

12-1-1984

# A Study of a Semi-Direct Method for Computer Analysis of Large-Scale Circuits

Marwan M. Hassoun  
*Purdue University*

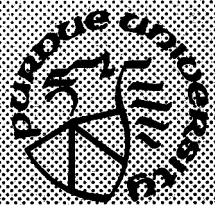
P. M. Lin  
*Purdue University*

Follow this and additional works at: <https://docs.lib.purdue.edu/ecetr>

---

Hassoun, Marwan M. and Lin, P. M., "A Study of a Semi-Direct Method for Computer Analysis of Large-Scale Circuits" (1984).  
*Department of Electrical and Computer Engineering Technical Reports*. Paper 530.  
<https://docs.lib.purdue.edu/ecetr/530>

This document has been made available through Purdue e-Pubs, a service of the Purdue University Libraries. Please contact [epubs@purdue.edu](mailto:epubs@purdue.edu) for additional information.



**FILE**

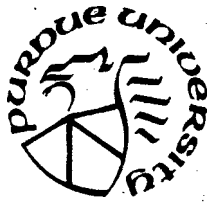
# **A Study of a Semi-Direct Method for Computer Analysis of Large-Scale Circuits**

**M.M. Hassoun  
P.M. Lin**

**TR-EE 84-46  
December 1984**

**School of Electrical Engineering  
Purdue University  
West Lafayette, Indiana 47907**

**This work was supported by: International Business Machines  
Corporation**



# A Study of a Semi-Direct Method for Computer Analysis of Large-Scale Circuits

M.M. Hassoun  
P.M. Lin

TR-EE 84-46  
December 1984

This work was supported by: International Business Machines  
Corporation

## ACKNOWLEDGEMENTS

We wish to thank the Computer Aided Circuit Design Department, at IBM East Fishkill Facility, for the financial support of the research which has resulted in a master's thesis for M. M. Hassoun. The thesis is hereby reproduced as a technical report for the third year effort of the research project.

## TABLE OF CONTENTS

	Page
ABSTRACT .	
CHAPTER 1 - INTRODUCTION.....	1
CHAPTER 2 - THE NEWTON-RAPHSON METHOD.....	4
2.1 Scalar Equations .....	4
2.2 Vector Equations.....	10
2.3 Convergence .....	12
CHAPTER 3 - THE GAUSS-SEIDEL METHOD .....	16
3.1 The Algorithm.....	16
3.2 Convergence.....	18
CHAPTER 4 - TEARING AND EQUATION FORMULATION.....	28
4.1 Tearing Techniques.....	30
4.2 Modified Nodal Analysis.....	32
4.3 Equation Formulation .....	34
4.4 A Newton-Raphson Algorithm for Bordered Block-Diagonal Matrices .....	40
CHAPTER 5 - THE SEMI-DIRECT METHOD .....	46
5.1 Algorithm.....	46
5.2 Convergence.....	54

<b>CHAPTER 6 - COMPARISON BETWEEN THE NEWTON-RAPHSON AND THE SEMI-DIRECT METHODS .....</b>	<b>76</b>
6.1 Storage .....	76
6.2 Execution Time.....	84
<b>CHAPTER 7 - TRANSIENT ANALYSIS .....</b>	<b>94</b>
7.1 Integration Methods .....	95
7.2 Application of the Semi-Direct Method.....	97
<b>CHAPTER 8 - CONCLUSIONS .....</b>	<b>103</b>
<b>LIST OF REFERENCES .....</b>	<b>105</b>
<b>APPENDICES</b>	
APPENDIX A - Program Listings.....	108
APPENDIX B - Results for Examples 7.1 and 7.2.....	143

## ABSTRACT

Hassoun, Marwan M. M.S., Purdue University. December 1984. A STUDY OF A SEMI-DIRECT METHOD FOR COMPUTER ANALYSIS OF LARGE-SCALE CIRCUITS. Major Professor: P. M. Lin.

In this thesis a study of a Semi-Direct method for the solution of large scale circuits is presented. The method combines features from the Newton-Raphson method and the Gauss-Seidel method. These two methods are both illustrated. The Semi-Direct method is presented both theoretically and empirically using three programs developed for this purpose. The Semi-Direct method and the Newton-Raphson method are compared. The comparison includes speed (number of iterations and execution time) and storage requirements. The Semi-Direct method definitely has storage advantages over the Newton-Raphson method at all circuit levels of 2 or more nodes. If some set conditions are met in the circuit, the Semi-Direct method will require less CPU time to reach the solution than the Newton-Raphson method.

## CHAPTER 1

### INTRODUCTION

The size of circuits has been growing at a rapid rate in the past two decades. The new technologies and advances in integrated circuits has supported this growth. The task of analyzing such large circuits using computer analysis programs involves two basic considerations, speed and storage. The larger the circuit, the more variables: node voltages, and branch currents. Therefore, memory storage requirements are increased, and grow quadratically with the number of variables in the circuit. To solve a circuit with  $n$  variables we need  $n$  characteristic equations that describe the circuit. A lumped nonlinear circuit can be characterized in the time domain by a set of differential algebraic equations of the form

$$\mathbf{f}(\mathbf{x}, \dot{\mathbf{x}}, t) = 0 \quad (1.1)$$

where  $\mathbf{x}$  is, as considered in this report, the vector of node voltages and branch currents. These variables are functions of time  $t$  (the case where  $\mathbf{x}(t) = \text{constant}$  is possible). The  $\dot{\mathbf{x}}$  vector is the derivative of  $\mathbf{x}$  with respect to  $t$ .

The formulation of these equations from a large scale circuit involves the task of decomposing it into several smaller subcircuits. This is done because it is easier and less time consuming to solve these subcircuits individually and then interconnect the solutions. Other advantages are that similar subcircuits have to be solved only once and the latency and near-latency of the subcircuits



can be exploited [14]. Several tearing techniques have been proposed [9,17]. The node tearing technique [17] has become the most popular one used.

The solution of the equations eq. (1.1) can be reached using two approaches: direct and semi-direct. The latter methods are sometimes referred to as relaxation methods [15]. The solution of eq. (1.1) at successive time points would produce a wave for each variable with respect to time. The process is called transient analysis. A special case of eq. (1.1) would be when all variables are independent of time (all input sources are constant). For the majority of practical circuits, there is only one solution point, the process is called dc analysis. The variable  $t$  would not be involved in the process.

In the transient analysis case the variables in  $\dot{\mathbf{x}}$  are replaced by an implicit and stiffly stable integration formulas. A widely used method is the backward differentiation formula (BDF) introduced in [2]. After substituting the BDF formula in eq. (1.1) for  $\dot{\mathbf{x}}$  the solution at times  $t_0, t_1, t_2 \dots$  is to be obtained. The process involves setting  $t = t_i$  and then using an iterative scheme to solve the resulting nonlinear algebraic equations. The solution at  $t_i$  is obtained and stored away or outputted. The values of  $\mathbf{x}$ ,  $\dot{\mathbf{x}}$  and  $t$  are then updated for  $t_{i+1}$  and the iterative scheme is repeated. The process at a certain time point resembles a dc analysis case. The collection of these dc-like solutions produce the waveform with respect to time. This approach is called "incremental in time". An early termination of the process does not affect the validity of the solutions at previous time steps. Another approach called "Global in time" or "waveform relaxation" [10] gradually updates the waveform over the whole time interval. The acceptable solution reached is for the entire time interval. Termination of the process before its completion does not validate the solution for any time point. Methods using the global in time approach have only

recently been used successfully with MOS digital circuits. Most simulation programs use the incremental in time approach for transient analysis.

In this thesis an incremental in time semi-direct method proposed by Odeh and Zein [15] is studied. It is referred to from this point on as the Semi-Direct method. The algorithm and its convergence properties are discussed in Chapter 4. In Chapter 5 a dc analysis comparison between the conventional Newton-Raphson method and the Semi-Direct method is studied. Chapter 6 includes a similar comparison for the transient analysis case where the advantages of the Semi-Direct method are clear. Five programs written in FORTRAN were developed for the purpose of this study, two for the dc analysis case, one implementing the Newton-Raphson method and the other implementing the Semi-Direct method, two more for the transient case and the last for the convergence properties of the Semi-Direct method. These programs are listed in the appendix. Chapters 1 and 2 are dedicated to the illustration of the basic building blocks of the Semi-Direct method, the Newton-Raphson method and the Gauss-Seidel method.

## CHAPTER 2

### THE NEWTON-RAPHSON METHOD

The Newton-Raphson method or simply the Newton method is one of the most well-known and widely used numerical methods to solve a set of (linear or nonlinear)  $n$  equations (where  $n = 1, 2, 3 \dots$ ). The case where  $n = 1$  is the scalar case, that is, one equation in one unknown. The solution to such an equation can be obtained analytically if it was linear, quadratic, cubic or even quartic. A solution formula does exist for these cases, but by the time we get to the cubic case the equation becomes too long and cumbersome. We resort to an iterative scheme to get the solution, usually for equations of degree three or higher. The scalar case ( $n = 1$ ) gives an intuitive way of how the Newton method works.

#### 2.1 Scalar Equations

Any equation can be written in the form

$$f(x) = 0 \tag{2.1}$$

where the only unknown is  $x$ . Let  $r$  be a valid solution for equation (1.1), that is,  $r$  satisfies  $f(r) = 0$ . The Newton algorithm to find  $r$  consists of repeated solutions of the following iterative formula [5]:

$$x^{i+1} = x^i - \frac{f(x^i)}{f'(x^i)} \quad (2.2)$$

where  $i = 0, 1, 2, \dots$   $x^0$  is the initial guess and  $x^i$  is the value of  $x$  in the  $i^{\text{th}}$  iteration.

This formula can be derived from the Taylor polynomial expansion for  $f(x)$  about  $r$  (see [3]), or by a geometric interpretation of the iterations as shown below and illustrated in Figure 2.1.

$$\tan \theta = f'(x^1) = \frac{f(x^1)}{x^1 - x^2} \quad (2.3)$$

equation (2.3) can be written

$$x^2 = x^1 - \frac{f(x^1)}{f'(x^1)} \quad (2.4)$$

Sequential application of equation (2.4) can be produced in the form of equation (2.2).

For an initial guess  $x^0$  the Newton iteration can converge, diverge or oscillate between two points. This is illustrated in Figures (2.2), (2.3) and (2.4) respectively.

The termination of the Newton iterations is based on two criteria:

- 1) The absolute increment, and
- 2) The number of iterations

The absolute increment is defined as

$$e^i = |x^{i+1} - x^i| \quad (2.5)$$

where  $i = 0, 1, 2, \dots$  is the iteration number.

So for a user specified absolute increment criterion "e" the iterations can be terminated when  $e^i < e$ . A problem may arise though if the iterations are

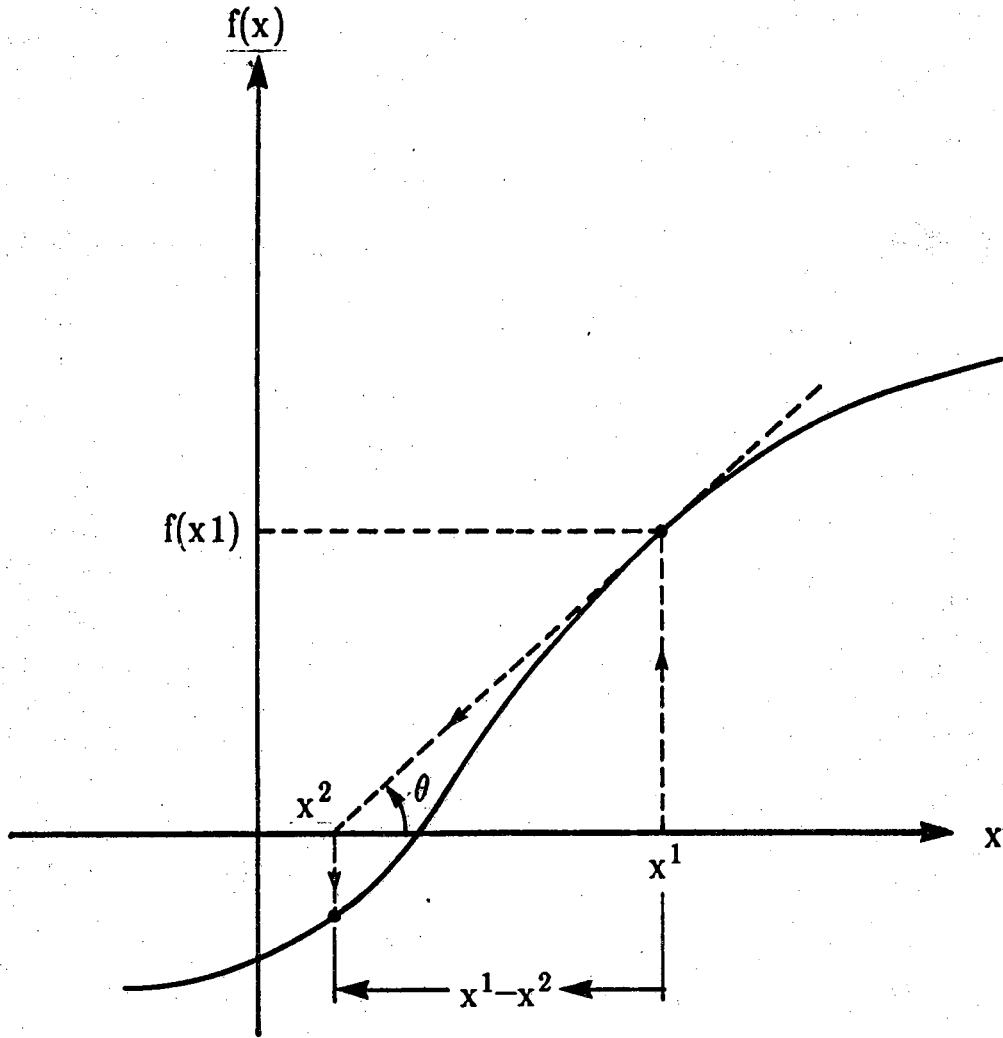


Figure 2.1: Geometric interpretation of scalar case.

