EQUAT PI, T.ON.CD,
SUBT TF. T. TU. EQUAT T.TF,
ETPHI PH TU.PI, HT,
MULT TU D3 34
MULT HT.D2. 35.
ADD \(34 \quad 35 \quad 34\)

RINT S, P
IF ZO.ZO.HEAD 8
HEAD 5BRING \(5 \mathrm{~T}, \mathrm{~T} 1, F, F \quad G \quad G \quad Q \quad Q \quad T \mathrm{~T} 2\)
RINT Tl. T
MULT IT, Q, 32,
MULT 32 TI 0.
MULT OT \(Q \quad Q\)
MULT OT 0 O
BSR 15
MULT TR.F. 32
MULT 32 TI F
MULT IR G G
MULT G K GK
SUBT GK GF
SAVE TCF,CF, K, K, T, T,
HEAD 1 SUBT ZR. F. ME.
TRANP G GT,
MULI RIGGT, \(C\),
MULT G.C, GC,
JUXTC MF,GC. TP
TRANP \(F\), \(F T\),
JUXTC Q.FT, BT,
JUXTR TP, BT, PH,
ADD TleT2, T1.
MULT •5.T1. T2
HEAD GIF PI.TZ,HEAD 2 EQUAT TZ, T,ZO,CD,
IF ZO,ZO.HEAD 3
HEAD 2EQUAT PI, T.ON.CD
HEAD 3SUBT TF, T, TU,
EQUAT T,TF。
ETPHI PH,TU,P1.HT,
MULT TU.D3. 34
MULT HT D2 35
ADD \(3435 \quad 34\)
RICAT S P1, C.34,PC, S. K,AL,
HEAD BMULT G.K, GK,
SUBT. F.GK, CF.
SAVE TCF,CF, K, K, T, T,
IF TW. T.HEAD 4
HEADIOIF •5,CD.HEAD 5
BRING 6 T.PI,
IF ZO.ZO.HEAD 6
\(\begin{array}{rrrrr}\text { HEAD } & \text { 4MULT } & O N & Q & Q \\ & \text { MULT } & O T & Q & Q\end{array}\)

A PRINT TIME MUST COME BETWEEN TL AND THE LAST BREAK TIME.
-



HEAD24BSR 77
SUBT TZ. T. TU.
ETPHI CF TU,PH,
MULT PHeXO. XO.
EQUAT TZ. T.

MULT K.XO.
MULT K,TR, KR,
MULT \(H \quad X \quad H X\)
JUXTR KR,RZ1 *4.
JUXTR *5 RZ 25
JUXTR Z5.HX Z6
JUXTR Z7 -U *7

Fig. 5
\begin{tabular}{lcc} 
RINT & T, & *7.INF \\
ADD & Ti.T2 & T3 \\
MULT & \(.5 . T 3\) & HT
\end{tabular}

SUBT HT. T T
ETPHI CF,TU,PH,
MULT PHOXO XO.
EQUAT HT, T.
IF TI.TL HEADIZHEAD 7
head gsubt ti, T, tu,
MTPHI CF.TU.PHe
EQUAT TH. T.
BRING 7 T,T1,CF,CF,K, K, T,T2,
IF I.TMAHEAD23
LOAD L.M
MULT LM.K. K K
MULT G K GK

SUBT F GK CF
HEAD23BSR 77
ADD T1.T2, T3.
MULT •5.T3, HT
SUBT HT, T. TU.
ETPHI CF.TU.PH.
MULT PH,XO, XO.
EQUAT HT, T,
IF T1.TLoHEAD12HEAD 7
```

HEAD12BRING 7CF.CF, K, K, T.T2,

```
SUBT TZ. T, TU,
ETPHI CF,TU,PH.

MULT PH,XO, 32,
MULT TI 32 • \(\times\)
MULT K,32 -U
MULT K,TR, KR
MULT \(H \quad X \quad H X\)
RINT TZ, KR. \(K \quad x\), \(X-U,-U H X A L\)
WRITE THE PRECEDING WERE \(K, ~ X\), AND \(-U\) AT FINAL TIME.
END


F'ig. 5


Fig. 5

\(\begin{array}{ccc}\text { CW } & 1 & 1 \\ \text { TL } 2.005 & 1 & 1 \\ R L & 20 . & \\ 100 & 1 & 1 \\ S & 6 & 6\end{array}\)


Fig. 5


Fig. 5


Fig. 5





Fig. 9



Fig. 9```


[^0]:    | EXPONFNT | 0 |  |  |  |
    | :--- | :--- | :--- | :--- | :--- | :--- |
    |  |  |  |  |  |
    | 1.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
    | 0.0000 | 1.2840 | 0.0000 | 0.0000 | 0.0000 |
    | 0.0000 | 0.0000 | 1.0487 | 0.8244 | 0.0000 |
    | 0.0000 | 0.0000 | 1.0000 | 1.0487 | 0.0000 |
    | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 2.7183 |


    $0.0000 \quad 1.2840 \quad 0.0000 \quad 0.0000$. | 0.0000 | 0.0000 | 1.0487 | 0.8244 |
    | :--- | :--- | :--- | :--- |
    | 0.0000 |  |  |  |
    | 0.0000 | 0.0000 | 1.0000 | 1.0487 |
    | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

[^1]:    $\square$

[^2]:    FIG. 56

[^3]:    

    - 6.79999 g97E U1 0.59999998 E O1
    $-0.19199999 \mathrm{EX}$
    10 $3666668+100$ 0.255999995 OL
    

    $$
    0.24 y 99 \dot{9} 99 E^{-0} 02
    $$

    U. $39999998 \mathrm{~L}-0 \mathrm{l}$
    0.94954990 E 00
    $-0.31994999 t-00$
    0.23999999E-00

    $$
    -0.78999991 E \cup 1
    $$

    $$
    0.59999998 \mathrm{E} \text { O1 }
    $$

[^4]:    *We may do this as follows: We pick $x(T)$ arbitrarily, set $p(T)=\lambda_{x}(T, x(T))$ and then integrate (4.5) from $T$ toward $\tau$.