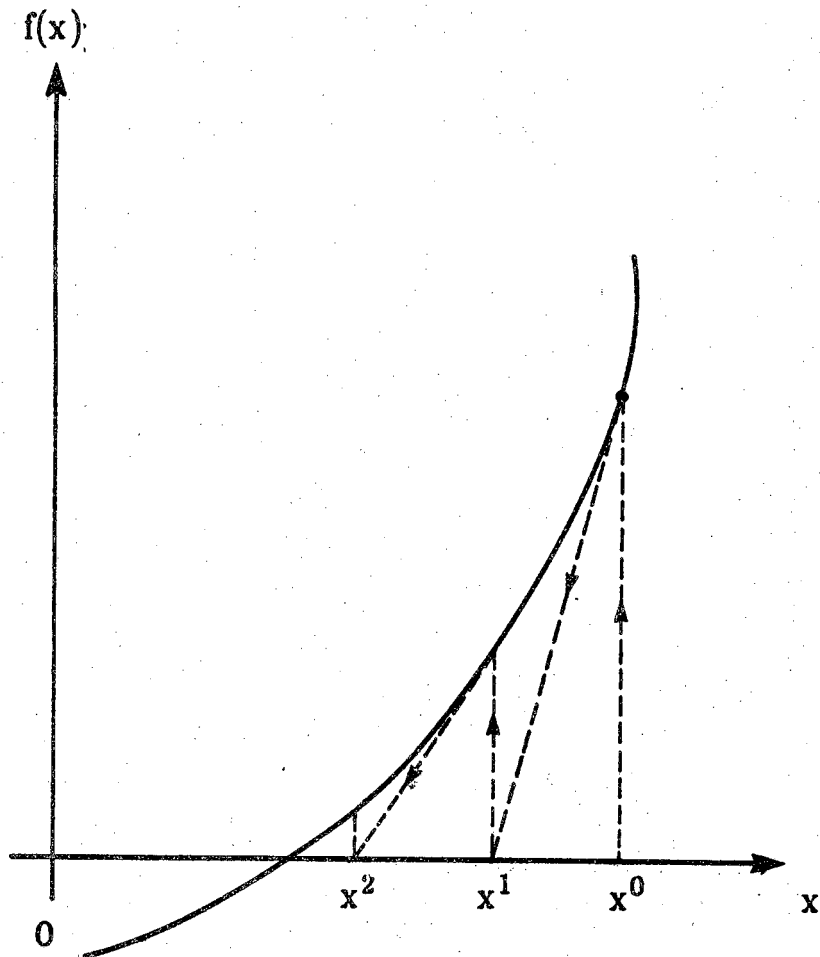


Figure 2.2: Convergent case.

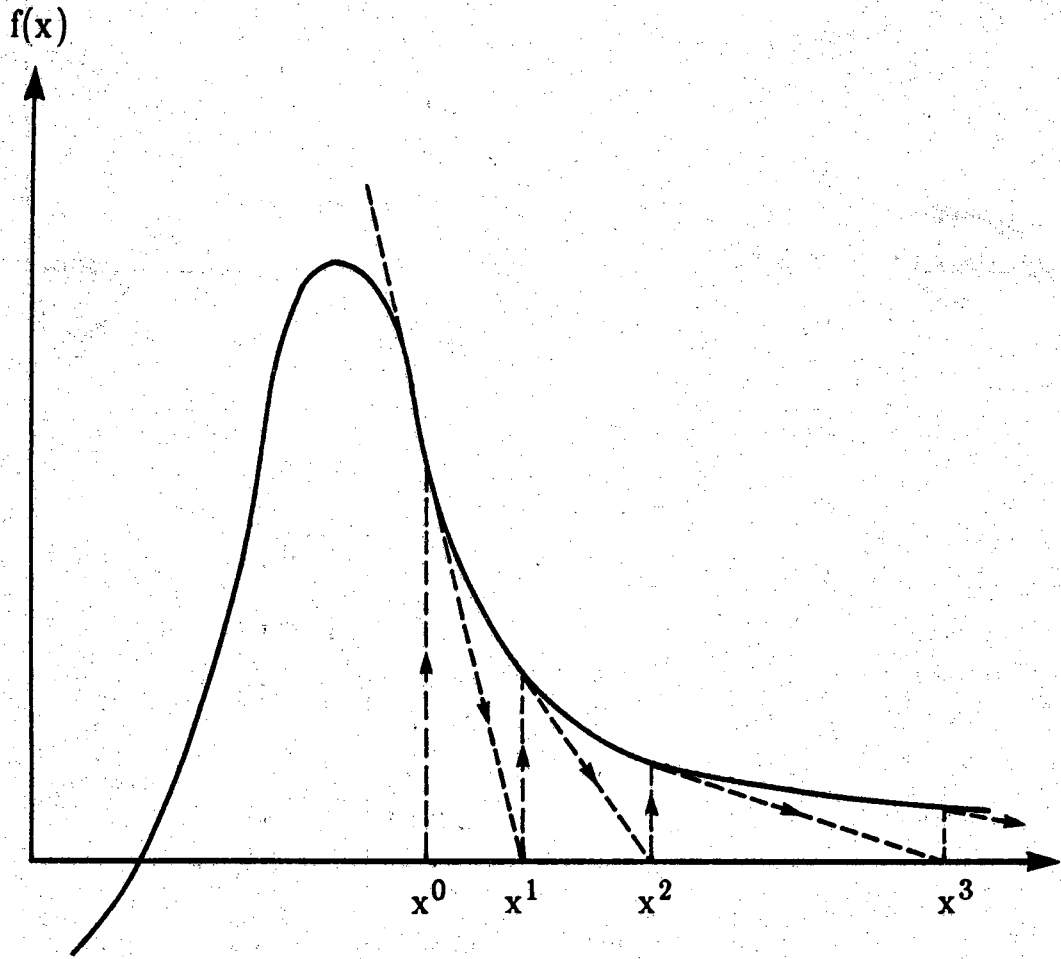


Figure 2.3: Divergent case.

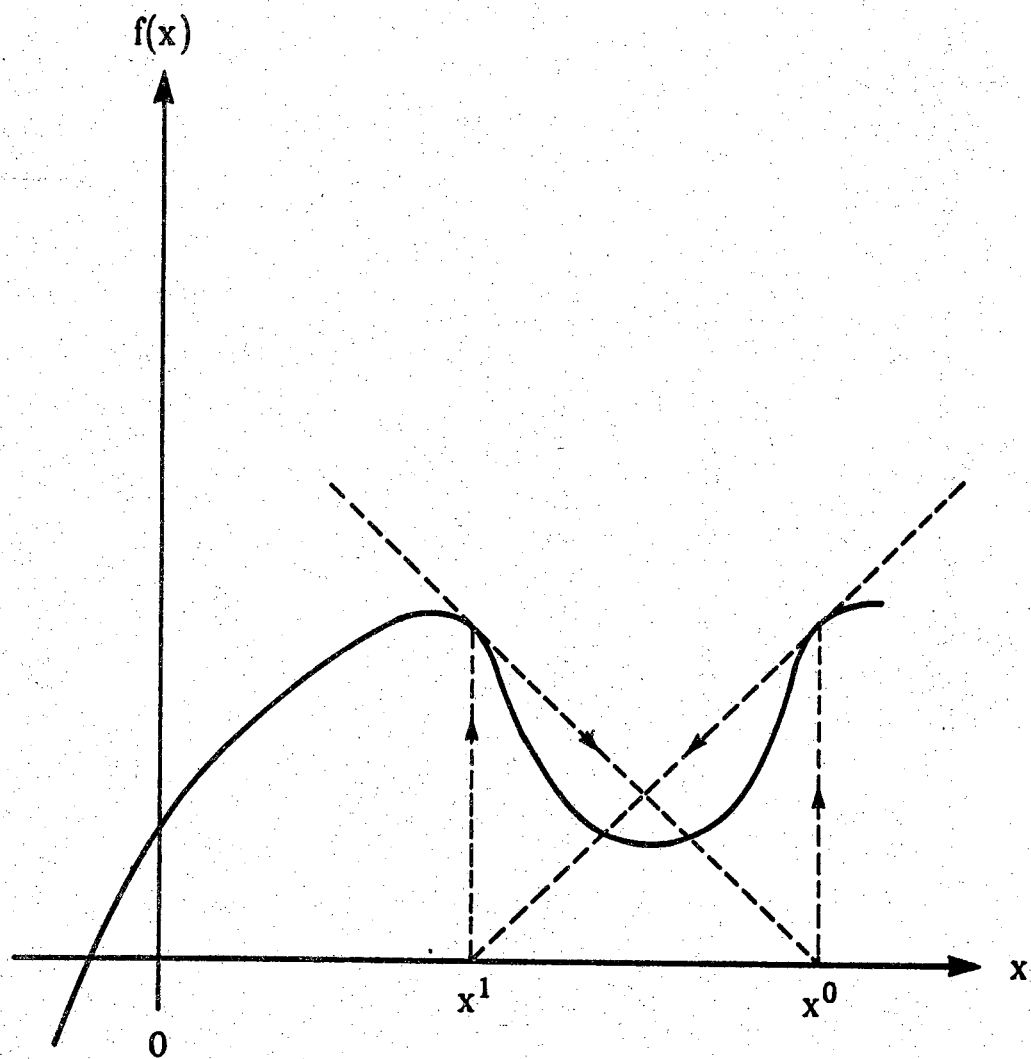


Figure 2.4: Oscillatory case.



diverging or oscillating, the absolute increment would be increasing or stay constant, respectively. In this case, the second criterion takes effect. A user specified maximum number of iterations would terminate the process. Since the Newton algorithm in general has a quadratic rate of convergence (see sec. 2.3), if the algorithm does not converge after a number of iterations that depends on the problem, the initial guess and the machine on which the algorithm is running, then the iterations are not converging to the solution or is converging but not fast enough.

## 2.2 Vector Equations

The Newton algorithm is also used to solve a set of  $n$  equations in  $n$  unknowns provided there is a solution to the system. An intuitive geometric interpretation of the method does not exist on this level ( $n > 1$ ) like in the scalar case ( $n = 1$ ). The solution scheme is obtained by the use of Linear Algebra techniques. Consider the equations in the form:

$$\begin{aligned} f_1(x_1, \dots, x_n) &= 0 \\ f_2(x_1, \dots, x_n) &= 0 \\ &\vdots \\ f_n(x_1, \dots, x_n) &= 0 \end{aligned}$$

which in vector form can be written as

$$\mathbf{f}(\mathbf{x}) = 0 \tag{2.6}$$

The solution using Newton's algorithm is obtained by [11]:

$$\mathbf{x}^{i+1} = \mathbf{x}^i - \mathbf{J}^{-1}(\mathbf{x}^i)\mathbf{f}(\mathbf{x}^i) \tag{2.7}$$

where  $i = 1, 2, \dots$ ,  $\mathbf{x}^0$  is the initial guess vector, and

$$\mathbf{J}(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_2}{\partial x_2} & \dots & \frac{\partial f_1}{\partial x_n} \\ \frac{\partial f_2}{\partial x_1} & & & \\ \vdots & & & \\ \frac{\partial f_n}{\partial x_1} & & \dots & \frac{\partial f_n}{\partial x_n} \end{bmatrix} \quad (2.8)$$

is the Jacobian matrix of the system of equations. When implementing this scheme on a digital computer, finding an inverse of a matrix is quite cumbersome. It takes time and a lot of storage. To get around this we manipulate equation (2.7) moving  $\mathbf{x}^i$  to the left hand side and multiplying by  $\mathbf{J}(\mathbf{x})$ , assuming  $\mathbf{J}(\mathbf{x})$  is nonsingular

$$\mathbf{J}(\mathbf{x}^i) [\mathbf{x}^{i+1} - \mathbf{x}^i] = -\mathbf{f}(\mathbf{x}^i) \quad (2.9)$$

The above equation cannot be derived geometrically as explained earlier, but the use of the Taylor polynomial expansion would lead to the same iterative equation [11]. Let us define  $\Delta \mathbf{x}^i$  as:

$$\Delta \mathbf{x}^i = \mathbf{x}^{i+1} - \mathbf{x}^i \quad (2.10)$$

So equation (2.9) becomes

$$\mathbf{J}(\mathbf{x}^i) \Delta \mathbf{x}^i = -\mathbf{f}(\mathbf{x}^i) \quad (2.11)$$

This is in the form  $\mathbf{A}\mathbf{y} = \mathbf{b}$  which can be solved at each iteration using several numerical methods like Gaussian-back substitution or LU factorization methods. The LU factorization method was used in implementing the programs for this thesis. The method can be illustrated as follows [4]:

$$\mathbf{J}(\mathbf{x}) = \mathbf{LU} \quad (2.12)$$

and hence

$$\mathbf{L}(\mathbf{x}^i)\mathbf{U}(\mathbf{x}^i)\Delta\mathbf{x}^i = -\mathbf{f}(\mathbf{x}^i) \quad (2.13)$$

call

$$\mathbf{U}(\mathbf{x}^i)\Delta\mathbf{x}^i = \mathbf{y} \quad (2.14)$$

So we first solve

$$\mathbf{L}(\mathbf{x}^i)\mathbf{Y} = -\mathbf{f}(\mathbf{x}^i) \quad (2.15)$$

for  $\mathbf{y}$ , and then solve equation (2.14) for  $\Delta\mathbf{x}^i$ . The last step to compute  $\mathbf{x}^{i+1}$  we get from equation (2.10)

$$\mathbf{x}^{i+1} = \mathbf{x}^i + \Delta\mathbf{x}^i \quad (2.16)$$

The same stopping criteria are used as in the scalar case (sec. 2.2) but we have to define a different absolute increment. We use the 2nd norm of the vector  $\Delta\mathbf{x}^i$ , which is defined as [13]

$$\|\Delta\mathbf{x}^i\|_2 = ((\Delta x_1^i)^2 + (\Delta x_2^i)^2 + \cdots + (\Delta x_n^i)^2)^{1/2} \quad (2.17)$$

as the absolute increment and we check if  $\|\Delta\mathbf{x}^i\|_2 < \epsilon$ , where  $\epsilon$  is the user specified absolute increment.

### 2.3 Convergence

One of the properties that makes the Newton method so widely used is that if the initial guess is sufficiently close to the true solution, then the algorithm converges and the rate of convergence is in general quadratic.

We show the quadratic convergence of the Newton algorithm using the Taylor series expansion for the case where  $\mathbf{f}'(\mathbf{r}) \neq \mathbf{0}$ . Let  $\mathbf{r}$  be a solution for  $\mathbf{f}(\mathbf{x}) = \mathbf{0}$  and let

$$x^{i+1} = g(x^i) \triangleq x^i - \frac{f(x^i)}{f'(x^i)} \quad (2.18)$$

so  $g(r) = r$  and we can write

$$x^{i+1} - r = g(x^i) - g(r) \quad (2.19)$$

Now expanding  $g(x^i)$  as a Taylor series in terms of  $(x^i - r)$  with the second-derivative term as the remainder:

$$g(x^i) = g(r) + g'(r)(x^i - r) + \frac{g''(\epsilon)}{2} (x^i - r)^2 \quad (2.20)$$

where  $\epsilon$  lies in the interval from  $x^i$  to  $r$ . Since

$$g'(r) = \frac{f(r)f'(r)}{[f'(r)]^2} = 0 \quad (2.21)$$

because  $f(r) = 0$ , we have

$$g(x^i) = g(r) + \frac{g''(\epsilon)}{2} (x^i - r)^2 \quad (2.22)$$

but  $g(x^i) = x^{i+1}$  and  $g(r) = r$  so by substituting back into equation (2.22) and letting  $x^i - r = \delta^i$  we get, (assuming  $g''(\epsilon) \neq 0$ ),

$$\delta^{i+1} = x^{i+1} - r = g(x^i) - g(r) = \frac{g''(\epsilon)}{2} (\delta^i)^2 \quad (2.23)$$

Let  $k = \frac{g''(\epsilon)}{2}$ ,

$$\delta^{i+1} = k(\delta^i)^2 \quad (2.24)$$

This says that the error in the  $i+1^{\text{th}}$  iteration is directly proportional to the square of the error at the  $i^{\text{th}}$  iteration. So when the iterations get close to the solution and  $\delta^i$  is less than 1,  $(\delta^i)^2$  becomes less than  $\delta^i$  and the quadratic convergence prevails.

Example 2.1:

As an example consider a system of two nonlinear equations  $f_1(x)$  and  $f_2(x)$  in two unknowns  $x_1$  and  $x_2$ .

$$f_1(x) = x_1^3 + 10x_1 + x_2 - 31$$

$$f_2(x) = 2(x_1 - x_2 - 1)^3 - x_2 + 19$$

the solution to this system is

$$x_1 = 2, \quad x_2 = 3$$

Using the Newton algorithm we first find the Jacobian matrix of the system

$$\mathbf{J}(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \frac{\partial f_1}{\partial x_2} \\ \frac{\partial f_2}{\partial x_1} & \frac{\partial f_2}{\partial x_2} \end{bmatrix}$$

where

$$\frac{\partial f_1}{\partial x_1} = 3x_1^2 + 10$$

$$\frac{\partial f_1}{\partial x_2} = 1$$

$$\frac{\partial f_2}{\partial x_1} = 6(x_1 - x_2 - 1)^2$$

$$\frac{\partial f_2}{\partial x_2} = -6(x_1 - x_2 - 1)^2 - 1$$

Solving by the use of equations (2.11), (2.16) and an initial guess  $x_1^0 = x_2^0 = 1$  produces the following results: where  $i$  is the iteration number and  $\Delta x$  is the increment ( $\Delta x = x^{i+1} - x^i$ ).

x 1	deltax 1	x 2	deltax 2
0. 100000e+01	0. 120619e+01	0. 100000e+01	0. 331959e+01
0. 220619e+01	-0. 209006e+00	0. 431959e+01	-0. 977583e+00
0. 199718e+01	0. 782370e-03	0. 334200e+01	-0. 297179e+00
0. 199796e+01	0. 199497e-02	0. 304483e+01	-0. 438442e-01
0. 199996e+01	0. 435395e-04	0. 300098e+01	-0. 981709e-03
0. 200000e+01	0. 214871e-07	0. 300000e+01	-0. 484090e-06
0. 200000e+01	0. 520838e-14	0. 300000e+01	-0. 117693e-12

To see the quadratic convergence rate we look at the delta x1 and delta x2 exponents starting at iteration 3. The exponents almost double after each iteration which is a quadratic relationship. We say almost because of the effect of the constant k in equation (2.24) and the fact that  $\text{deltax} = (x^{i+1} - x^i)$  not  $(x^{i+1} - r)$ .



$$\mathbf{Ax} = \mathbf{B} \quad (3.4)$$

The system will have a unique solution if and only if  $\det \mathbf{A} \neq 0$ . That matrix  $\mathbf{A}$  is called the coefficient matrix and its determinant, the coefficient determinant. There exist many iterative techniques to solve such a system of equations [3], but the Gauss-Seidel method is specifically useful if the coefficient matrix has many zero terms.

It is essential to assume that the diagonal elements of  $\mathbf{A}$  be non-zero for reasons we will see in the following. Let us solve the  $j^{\text{th}}$  equation of (3.3) for  $x_j$ .

$$\begin{aligned} x_1 &= \frac{1}{a_{11}} (b_1 - a_{12}x_2 - a_{13}x_3 - \cdots - a_{1n}x_n) \\ x_2 &= \frac{1}{a_{22}} (b_2 - a_{21}x_1 - a_{23}x_3 - \cdots - a_{2n}x_n) \\ &\vdots \\ x_n &= \frac{1}{a_{nn}} (b_n - a_{n1}x_1 - a_{n2}x_2 - \cdots - a_{n,n-1}x_{n-1}) \end{aligned} \quad (3.5)$$

The necessity for the diagonal of  $\mathbf{A}$  be non-zero is now obvious. The terms  $\frac{1}{a_{11}}, \frac{1}{a_{22}}, \dots, \frac{1}{a_{nn}}$  have to exist in order for the scheme to work. In the case where one or more of the diagonal elements is zero, a rearrangement of the order of the equations is possible in order to satisfy this condition.

The iteration process begins by a choice of an initial guess vector  $\mathbf{x}^0 = (x_1^0, x_2^0, \dots, x_n^0)^T$ . The first equation is evaluated using this initial guess and a new value for  $x_1$  is obtained,  $x_1^1$ . Now the second equation is evaluated using  $\mathbf{x}^0$  but with the  $x_1^0$  replaced by the updated value  $x_1^1$ . Therefore the choice of  $x_1^0$  has no effect on the iteration on the evaluation processes because it is actually never used. Now we have two updated values  $x_1^1$  and  $x_2^1$  resulting from the evaluations of the first two equations of (3.5). These updated values



and the rest of  $\mathbf{x}^0$  are used to evaluate  $x_3^1$  from the third equation, and the process continues. So when we reach the  $n^{\text{th}}$  equation the  $\mathbf{x}^0$  vector would be  $\mathbf{x}^0 = (x_1^1, x_2^1, x_3^1, \dots, x_n^0)^T$ .  $x_n^0$  is then evaluated and we have a new value for  $\mathbf{x}$  called  $\mathbf{x}^1 = (x_1^1, x_2^1, \dots, x_n^1)^T$ , and the first iteration is completed. The process is then repeated starting with the first equation again to obtain  $\mathbf{x}^2, \mathbf{x}^3, \dots$ . The termination of the process depends on two criteria:

- 1) The number of iteration equals or exceeds a user specified maximum number of iterations.
- 2) The second norm of  $\mathbf{x}^k - \mathbf{x}^{k-1}$  is less than a user specified increment  $e$  [13]. That is

$$\|\mathbf{x}^{i+1} - \mathbf{x}^i\| \triangleq ((x_1^{i+1} - x_1^i)^2 + (x_2^{i+1} - x_2^i)^2 + \dots + (x_n^{i+1} - x_n^i)^2)^{1/2} \quad (3.6)$$

less than  $e$ . Termination of the process under the first criterion means that the iterations are either diverging or converging at a very slow rate. Termination under the second criterion implies that the iterations are close enough to the true solution, that is, they are converging. The rate of convergence of the Gauss-Seidel method is linear. This is illustrated in the next section.

### 3.2 Convergence

The greatest advantage of the Newton-Raphson method is its unconditional convergence if the initial guess is chosen close enough to the true solution. This does not apply to the Gauss-Seidel method. The method is not always convergent. It will converge if, in the coefficient matrix, each term on the main diagonal is larger (in absolute value) than the sum of the absolute values of all the other terms in the same row [19]. That is,

$$|a_{ii}| > \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}| \quad \text{for all } i=1,2,\dots,n \quad (3.7)$$

will guarantee convergence of the iterations to the true solution. A matrix that satisfies equation (3.7) is said to have a dominant diagonal. So by rearranging the equations we can try to create a diagonal dominant coefficient matrix.

**Example 3.1:**

Consider the equations

$$x_1 + 3x_2 = 9$$

$$2x_1 + x_2 = 8$$

The solution to the system is known

$$x_1 = 3, \quad x_2 = 2$$

The coefficient matrix is  $\mathbf{A} = \begin{bmatrix} 1 & 3 \\ 2 & 1 \end{bmatrix}$ , obviously the diagonal elements do not satisfy equation (3.7). That is the diagonal is not dominant. Performing the iteration with  $\mathbf{x}^0 = (1,1)$

$$x_1 = 9 - 3x_2$$

$$x_2 = 8 - 2x_1$$

x 1	deltax 1	x 2	deltax 2
0. 100000e+01	0. 500000e+01	0. 100000e+01	-0. 500000e+01
0. 600000e+01	0. 150000e+02	-0. 400000e+01	-0. 300000e+02
0. 210000e+02	0. 900000e+02	-0. 340000e+02	-0. 180000e+03
0. 111000e+03	0. 540000e+03	-0. 214000e+03	-0. 108000e+04
0. 651000e+03	0. 324000e+04	-0. 129400e+04	-0. 648000e+04
0. 389100e+04	0. 194400e+05	-0. 777400e+04	-0. 388800e+05
0. 233310e+05	0. 116640e+06	-0. 466540e+05	-0. 233280e+06
0. 139971e+06	0. 699840e+06	-0. 279934e+06	-0. 139968e+07
0. 839811e+06	0. 419904e+07	-0. 167961e+07	-0. 839808e+07
0. 503885e+07	0. 251942e+08	-0. 100777e+08	-0. 503885e+08
0. 302331e+08	0. 151165e+09	-0. 604662e+08	-0. 302331e+09
0. 181399e+09	0. 906993e+09	-0. 362797e+09	-0. 181399e+10
0. 108839e+10	0. 544196e+10	-0. 217678e+10	-0. 108839e+11
0. 653035e+10	0. 326517e+11	-0. 130607e+11	-0. 653035e+11
0. 391821e+11	0. 195910e+12	-0. 783642e+11	-0. 391821e+12
0. 235092e+12	0. 117546e+13	-0. 470185e+12	-0. 235092e+13
0. 141055e+13	0. 705277e+13	-0. 282111e+13	-0. 141055e+14
0. 846333e+13	0. 423166e+14	-0. 169267e+14	-0. 846333e+14
0. 507800e+14	0. 253900e+15	-0. 101560e+15	-0. 507800e+15
0. 304680e+15	0. 152340e+16	-0. 609360e+15	-0. 304680e+16
0. 182808e+16	0. 914040e+16	-0. 365616e+16	-0. 182808e+17
0. 109685e+17	0. 548424e+17	-0. 219370e+17	-0. 109685e+18
0. 658109e+17	0. 329054e+18	-0. 131622e+18	-0. 658109e+18
0. 394865e+18	0. 197433e+19	-0. 789730e+18	-0. 394865e+19

Clearly the iterations are diverging. If we rearrange the equations as follows:

$$2x_1 + x_2 = 8$$

$$x_1 + 3x_2 = 9$$

so that  $A = \begin{bmatrix} 2 & 1 \\ 1 & 3 \end{bmatrix}$  has a dominant diagonal, we have

$$x_1 = \frac{8-x_2}{2}$$

$$x_2 = \frac{9-x_1}{3}$$

Use  $x^0 = (1,1)$  we get

x 1	deltax 1	x 2	deltax 2
0. 100000e+01	0. 250000e+01	0. 100000e+01	0. 833333e+00
0. 350000e+01	-0. 416667e+00	0. 183333e+01	0. 138889e+00
0. 308333e+01	-0. 694444e-01	0. 197222e+01	0. 231481e-01
0. 301389e+01	-0. 115741e-01	0. 199537e+01	0. 385802e-02
0. 300231e+01	-0. 192901e-02	0. 199923e+01	0. 643004e-03
0. 300039e+01	-0. 321502e-03	0. 199987e+01	0. 107167e-03
0. 300006e+01	-0. 535837e-04	0. 199998e+01	0. 178612e-04
0. 300001e+01	-0. 893061e-05	0. 200000e+01	0. 297687e-05
0. 300000e+01	-0. 148844e-05	0. 200000e+01	0. 496145e-06
0. 300000e+01	-0. 248073e-06	0. 200000e+01	0. 826909e-07
0. 300000e+01	-0. 413454e-07	0. 200000e+01	0. 137818e-07
0. 300000e+01	-0. 689090e-08	0. 200000e+01	0. 229697e-08

The iterations converge to the true solution on 11th iteration (accurate to 8 digits that is  $e = 10^{-9}$ ).

The condition of diagonal dominance is a sufficient but not a necessary one. A set of equations with a coefficient matrix  $A$  not satisfying equation (3.7) could converge. Example 3.2 illustrates that.

Example 3.2:

Consider the equations with solution  $x_1 = 2$  and  $x_2 = 3$

$$8x_1 + 3x_2 = 25$$

$$7x_1 + 7x_2 = 26$$

The coefficient matrix  $A = \begin{bmatrix} 8 & 3 \\ 7 & 4 \end{bmatrix}$  does not have a dominant diagonal since  $a_{22} < a_{21}$ . Solving the system using the Gauss-Seidel method with initial guess  $\mathbf{x}^0 = (1,1)$  produces

x 1	deltax 1	x 2	deltax 2
0. 100000e+01	0. 175000e+01	0. 100000e+01	0. 687500e+00
0. 275000e+01	-0. 257813e+00	0. 168750e+01	0. 451172e+00
0. 249219e+01	-0. 169189e+00	0. 213867e+01	0. 296082e+00
0. 232300e+01	-0. 111031e+00	0. 243475e+01	0. 194304e+00
0. 221197e+01	-0. 728638e-01	0. 262906e+01	0. 127512e+00
0. 213910e+01	-0. 478169e-01	0. 275657e+01	0. 836795e-01
0. 209129e+01	-0. 313798e-01	0. 284025e+01	0. 549147e-01
0. 205991e+01	-0. 205930e-01	0. 289516e+01	0. 360378e-01
0. 203931e+01	-0. 135142e-01	0. 293120e+01	0. 236498e-01
0. 202580e+01	-0. 886867e-02	0. 295485e+01	0. 155202e-01
0. 201693e+01	-0. 582006e-02	0. 297037e+01	0. 101851e-01
0. 201111e+01	-0. 381942e-02	0. 298056e+01	0. 668398e-02
0. 200729e+01	-0. 250649e-02	0. 298724e+01	0. 438636e-02
0. 200479e+01	-0. 164489e-02	0. 299163e+01	0. 287855e-02
0. 200314e+01	-0. 107946e-02	0. 299450e+01	0. 188905e-02
0. 200206e+01	-0. 708393e-03	0. 299639e+01	0. 123969e-02
0. 200135e+01	-0. 464883e-03	0. 299763e+01	0. 813545e-03
0. 200089e+01	-0. 305080e-03	0. 299845e+01	0. 533889e-03
0. 200058e+01	-0. 200208e-03	0. 299898e+01	0. 350365e-03
0. 200038e+01	-0. 131387e-03	0. 299933e+01	0. 229927e-03
0. 200025e+01	-0. 862226e-04	0. 299956e+01	0. 150890e-03
0. 200016e+01	-0. 565836e-04	0. 299971e+01	0. 990212e-04
0. 200011e+01	-0. 371330e-04	0. 299981e+01	0. 649827e-04
0. 200007e+01	-0. 243685e-04	0. 299988e+01	0. 426449e-04
0. 200005e+01	-0. 159918e-04	0. 299992e+01	0. 279857e-04
0. 200003e+01	-0. 104946e-04	0. 299995e+01	0. 183656e-04
0. 200002e+01	-0. 688711e-05	0. 299996e+01	0. 120524e-04
0. 200001e+01	-0. 451966e-05	0. 299998e+01	0. 790941e-05
0. 200001e+01	-0. 296603e-05	0. 299998e+01	0. 519055e-05
0. 200001e+01	-0. 194646e-05	0. 299999e+01	0. 340630e-05
0. 200000e+01	-0. 127736e-05	0. 299999e+01	0. 223538e-05
0. 200000e+01	-0. 838269e-06	0. 300000e+01	0. 146697e-05
0. 200000e+01	-0. 550114e-06	0. 300000e+01	0. 962700e-06
0. 200000e+01	-0. 361012e-06	0. 300000e+01	0. 631772e-06
0. 200000e+01	-0. 236914e-06	0. 300000e+01	0. 414600e-06
0. 200000e+01	-0. 155475e-06	0. 300000e+01	0. 272081e-06
0. 200000e+01	-0. 102031e-06	0. 300000e+01	0. 178553e-06
0. 200000e+01	-0. 669575e-07	0. 300000e+01	0. 117176e-06
0. 200000e+01	-0. 439409e-07	0. 300000e+01	0. 768965e-07
0. 200000e+01	-0. 288362e-07	0. 300000e+01	0. 504633e-07
0. 200000e+01	-0. 189238e-07	0. 300000e+01	0. 331166e-07
0. 200000e+01	-0. 124187e-07	0. 300000e+01	0. 217327e-07
0. 200000e+01	-0. 814978e-08	0. 300000e+01	0. 142621e-07
0. 200000e+01	-0. 534829e-08	0. 300000e+01	0. 935951e-08
0. 200000e+01	-0. 350982e-08	0. 300000e+01	0. 614218e-08

$$x_1 = \frac{25-3x_2}{8}$$

$$x_2 = \frac{26-7x_1}{4}$$

The iterations converge to the true solution although  $\mathbf{A}$  does not have a dominant diagonal.

To find a more strict convergence condition than that of equation (3.7), that is a sufficient and necessary one, we partition the coefficient matrix  $\mathbf{A}$  of equation (3.4) into two matrices  $\mathbf{P}$  and  $\mathbf{Q}$  so that

$$\mathbf{A} = \mathbf{P} + \mathbf{Q} \quad (3.8)$$

$\mathbf{P}$  consists of the diagonal elements of  $\mathbf{A}$  in addition to the lower triangular elements.  $\mathbf{Q}$  consists of the upper triangular elements of  $\mathbf{A}$ . The Gauss-Seidel method for solving equation (3.4) may be described by the following difference equation

$$\mathbf{P}\mathbf{x}^{i+1} = -\mathbf{Q}\mathbf{x}^i + \mathbf{B} \quad (3.9)$$

where  $i = 0, 1, 2, \dots$  and  $\mathbf{x}^0$  is the initial guess vector.

**Example 3.3:**

Consider the following system of equations

$$\begin{bmatrix} 4 & 2 & 1 \\ -1 & 6 & 2 \\ 3 & -2 & 8 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 18 \\ 24 \\ 32 \end{bmatrix}$$

the matrices  $\mathbf{P}$  and  $\mathbf{Q}$  are

$$\mathbf{P} = \begin{bmatrix} 4 & 0 & 0 \\ -1 & 6 & 0 \\ 3 & -2 & 8 \end{bmatrix} \quad \mathbf{Q} = \begin{bmatrix} 0 & 2 & 1 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix}$$

Substituting in equation (3.9) we get

$$\begin{bmatrix} 4 & 0 & 0 \\ -1 & 6 & 0 \\ 3 & -2 & 8 \end{bmatrix} \mathbf{x}^{i+1} = - \begin{bmatrix} 0 & 2 & 1 \\ 0 & 0 & 2 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{x}^i + \begin{bmatrix} 18 \\ 24 \\ 32 \end{bmatrix}$$

which represents the iterations of the Gauss-Seidel method.

The matrix  $\mathbf{P}$  is nonsingular because its diagonal elements which are the diagonal elements of the coefficient matrix  $\mathbf{A}$  must not contain a zero (see section 3.1 and equations (3.5)). So equation (3.9) can be written in the form

$$\mathbf{x}^{i+1} = -\mathbf{P}^{-1}\mathbf{Q} \mathbf{x}^i + \mathbf{P}^{-1}\mathbf{B} \quad (3.10)$$

The Gauss-Seidel method described by equation (3.10) will converge to the solution of  $\mathbf{Ax} = \mathbf{B}$  if and only if all eigenvalues of the matrix  $\mathbf{P}^{-1}\mathbf{Q}$  have magnitude less than unity [20].

For a given matrix  $\mathbf{C}$  a way to determine whether all its eigenvalues have magnitudes less than unity is by the use of Gersgorin circle theorem [20]. The theorem states:

The eigenvalues of a matrix  $\mathbf{C}$  lie in the union of the circles 1 to  $n$ , where each circle  $j$  is centered at  $c_{jj}$  with a radius  $= \sum_{m \neq j} |c_{jm}|$ .

So the Gauss-Seidel method will converge for equation (3.4) if the union of the Gersgorin circles for the matrix  $\mathbf{P}^{-1}\mathbf{Q}$  lies within the unit circle.

The convergence rate of equation (3.10) (the Gauss-Seidel method) can be determined using the eigenvalue with largest magnitude,  $\lambda_m$ , of the matrix  $\mathbf{P}^{-1}\mathbf{Q}$  (see equation (3.8) and (3.4)). Defining the error  $e^i$  at iteration  $i$  as follows

$$e_j^i = (x_j^i - r_j) \quad (3.11)$$

where  $x_j^i$  is the value of the  $j^{\text{th}}$  variable at iteration  $i$ , and  $r_j$  is the true value of  $x_j$ . The convergence rate of the Gauss-Seidel method is linear and can be given by [3]

$$|e_j^{i+1}| = |\lambda_m| \cdot |e_j^i| \quad (3.12)$$

The case where  $|\lambda_m| \geq 1 \Rightarrow |e_j^{i+1}| \geq |e_j^i|$  and the iterations diverge. The case where  $|\lambda_m| < 1 \Rightarrow |e_j^{i+1}| < |e_j^i|$  and the iterations converge.

Example 3.4:

For the first case of example 3.1 the iterations diverged. To confirm that we compute the eigenvalues of  $\mathbf{P}^{-1}\mathbf{Q}$ .

$$\mathbf{A} = \begin{bmatrix} 1 & 3 \\ 2 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 2 & 1 \end{bmatrix} + \begin{bmatrix} 0 & 3 \\ 0 & 0 \end{bmatrix} = \mathbf{P} + \mathbf{Q}$$

$$\mathbf{P}^{-1}\mathbf{Q} = \begin{bmatrix} 1 & 0 \\ -2 & 1 \end{bmatrix} \begin{bmatrix} 0 & 3 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 3 \\ 0 & -6 \end{bmatrix}$$

$\mathbf{P}^{-1}\mathbf{Q}$  has only one eigenvalue  $\lambda = -6$  which has magnitude greater than unity confirming the divergence of the iterations.

For the second case of example 3.1 where the iterations converged we had



$$\mathbf{A} = \begin{bmatrix} 2 & 1 \\ 1 & 3 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 1 & 3 \end{bmatrix} + \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \mathbf{P} + \mathbf{Q}$$

$$\mathbf{P}^{-1}\mathbf{Q} = \begin{bmatrix} 0.5 & 0 \\ 0.1667 & 0.3333 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0.5 \\ 0 & 0.1667 \end{bmatrix}$$

$\mathbf{P}^{-1}\mathbf{Q}$  has one eigenvalue  $\lambda = 0.1667$  which has magnitude less than unity confirming the convergence of the iterations.

To show the linear rate of convergence, equation (3.12), we look at the results of the iterations of example 3.1, the convergent case. At iterations 9 and 10 we have

$$\text{delta } x_1^9 = -0.248073 \times 10^{-6}$$

$$\text{delta } x_1^{10} = -0.413454 \times 10^{-7}$$

$$\text{delta } x_2^9 = 0.826909 \times 10^{-7}$$

$$\text{delta } x_2^{10} = 0.137818 \times 10^{-7}$$

where  $\text{delta } x_j^i = x_j^{i+1} - x_j^i$  applying equation (3.12) but using  $\text{delta } x_j^i$  instead of  $e_j^i$  we get

$$\frac{\text{delta } x_1^{10}}{\text{delta } x_1^9} = \frac{-0.413454 \times 10^{-7}}{-0.24807 \times 10^{-6}} = 0.1667 = \lambda$$

$$\text{and } \frac{\text{delta } x_2^{10}}{\text{delta } x_2^9} = \frac{0.137818 \times 10^{-7}}{0.826909 \times 10^{-7}} = 0.1667 = \lambda$$

As another case consider example 3.2. The maximum eigenvalue of  $\mathbf{P}^{-1}\mathbf{Q}$  is  $\lambda_m = 0.6563$ , which implies a slower convergence rate than the above case. That is why it took 44 iterations to get within  $\sim 10^{-8}$  of the true solution. We check this out

$$\frac{\text{delta } x_1^{42}}{\text{delta } x_1^{41}} = \frac{-0.814978 \times 10^{-8}}{-0.124187 \times 10^{-7}} = 0.6563 = \lambda_m$$

$$\frac{\text{delta } x_2^{42}}{\text{delta } x_2^{41}} = \frac{0.142621 \times 10^{-7}}{0.217327 \times 10^{-7}} = 0.6563 = \lambda_m$$

To determine the convergence condition of a system of equations in practical applications the diagonal dominance condition is much easier to evaluate than the eigenvalues magnitudes condition. The calculation of the eigenvalues of a matrix requires a fair amount of computer execution time and storage. The diagonal dominance condition can only confirm if the Gauss-Seidel method will converge but cannot determine if a system will diverge. The eigenvalues condition can state precisely if a system will converge or diverge.

## CHAPTER 4

### TEARING AND EQUATION FORMULATION

In any circuit analysis program the fundamental process is to solve a set of nonlinear algebraic equations. The way in which a circuit is translated into a set of equations has a significant affect on several aspects of the solution like the time it takes to reach it and the amount of storage required. Solving large-scale circuits starts with some decomposition technique to break the circuit into several smaller subcircuits. The purpose is to obtain a Jacobian matrix, referred to from now on as a "dependency matrix" [6] of a bordered block-diagonal form as in Fig. 4.1. The advantages of such a form are:

- 1) The diagonal blocks can either be processed in parallel for savings in processing time or in sequence for savings in storage requirements.
- 2) The repetitiveness of some diagonal blocks will have speed and storage advantages. Only one block has to be processed and saved. A set of pointers can relate the similar blocks.
- 3) The latency of some parts of the circuit may be exploited for more saving in time during transient analysis.

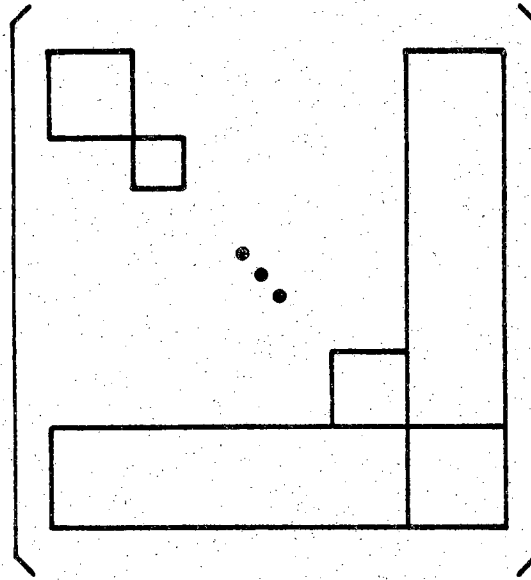


Figure 4.1 Bordered block-diagonal matrix form.

#### 4.1 Tearing Techniques

The process of decomposing a circuit into subcircuits is referred to as tearing or diakoptics [9]. Several tearing techniques would result in a dependency matrix of the form of Figure 4.1. We will use a node tearing technique [17,21] that produces the dependency matrix of Figure 4.1.

The circuit is partitioned into  $m$  subcircuits as shown in Fig. 4.2.

The blocks labeled  $\mathbf{F}^1$  through  $\mathbf{F}^m$  correspond to the subcircuits we have chosen and the  $\mathbf{H}$  block, which is a subcircuit itself, correspond to the rest of the circuit elements. There are  $n_u$  nodes contained in block  $\mathbf{G}$  in Figure 4.2. These nodes connect the subcircuits together, they are called the tearing nodes [17]. The tearing nodes are labeled as  $u_j$ 's, ( $1 \leq j \leq n_u$ ), and referred to as the vector  $\mathbf{u}$  ( $\mathbf{u} = (u_1, u_2, \dots, u_{n_u})^T$ ). The  $\mathbf{G}$  block can be thought of as a subcircuit with no internal nodes. The node-to-datum voltages of the tearing nodes are used as variables in the equation formulation process. Each of the other subcircuits has a number of internal nodes not shared with any other subcircuits. The node-to-datum voltages of these nodes in addition to selected branch currents are used as variables in the equation formulation process. The  $\mathbf{H}$  subcircuit variables are labeled  $z_k$ 's, ( $1 \leq k \leq n_z$ ), where  $n_z$  is the number of variables in  $\mathbf{H}$ . The vector  $\mathbf{z}$  consists of all the  $z$  variables ( $\mathbf{z} = (z_1, z_2, \dots, z_{n_z})^T$ ). The  $\mathbf{F}^i$  subcircuit variables are labeled  $x_\ell^i$ 's, ( $1 \leq \ell \leq n_f^i$ ), where  $n_f^i$  is the total number of variables in subcircuit  $\mathbf{F}^i$ . The vector  $\mathbf{x}^i$  consists of all the  $x^i$  variables ( $\mathbf{x}^i = (x_1^i, x_2^i, \dots, x_{n_f^i}^i)^T$ ). The total number of  $x$  variables in all the  $\mathbf{F}$  subcircuits is  $n_x$ .

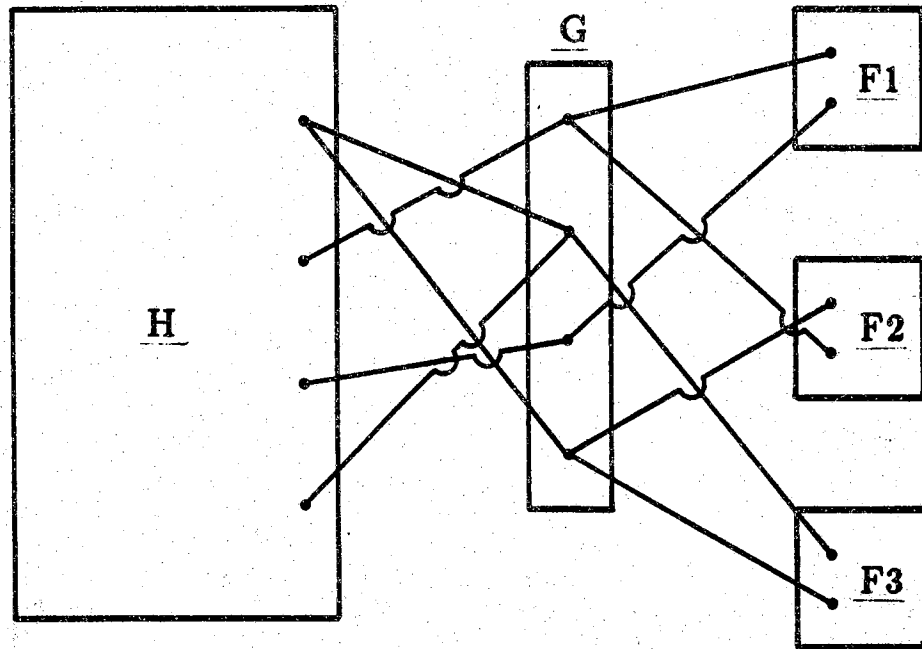


Figure 4.2 Tearing the circuit.

## 4.2 Modified Nodal Analysis

In formulating the equations for a circuit we use the modified nodal analysis approach, abbreviated MNA [7]. We start with the node-to-datum voltages and then write an equation for each node using Kirchhoff's current law such that the summation of all currents leaving the node is equal to zero. For a circuit containing only linear conductances and capacitances, and independent current sources, the first portion of the MNA equations at a certain time instance  $t$  would have the form [7]

$$\mathbf{YV} = \mathbf{J} \quad (4.1)$$

where  $\mathbf{Y}$  is the node admittance matrix,  $\mathbf{V}$  the node-to-datum voltage vector and  $\mathbf{J}$  the current source vector. Capacitors are replaced by a linear model, Figure 4.3 [4]. The value of  $v(t-h)$ , where  $t$  is the time variable and  $h$  is the time step taken, is the voltage at the previous time point. The value of  $v(t-h)$  would be readily available from the solution of equation (4.1) at  $t-h$ . The next step is introducing some branch currents as additional variables and the corresponding voltage-current branch relationships as additional equations. These additional variables are chosen to be the currents through voltage sources and any controlling currents (e.g. inductor currents). Adding voltage sources and linear inductances to the above circuit, the MNA equations would have the form [7]

$$\begin{bmatrix} \mathbf{Y}^* & \mathbf{B} \\ \mathbf{C} & \mathbf{D} \end{bmatrix} \begin{bmatrix} \mathbf{V} \\ \mathbf{I} \end{bmatrix} = \begin{bmatrix} \mathbf{J} \\ \mathbf{K} \end{bmatrix} \quad (4.4)$$

where  $\mathbf{Y}^*$  excludes contribution due to branches whom currents are variables. The contributions are covered in  $\mathbf{B}$  as  $\pm 1$ 's.  $\mathbf{C}$  and  $\mathbf{D}$  represent the branch voltage-current relationships.  $\mathbf{J}$  and  $\mathbf{K}$  are excitations (voltage and current

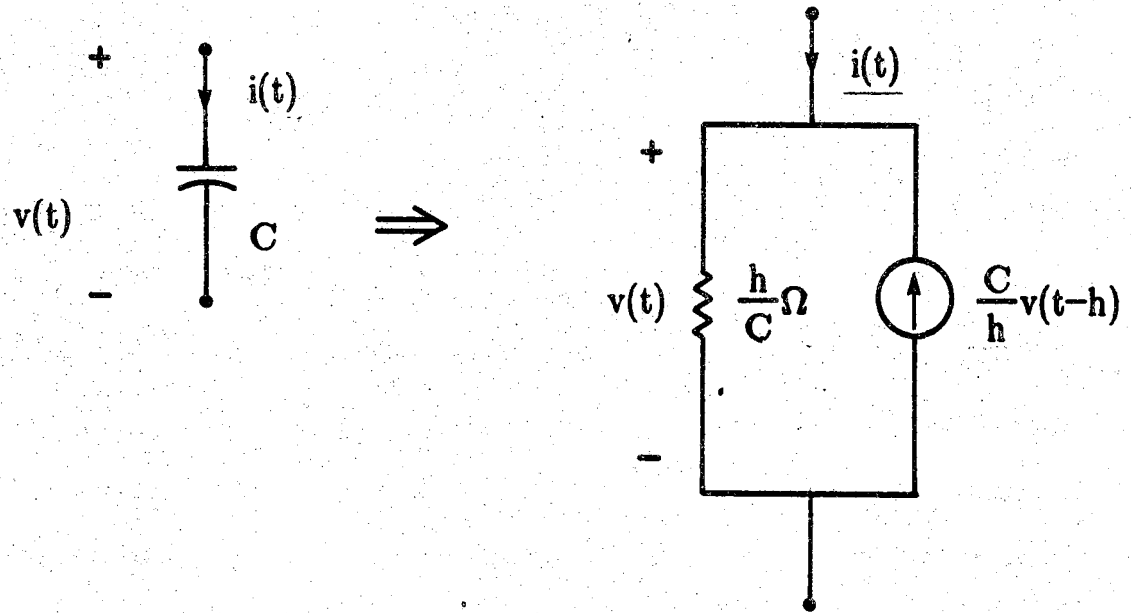


Figure 4.3 Linear model for a capacitor using 1st order BDF (see section 7.1)



sources values). Inductors are replaced by a linear model, Figure 4.4 [4]. It is obvious that a previous value for the inductor current is needed at time  $t-h$ . That is why it is introduced as a variable in MNA equations.

### 4.3 Equation Formulation

The MNA approach is used to formulate the equations for each of the subcircuits described in section 4.1. Each subcircuit is treated as an individual circuit in the formulation process. Given a circuit, the equation formulation process proceeds as follows:

- 1) Replace all devices which have three terminals or more by their appropriate models (e.g. replace a BJT-transistor by its Ebers-Moll model [4]).
- 2) Tear the circuit into subcircuits labeling the node and current variables as described in section 4.1; (refer to Figure 4.2).
- 3) Write the nonlinear algebraic equations using MNA for the circuit treating each block in Figure 4.2 as an individual circuit with some constraints as illustrated below:
  - a) The  $\mathbf{G}$  block has  $n_u$  variables, so we write  $n_u$  nonlinear equations by applying Kirchhoff's current law at each tearing node  $u_j$ . The equations will be functions of  $\mathbf{u}$  in addition to  $\mathbf{x}^i$ 's and  $\mathbf{z}$ . In the solution process for  $\mathbf{u}$ , using the Semi-Direct method,  $\mathbf{z}$  and  $\mathbf{x}^i$  are treated as constants. The equations can be expressed in the following form

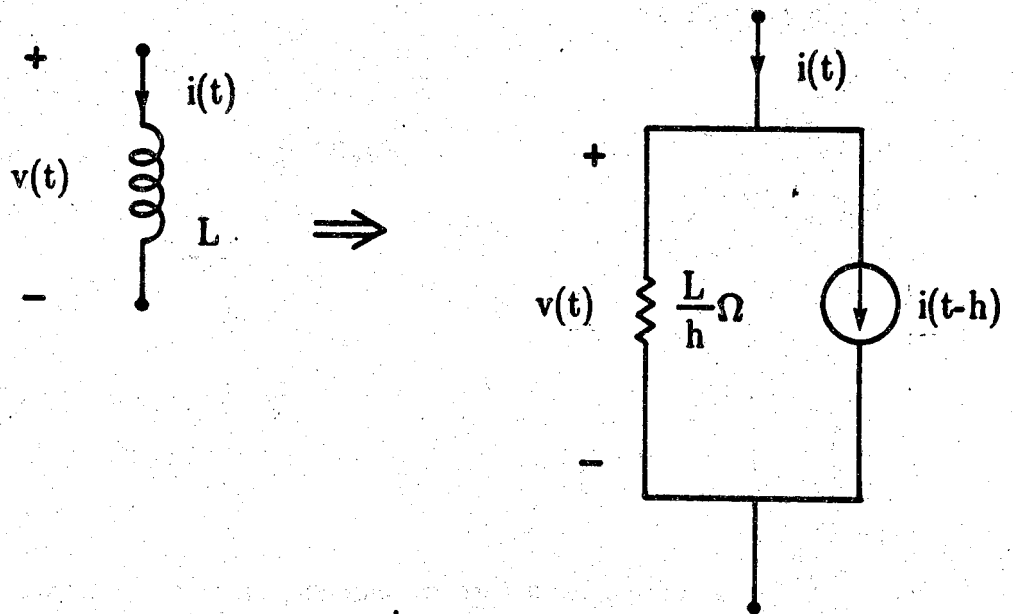


Figure 4.4 Linear model for an inductor using 1st order BDF  
(see section 7.1)

$$\mathbf{G}(\mathbf{x}^1, \mathbf{x}^2, \dots, \mathbf{x}^m, \mathbf{z}, \mathbf{u}) = \mathbf{0} \quad (4.5)$$

- b) The  $\mathbf{H}$  block has  $n_z$  variables. At the node variables we apply Kirchhoff's current law, and for the current variables we apply the voltage-current branch relationships. The result is  $n_z$  equations of the form of equation (4.4). These equations are a function of  $\mathbf{z}$  and  $\mathbf{u}$  only. They are not connected to any of the  $\mathbf{F}^i$  subcircuits. In the solution process for  $\mathbf{z}$  using the Semi-Direct method,  $\mathbf{u}$  will be treated as a constant vector. This block of equations can be written as

$$\mathbf{H}(\mathbf{z}, \mathbf{u}) = \mathbf{0} \quad (4.6)$$

- c) Each  $\mathbf{F}^i$  block has  $n_f^i$  variables. At the node variables we apply Kirchhoff's current law, and for the current variables we apply the voltage-current branch relationships. The result is  $n_f^i$  equations for each block  $\mathbf{F}^i$  in the form of equation (4.4). These equations are functions of  $\mathbf{x}^i$  and  $\mathbf{u}$  only. They are not connected to the  $\mathbf{H}$  subcircuit. In the solution process for  $\mathbf{x}^i$ , using the Semi-Direct method,  $\mathbf{u}$  will be treated as a constant vector. The blocks of equations can be written as

$$\begin{aligned} \mathbf{F}^1(\mathbf{x}^1, \mathbf{u}) &= \mathbf{0} \\ \mathbf{F}^2(\mathbf{x}^2, \mathbf{u}) &= \mathbf{0} \\ &\vdots \\ \mathbf{F}^m(\mathbf{x}^m, \mathbf{u}) &= \mathbf{0} \end{aligned}$$

or in a more compact form

$$\mathbf{F}^i(\mathbf{x}^i, \mathbf{u}) = \mathbf{0} \quad (4.7)$$

The result of step 3 is  $m+2$  blocks of equations, each has an equal number of assigned unknowns (variables) and equations. That is, for



b) For the Semi-Direct Method:

Each block is treated as an independent system of equations. So we write a Jacobian matrix for each block taking into consideration which variables are to be treated as a constant in each block as described in step 3. These smaller Jacobian matrices can be related to equation (4.9) as follow:

$$\mathbf{J}_f(\mathbf{x}^i) = \mathbf{A}_{ssi} \quad (4.10)$$

$$\mathbf{J}_h(\mathbf{Z}) = \mathbf{A}_{ss(m+1)} \quad (4.11)$$

$$\mathbf{J}_g(\mathbf{u}) = \mathbf{A}_{rr} \quad (4.12)$$

The Semi-Direct method is then used to solve the system. The algorithm is described in chapter 5.

5) Input the equations into the appropriate algorithm.

From the above discussion we can see an advantage for the Semi-Direct method. There is no need to calculate the partial derivatives in the submatrices  $\mathbf{A}_{rs}$  and  $\mathbf{A}_{sr}$ . This means they do not have to be stored either which accounts for computer storage space savings. The relationship between the subcircuits and the equations can be easily illustrated by labeling the blocks of equation (4.9) (Figure 4.5).

To illustrate the above procedure, consider this example:

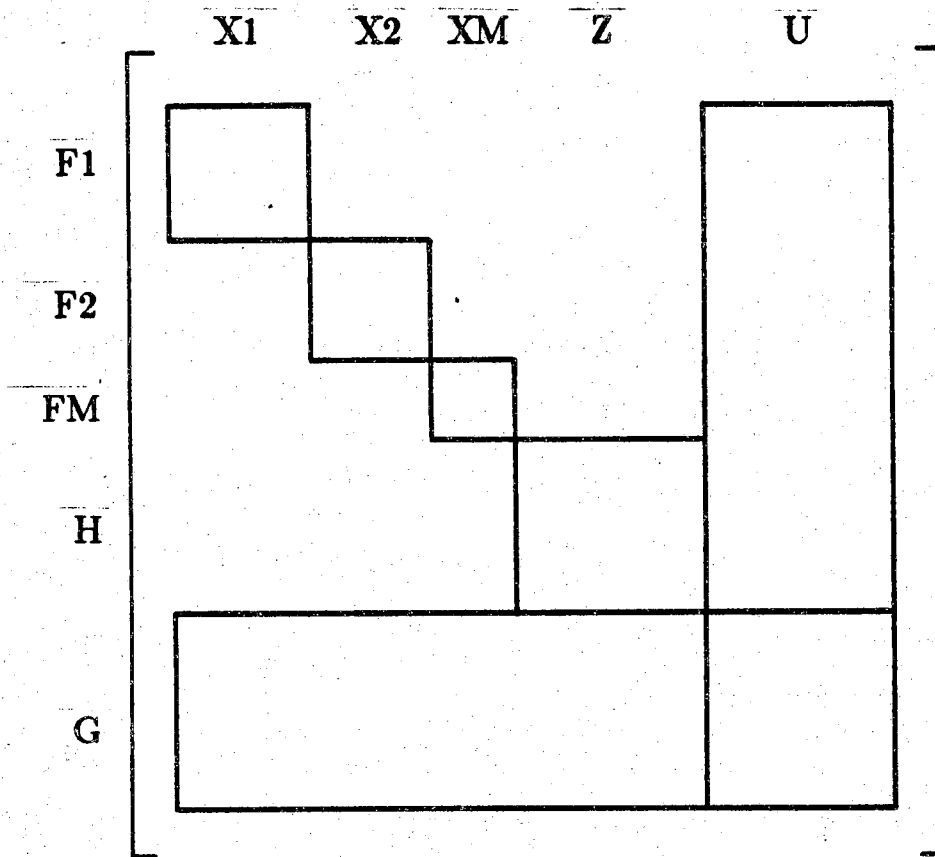


Figure 4.5 The Jacobian matrix.

### Example 4.1

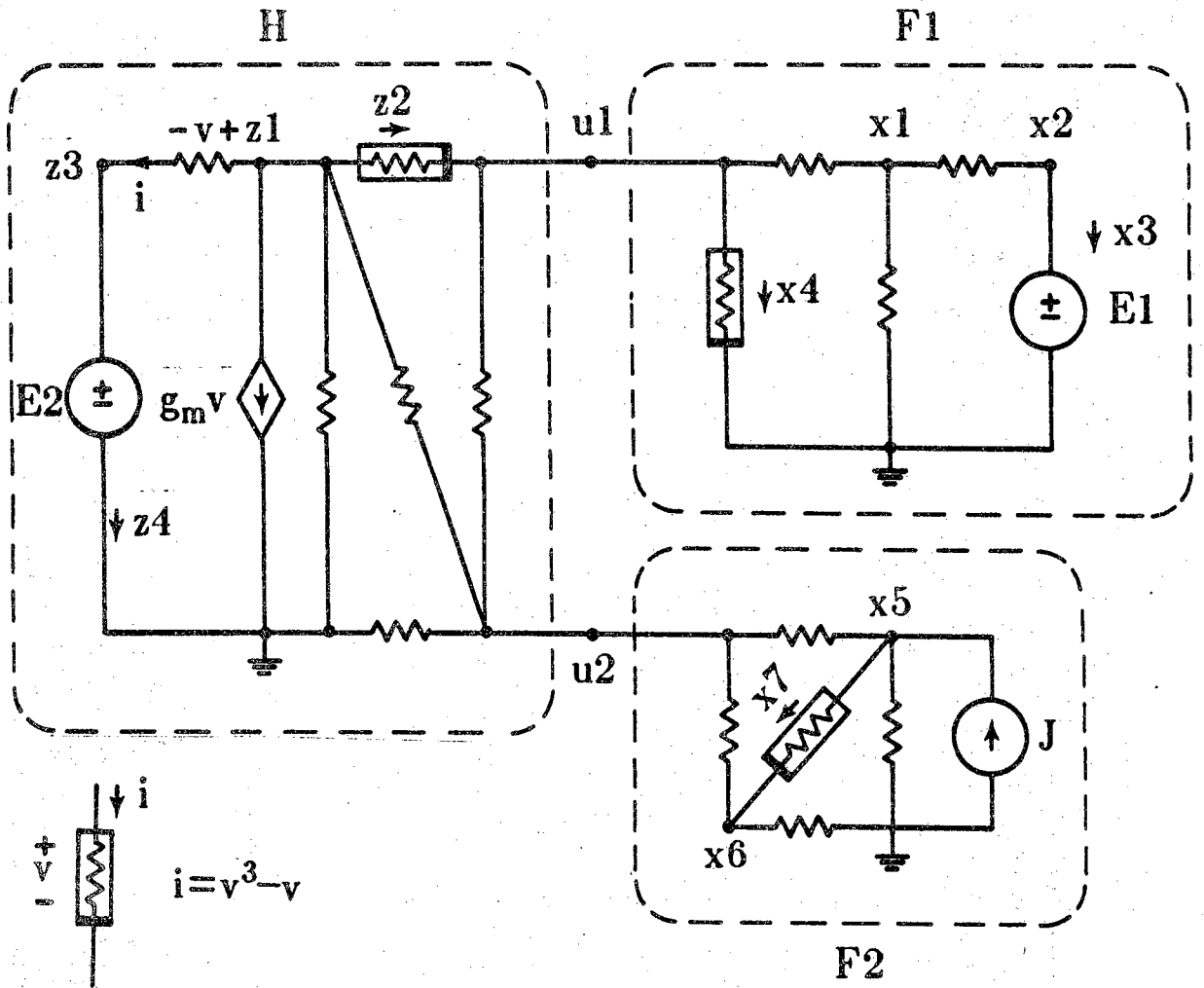
Consider the circuit in Figure 4.6 which has nonlinear resistors as illustrated. The circuit is partitioned into three subcircuits using two tearing nodes.

Applying Kirchhoff current laws at the node variables and voltage current relationships for the current variables we would obtain 4  $\mathbf{F}^1$  equations, 3  $\mathbf{F}^2$  equations, 4  $\mathbf{H}$  equations and 2  $\mathbf{G}$  equations. The Jacobian matrix will have the form of Figure 4.5 where  $\mathbf{A}_{ss1}$  is a  $4 \times 4$  matrix,  $\mathbf{A}_{ss2}$  is a  $3 \times 3$  matrix,  $\mathbf{A}_{ss3}$  is a  $4 \times 4$  matrix and  $\mathbf{A}_{rr}$  is a  $2 \times 2$  matrix. (See example 5.5).

## 4.4 A Newton-Raphson Algorithm for Bordered Block-Diagonal Matrices

We have seen in sections 4.1-3 how the dependency matrix is formulated in bordered block-diagonal form. We must note that a common reference node is assumed to be shared by all the torn subcircuits (each subcircuit should have a branch connected to the reference node). The reason for such an assumption, which is a very practical one, is to simplify the bordered block-diagonal form of the dependency matrix. If floating reference nodes are used by each subcircuit the dependency matrix would have a form as in Figure 4.7. An algorithm using the Newton-Raphson method to solve a system with such a dependency matrix was proposed in [21]. A simplified version is extracted to serve the simpler dependency matrix form of equation (4.9).

The regular Newton-Raphson algorithm illustrated in section 2.2 would be sufficient to obtain a solution for any general case, but to make use of the sparsity of the dependency matrix we have to utilize the simplified algorithm.



All Conductance =  $1\Omega$

$E_1 = E_2 = 2V$

$J = 1A$

Figure 4.6 Tearing a circuit



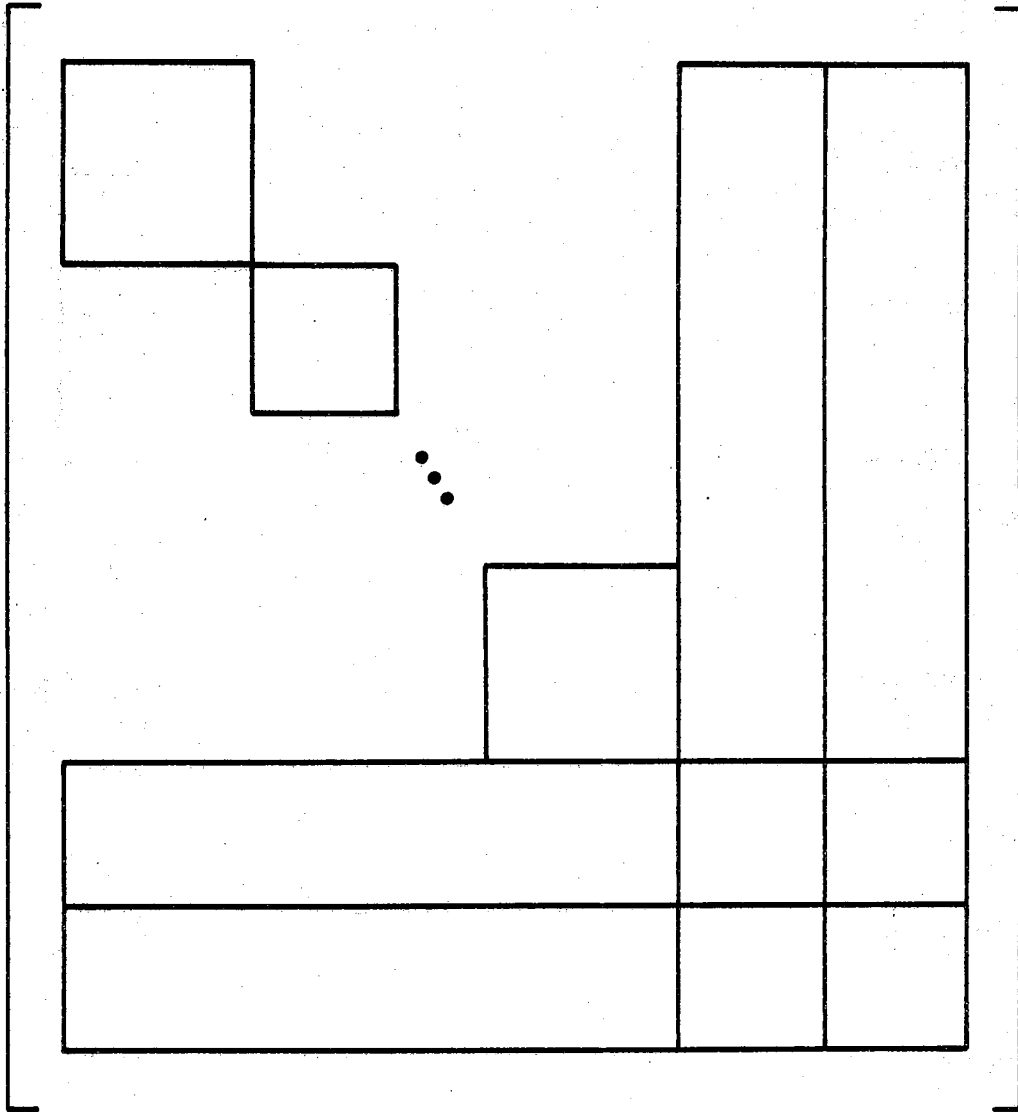


Figure 4.7 Bordered block-diagonal form of a dependency matrix for a circuit with a floating reference node.

Referring to Section 2.2 the equation to be solved at a time instant  $t$  is equation (2.9) which is in the form

$$\mathbf{Ax} = \mathbf{b} \quad (4.13)$$

We are assuming  $\mathbf{A}$  has the form of the dependency matrix in equation (4.9) so

$$\mathbf{Ax} = \begin{bmatrix} \mathbf{A}_{ss} & \mathbf{A}_{sr} \\ \mathbf{A}_{rs} & \mathbf{A}_{rr} \end{bmatrix} \begin{bmatrix} \mathbf{x}_s \\ \mathbf{u}_r \end{bmatrix} = \begin{bmatrix} \mathbf{b}_s \\ \mathbf{b}_r \end{bmatrix} \quad (4.14)$$

where the  $\mathbf{z}$ 's are included in  $\mathbf{x}_s$ .

The restriction on the block diagonal matrices is that they be nonsingular or else this algorithm fails. We solve equations (4.5) by solving for  $\mathbf{u}$  from

$$(\mathbf{A}_{rr} - \mathbf{A}_{rs} \mathbf{A}_{ss}^{-1} \mathbf{A}_{sr}) \mathbf{u}_r = (\mathbf{b}_r - \mathbf{A}_{rs} \mathbf{A}_{ss}^{-1} \mathbf{b}_s) \quad (4.15)$$

then for  $\mathbf{x}_s$  from

$$\mathbf{A}_{ss} \mathbf{x}_s = (\mathbf{b}_s - \mathbf{A}_{sr} \mathbf{u}_r) \quad (4.16)$$

The inverse of  $\mathbf{A}_{ss}$  is simply the direct sum of the inverse of the diagonal blocks. The procedure can be restated in terms of LU factors which is convenient for programming. There are five steps to the procedure:

1) LU decomposition

$$\mathbf{A}_{ssi} = \mathbf{L}_{ssi} \mathbf{U}_{ssi} \quad (4.17)$$

2) Solve for

$$\phi_i \text{ from } \mathbf{L}_{ssi} \phi_i = \mathbf{A}_{sri} \quad (4.18)$$

$$\psi_i \text{ from } \phi_i \mathbf{U}_{ssi} = \mathbf{A}_{rsi} \quad (4.19)$$

$$\xi_i \text{ from } \mathbf{L}_{ssi} \xi_i = \mathbf{b}_{si} \quad (4.20)$$

3) Solve for  $\mathbf{u}$  from

$$\left[ \mathbf{A}_{rr} - \sum_{i=1}^{m+1} \psi_i \phi_i \right] \mathbf{u}_r = \left[ \mathbf{b}_r - \sum_{i=1}^{m+1} \psi_i \xi_i \right] \quad (4.21)$$

4) Solve for  $\mathbf{Y}_{si}$  from

$$\mathbf{L}_{ssi} \mathbf{Y}_{si} = [\mathbf{b}_{si} - \mathbf{A}_{sri} \mathbf{u}_r] . \quad (4.22)$$

5) Solve for  $\mathbf{x}_{si}$  from

$$\mathbf{U}_{ssi} \mathbf{x}_{si} = \mathbf{Y}_{si} \quad (4.23)$$

The advantages are clearly the same as stated in the opening of this chapter.

#### 4.5 Remarks

The tearing and equation formulation techniques in addition to the Newton-Raphson algorithm explained in this chapter have some restrictions. Such restrictions are common and practical ones. They are listed below with a justification of their practicality.

- 1) Common reference node: Almost all Integrated Circuits fulfill this requirement.
- 2) Nonsingularity of the block-diagonal matrices of the dependency matrix. Each block represents a subcircuit, the possibility of it being singular is very slim in real circuit application. Even if it occurs, an addition of a small conductance in parallel to some element in the circuit would take care of that problem.

- 3) Non-zero diagonal entries on the diagonal of the dependency matrix. This is for LU factorization purposes. This can be satisfied by exchanging one or more rows.
- 4) An ideal voltage source connected to one of the  $u$  nodes. This would require the introduction of the current through the source as an extra  $u$  variable. The ideal voltage source though is nonexistent in reality so the introduction of a small resistance in series (an extra node variable) would enable us to keep the tearing configuration as in Figure 4.2.

## CHAPTER 5

### THE SEMI-DIRECT METHOD

The Semi-Direct method proposed in [15] makes use of the two numerical analysis methods illustrated in Chapters 1 & 2, namely the Newton-Raphson and the Gauss-Siedel methods. The equations to be solved are in the form of Eq. (4.5), (4.6) and (4.7) which are

$$\mathbf{F}_i(\mathbf{x}^i, \mathbf{u}) = \mathbf{0} \quad 1 \leq i \leq m \quad (5.1)$$

$$\mathbf{H}(\mathbf{z}, \mathbf{u}) = \mathbf{0} \quad (5.2)$$

$$\mathbf{G}(\mathbf{x}^1, \dots, \mathbf{x}^m, \mathbf{z}, \mathbf{u}) = \mathbf{0} \quad (5.3)$$

and the dependency matrix has the form of equation (4.9), where  $\mathbf{F}_i$ ,  $\mathbf{H}$ ,  $\mathbf{G}$ ,  $\mathbf{x}^i$ ,  $\mathbf{z}$  and  $\mathbf{u}$  are all as defined in Chapter 4.

#### 5.1 Algorithm

The Semi-Direct method if used to solve equations (5.1), (5.2) and (5.3) would take the following steps:

- 1) Make an initial guess of the vector  $\mathbf{u}$ .
- 2) Solve equations (5.1) and (5.2) for all  $\mathbf{x}^i$  and  $\mathbf{z}$  vectors, (sequentially or in parallel).

- 3) Using the new values of  $x_i$ 's and  $z$  solve for an updated value of  $u$  using equations (5.3).
- 4) Repeat steps 2 and 3 until some termination criterion is met. Each iteration of steps 2 and 3 is called a sweep.

Let us consider a special case where the  $u$  vector has length 1 and there is only one  $x^i$  vector and it is of length 1. So we only have two equations in two unknowns  $x$  and  $u$  such that

$$f(x,u) = 0 \quad (5.4)$$

$$g(x,u) = 0 \quad (5.5)$$

Using the above Semi-Direct algorithm to solve equations (5.4) and (5.5) we take a look at two cases:

- 1)  $f$  and  $g$  are linear equations in which case they can be reduced to the explicit forms

$$x = f^*(u) \quad (5.6)$$

$$u = g^*(x) \quad (5.7)$$

Applying the Semi-Direct algorithm in this case would reduce to the Gauss-Seidel method. Steps 2 and 3 can be directly evaluated from equations (5.6) and (5.7).

- 2)  $f$  and  $g$  are nonlinear equations in which case steps 2 and 3 have to be executed using some numerical analysis technique. (We are assuming a general case where  $f$  and  $g$  are of order  $\geq 2$ ). The algorithm in this case is sometimes referred to as a nonlinear Gauss-Seidel method [15].

The Newton-Raphson method is used to execute steps 2 and 3. It was chosen because of its convergence characteristics advantages (Chapter 1).

A geometric interpretation for the 2-dimensional case discussed above does exist. The two equations (5.4) and (5.5) can be plotted as shown in Figure 5.1. The initial guess is  $u^0$ . Then tracing steps 2 through 4 of the previous algorithm would produce the dotted line which is converging to the solution point  $p$ . There are cases however that the system can diverge or oscillate as illustrated in Figures 5.2 and 5.3, respectively. The case where the graphs in Figure 5.1, 5.2, and 5.3 are straight lines is the linear case of the Semi-Direct method which is simply the Gauss-Seidel method.

The stopping criteria for the algorithm are the same as for the Newton-Raphson method and the Gauss-Seidel method discussed in Chapters 1 and 2 respectively. They are

- 1) The increment  $\Delta x_{j+1}$  becomes less than a user specified increment  $\epsilon$ . Which implies the sweeps are converging.
- 2) The number of sweeps exceed a user specified maximum number in which case the sweeps are diverging, oscillating or converging too slow for a satisfactory performance.

Example 5.1:

Let  $f$  and  $g$  in equations (5.4) and (5.5) be

$$f(x,u) = x^3 + 10x + u - 31 = 0 \quad (5.8)$$

$$g(x,u) = 2(x-u-1)^3 - u + 19 = 0 \quad (5.9)$$

Using the Newton-Raphson algorithm and an initial guess of  $x^0 = 1$  and  $u^0 = 1$

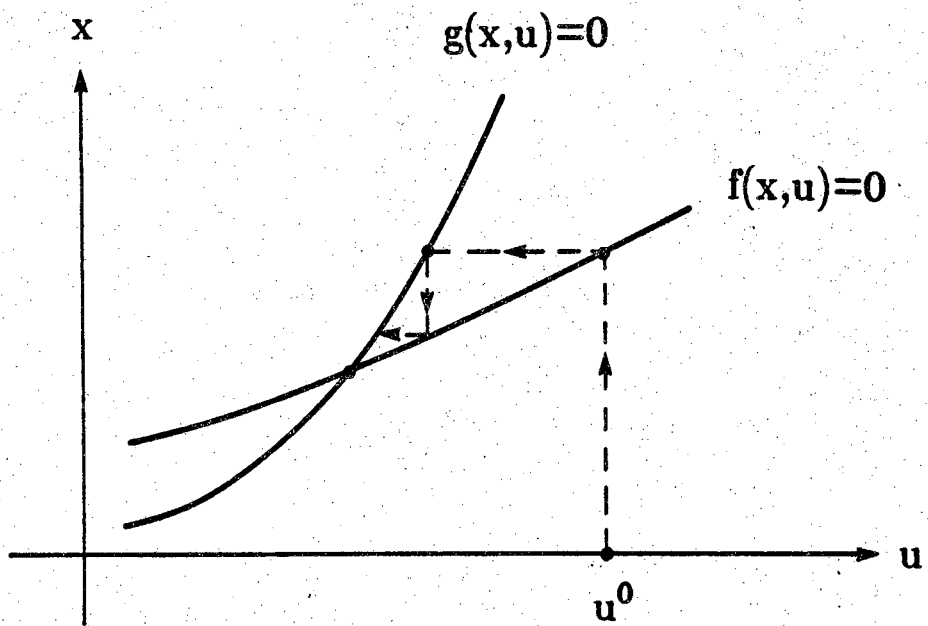


Figure 5.1: Convergent case (Semi-Direct)



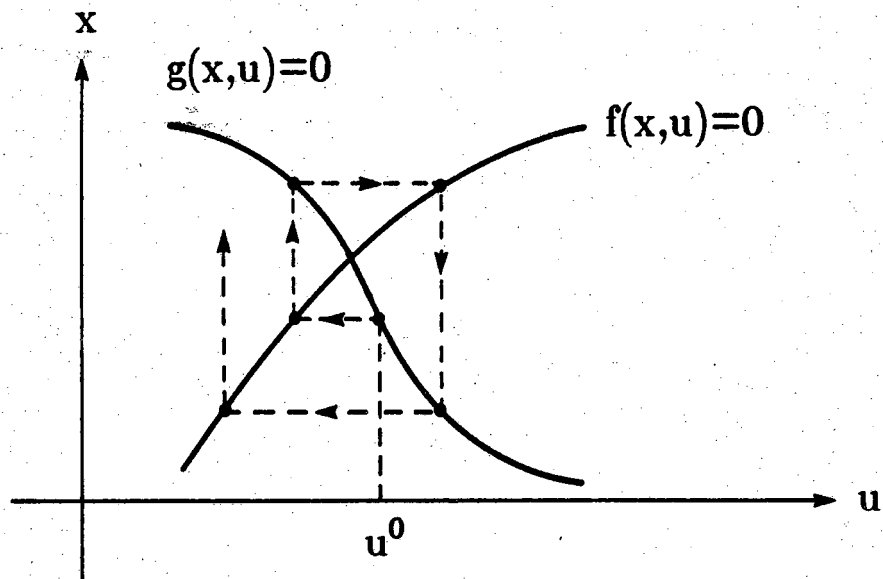


Figure 5.2: Divergent case (Semi-Direct)

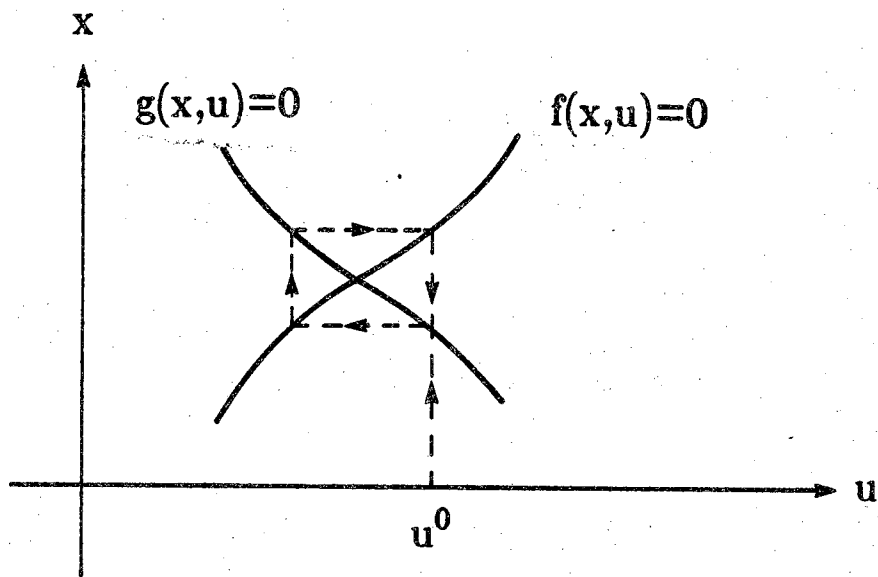


Figure 5.3: Oscillatory case (Semi-Direct)

we get the following results:

x 1	deltax 1	x 2	deltax 2
0. 100000e+01	0. 120619e+01	0. 100000e+01	0. 331959e+01
0. 220619e+01	-0. 209006e+00	0. 431959e+01	-0. 977583e+00
0. 199718e+01	0. 782370e-03	0. 334200e+01	-0. 297179e+00
0. 199796e+01	0. 199497e-02	0. 304483e+01	-0. 438442e-01
0. 199996e+01	0. 435395e-04	0. 300098e+01	-0. 981709e-03
0. 200000e+01	0. 214871e-07	0. 300000e+01	-0. 484090e-06
0. 200000e+01	0. 520838e-14	0. 300000e+01	-0. 117693e-12

The algorithm converges to the solution  $x = 2$  and  $u = 3$  in 7 iterations. To get the solution using the Semi-Direct method. Let us define  $u_j$  and  $x_j$  as the  $j$ th sweep results. We first treat  $u$  as a constant in equation (5.8) and using equation (2.2) we can write

$$x_j^{k+1} = x_j^k - \frac{f(x_j^k, u_j)}{\left. \frac{\partial f}{\partial x} \right|_{x=x_j^k}} \quad (5.10)$$

where  $k = 0, 1, 2, \dots$ , is the iteration number for  $x$ . We evaluate the partial derivative from

$$\frac{\partial f(x, u)}{\partial x} = 3x^2 + 10 \quad (5.11)$$

After obtaining a solution from (5.10) for  $x_j$  we substitute that value into the iterative expression for equation (5.9)

$$u_j^{k+1} = u_j^k - \frac{g(x_j, u_j^k)}{\left. \frac{\partial g}{\partial u} \right|_{u=u_j^k}} \quad (5.12)$$

where

$$\frac{\partial g}{\partial u} = -6(x-u-1)^2-1 \quad (5.13)$$

The result of this iteration process would produce  $u_{j+1}$  which is then used in place of  $u_j$  (updating the value of  $u$ ) in equation (5.10) to obtain  $x_{j+1}$  and the process continues. The following are the sweep results, it took the Semi-Direct method 8 sweeps to reach the solution  $x = 2$  and  $u = 3$ .

x 1	deltax 1	x 2	deltax 2
0. 100000e+01	0. 108873e+01	0. 100000e+01	0. 208517e+01
0. 208873e+01	-0. 926058e-01	0. 308517e+01	-0. 888955e-01
0. 199612e+01	0. 404479e-02	0. 299628e+01	0. 388301e-02
0. 200017e+01	-0. 176493e-03	0. 300016e+01	-0. 169433e-03
0. 199999e+01	0. 770152e-05	0. 299999e+01	0. 739346e-05
0. 200000e+01	-0. 336066e-06	0. 300000e+01	-0. 322624e-06
0. 200000e+01	0. 146647e-07	0. 300000e+01	0. 140781e-07
0. 200000e+01	-0. 639914e-09	0. 300000e+01	-0. 614318e-09

The dependency matrix of example 5.1 is a degenerate form of eq. (4.9), it has the form

$$J(x,u) = \begin{bmatrix} 3x^2+10 & 1 \\ +6(x-u-1)^2 & -6(x-u-1)^2-1 \end{bmatrix} \quad (5.14)$$

so the submatrices of eq. (4.9) would be

$$A_{ss1} = [3x^2+10], \quad (5.15)$$

$$A_{rr} = [-6(x-u-1)^2], \quad (5.16)$$

$$A_{sr} = [1], \quad (5.17)$$

and

$$A_{rs} = [6(x-u-1)^2-1] \quad (5.18)$$

The Semi-Direct method only needed the two submatrices  $\mathbf{A}_{ss1}$  and  $\mathbf{A}_{rr}$  (equations (5.15) and (5.16)) to calculate the solution for  $x$  and  $u$  in equations (5.8) and (5.9). There was no need to calculate or store the expressions for  $\mathbf{A}_{sr}$  and  $\mathbf{A}_{rs}$  which in this example are half the entries to the dependency matrix. These savings may be further amplified in a more general case of the dependency matrix as in example 5.3 in the next section.

## 5.2 Convergence

We expect the Semi-Direct or the nonlinear Gauss-Seidel method to have convergence properties similar to the regular linear Gauss-Seidel method (Chapter 3).

The global convergence properties of the Semi-Direct method is discussed in [2]. They are derived and stated in terms of the contractions requirement on the function. These conditions are extremely difficult to apply in practice, e.g., a computer program. A more practical approach would be to study the local convergence properties of the method. Since we will use the Semi-Direct method mainly in transient analysis applications, the solution at a certain time point using a sufficiently small time step, which usually is the case in transient analysis, can be considered within the local area of the solution at the next time point. So the initial guess at a time point will be relatively close to the time solution if the result at the previous time point is used and even closer if a predictor formula in time is used to approximate the next solution.

The Gauss-Seidel method was designed to solve a set of linear equations (equations (3.3)) of the form

$$\mathbf{Ax} = \mathbf{B} \quad (5.19)$$

The coefficient matrix  $\mathbf{A}$  in this case is simply the same as the Jacobian matrix equations (3.3). As the sweeps of the Semi-Direct method approaches the true solution the nonlinear equations can be approximated by a linear version. In which case the Jacobian Matrix of the nonlinear system at the solution point can be considered as the coefficient matrix of the linearized system. So, the convergence conditions for the linear Gauss-Seidel method can be applied to the Jacobian matrix evaluated at the solution point.

Consider the 2 nonlinear equation case of equations (5.4) and (5.5).

The Jacobian matrix at the solution  $\mathbf{x}$  and  $\mathbf{u}$

$$\mathbf{J}(\mathbf{x}, \mathbf{u}) = \begin{bmatrix} \frac{\partial f}{\partial \mathbf{x}} & \frac{\partial f}{\partial \mathbf{u}} \\ \frac{\partial \mathbf{g}}{\partial \mathbf{x}} & \frac{\partial \mathbf{g}}{\partial \mathbf{u}} \end{bmatrix} \bigg|_{\substack{\mathbf{x}=\mathbf{x} \\ \mathbf{u}=\mathbf{u}}} \quad (5.20)$$

which can be written as

$$\mathbf{J} = \mathbf{P} + \mathbf{Q} = \begin{bmatrix} \frac{\partial f}{\partial \mathbf{x}} & 0 \\ \frac{\partial \mathbf{g}}{\partial \mathbf{x}} & \frac{\partial \mathbf{g}}{\partial \mathbf{u}} \end{bmatrix} + \begin{bmatrix} 0 & \frac{\partial f}{\partial \mathbf{u}} \\ 0 & 0 \end{bmatrix} \quad (5.21)$$

The system will converge if and only if the eigenvalues of  $\mathbf{P}^{-1}\mathbf{Q}$  have magnitude less than 1. That is the eigenvalues of

$$\begin{bmatrix} \frac{\partial f}{\partial \mathbf{x}} & 0 \\ \frac{\partial \mathbf{g}}{\partial \mathbf{x}} & \frac{\partial \mathbf{g}}{\partial \mathbf{u}} \end{bmatrix}^{-1} \begin{bmatrix} 0 & \frac{\partial f}{\partial \mathbf{u}} \\ 0 & 0 \end{bmatrix}, \text{ or } \begin{bmatrix} 0 & \frac{\partial \mathbf{g}}{\partial \mathbf{u}} \cdot \frac{\partial f}{\partial \mathbf{u}} \\ 0 & -\frac{\partial \mathbf{g}}{\partial \mathbf{x}} \cdot \frac{\partial f}{\partial \mathbf{u}} \end{bmatrix} \frac{1}{\frac{\partial f}{\partial \mathbf{x}} \cdot \frac{\partial \mathbf{g}}{\partial \mathbf{u}}} \quad (5.22)$$

evaluated at  $\mathbf{x}=\mathbf{x}$  and  $\mathbf{u}=\mathbf{u}$  should have magnitudes less than 1

$$|\lambda| = \left| \frac{\frac{\partial f}{\partial u} \cdot \frac{\partial g}{\partial x}}{\frac{\partial f}{\partial x} \cdot \frac{\partial g}{\partial u}} \right| < 1 \quad (5.23)$$

The convergence rate is linear and is given by

$$|e_{j+1}| = \max |\lambda| \cdot |e_j| \quad (5.24)$$

where

$$e_j = a_j - \mathbf{a} \quad (5.25)$$

and  $\mathbf{a}$  can be any  $x$ ,  $y$  or  $z$  variables. (see section 3.2). As an approximation for (5.24) when the sweeps are close to the time solution. We can write

$$|\Delta a_{j+1}| = \max |\lambda| \cdot |\Delta a_j| \quad (5.26)$$

where

$$\Delta a_j = a_{j+1} - a_j \quad (5.27)$$

**Example 5.2:**

For equation (5.8) and (5.9) in example 5.1 we can evaluate their Jacobian matrix (equation (5.14)) at the solution  $x=2$   $u=3$

$$\mathbf{J}(2,3) = \begin{bmatrix} 22 & 1 \\ 24 & -25 \end{bmatrix}$$

Separating into  $\mathbf{P}$  and  $\mathbf{Q}$  we have

$$\mathbf{J} = \mathbf{P} + \mathbf{Q} = \begin{bmatrix} 22 & 0 \\ 24 & -25 \end{bmatrix} + \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$$

The convergence condition then is that the magnitude of the eigenvalues of  $\mathbf{P}^{-1}\mathbf{Q}$  be less than 1.

$$\begin{aligned} & \begin{bmatrix} 22 & 0 \\ 24 & -25 \end{bmatrix}^{-1} \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \\ & = \begin{bmatrix} 0 & 0.0455 \\ 0 & 0.04364 \end{bmatrix} \end{aligned}$$

The eigenvalue  $\lambda$  of  $\mathbf{P}^{-1}\mathbf{Q}$  is 0.04364 whose magnitude is less than 1.

So the system is convergent and the results were obtained in example 5.1

Checking values of  $x$  and  $u$  close to the solution and using equation (5.24) we should obtain this approximate relationship,

$$\left| \frac{\Delta x_{j+1}}{\Delta x_j} \right| \approx |\lambda| \quad (5.28)$$

and

$$\left| \frac{\Delta u_{j+1}}{\Delta u_j} \right| \approx |\lambda| \quad (5.29)$$

From example 5.1 Semi-Direct results we have

$$\begin{aligned} \left| \frac{\Delta x_7}{\Delta x_6} \right| &= \left| \frac{-0.6399140 \times 10^{-9}}{0.146647 \times 10^{-7}} \right| = 0.04364 = |\lambda| \\ \left| \frac{\Delta u_7}{\Delta u_6} \right| &= \left| \frac{-0.614318 \times 10^{-9}}{0.140781 \times 10^{-7}} \right| = 0.04364 = |\lambda| \\ \left| \frac{\Delta x_5}{\Delta x_6} \right| &= \left| \frac{+0.146647 \times 10^{-7}}{-0.336066 \times 10^{-6}} \right| = 0.04364 = |\lambda| \\ \left| \frac{\Delta u_5}{\Delta u_6} \right| &= \left| \frac{0.140781 \times 10^{-7}}{-0.322624 \times 10^{-6}} \right| = 0.04364 = |\lambda| \end{aligned}$$

For the general case of the dependency matrix in the form of equation (4.9) the Semi-Direct method converges if and only if the eigenvalues of  $\mathbf{P}^{-1}\mathbf{Q}$



(see sec. 4.2) evaluated at the solution point have magnitude less than unity. So as we get close to the solution point the equations can be written in the form of equation (5.19), where  $\mathbf{A}$  is the Jacobian matrix of the nonlinear system evaluated at the solution point. It can be rewritten as

$$\begin{bmatrix} \mathbf{A}_{ss} & \mathbf{A}_{sr} \\ \mathbf{A}_{rs} & \mathbf{A}_{rr} \end{bmatrix} \begin{bmatrix} \mathbf{x}_s \\ \mathbf{x}_r \end{bmatrix} = \begin{bmatrix} \mathbf{B}_s \\ \mathbf{B}_r \end{bmatrix} \quad (5.30)$$

The Semi-Direct iterations can be expressed in the form of a difference equation (see section 4.2)

$$\mathbf{x}_{j+1} = -\mathbf{P}^{-1}\mathbf{Q} \mathbf{x}_j + \mathbf{P}^{-1}\mathbf{B} \quad (5.31)$$

where

$$\mathbf{P} = \begin{bmatrix} \mathbf{A}_{ss} & 0 \\ \mathbf{A}_{rs} & \mathbf{A}_{rr} \end{bmatrix} \text{ and } \mathbf{Q} = \begin{bmatrix} 0 & \mathbf{A}_{sr} \\ 0 & 0 \end{bmatrix}$$

we have

$$\mathbf{P}^{-1} = \begin{bmatrix} \mathbf{A}_{ss}^{-1} & 0 \\ -\mathbf{A}_{rr}^{-1}\mathbf{A}_{rs}\mathbf{A}_{ss}^{-1} & \mathbf{A}_{rr}^{-1} \end{bmatrix}$$

so  $\mathbf{P}^{-1}\mathbf{Q}$  has the form

$$\mathbf{P}^{-1}\mathbf{Q} = \begin{bmatrix} 0 & \mathbf{A}_{ss}^{-1}\mathbf{A}_{sr} \\ 0 & \mathbf{A}_{rr}^{-1}\mathbf{A}_{rs}\mathbf{A}_{ss}^{-1}\mathbf{A}_{sr} \end{bmatrix} \quad (5.32)$$

The eigenvalues of  $\mathbf{P}^{-1}\mathbf{Q}$  (equation (5.32)) are 0 and the eigenvalues of  $\mathbf{A}_{rr}^{-1}\mathbf{A}_{rs}\mathbf{A}_{ss}^{-1}\mathbf{A}_{sr}$ . So, the Semi-Direct iterations converge if and only if the magnitude of the eigenvalues of

$$\mathbf{A}_{rr}^{-1}\mathbf{A}_{rs}\mathbf{A}_{ss}^{-1}\mathbf{A}_{sr} \quad (5.33)$$

are all less than unity.

The rate of convergence is linear and is equal to the eigenvalue of (5.33) with the largest magnitude as explained earlier in this section.

Example 5.3:

Consider this system of 10 equations in 10 unknowns.

```

fx(1)= x(1)**3 + 10*x(1) + x(2) -u(1)**2+2*u(2)**2-60
fx(2)= 2*(x(1)-x(2)-1)**3 -x(2) +6*u(1)*u(2) -16
jac(1,1,1)= 3*x(1)**2 + 10
jac(1,1,2)= 1
jac(1,2,1)= 6*(x(1)-x(2)-1)**2
jac(1,2,2)= -6*(x(1)-x(2)-1)**2 -1
fx(3)=x(3)**3+10*x(3)+x(4) -u(1)**2+2*u(2)**2+27
fx(4)= 2*(x(3)-x(4)-1)**3 -x(4) +6*u(1)*u(2) +216
jac(2,1,1)= 3*x(3)**2 + 10
jac(2,1,2)= 1
jac(2,2,1)= 6*(x(3)-x(4)-1)**2
jac(2,2,2)= -6*(x(3)-x(4)-1)**2 -1
fx(5)=x(5)+ 4*x(6)**3 +u(1)**3-u(2)**3 +84
fx(6)=-x(6)**2+ x(5)**2+x(6) +2*u(1)**3+u(2)-69
jac(3,1,1) = 1
jac(3,1,2)= 12*x(6)**2
jac(3,2,1)=x(5)*2
jac(3,2,2) = -2*x(6) + 1
fx(7) = u(1)**3 -u(2) +z(1)**2 +z(1) +z(2) -29
fx(8)=z(1)+u(1)**3+u(2)**3+4*(z(1)*z(2))**2-176
jac(4,1,1) = 2*z(1) +1
jac(4,1,2)=1
jac(4,2,1)=1+8*z(1)*z(2)**2
jac(4,2,2)=8*z(2)*z(1)**2
fx(9)=x(1)**2+x(3)**2+x(6)**2+10*u(1)**2+u(2)*u(1)
      +2*z(1)*z(2)+120*u(1)-490+120*u(1)-490
fx(10)=x(2)**3+x(4)**2-x(5)**2+u(1)-150*u(2)+z(1)**3
      +z(2)**3+289
jac(5,1,1)=120+u(2)+20*u(1)
jac(5,1,2)=u(1)
jac(5,2,1)=1
jac(5,2,2)=-150

```

The system is partitioned as follows:

$$\mathbf{F}^1 = \begin{bmatrix} \text{fx}(1) \\ \text{fx}(2) \end{bmatrix} \quad \mathbf{x}^1 = \begin{bmatrix} \text{x}(1) \\ \text{x}(2) \end{bmatrix}$$

$$\mathbf{F}^2 = \begin{bmatrix} \text{fx}(3) \\ \text{fx}(4) \end{bmatrix} \quad \mathbf{x}^2 = \begin{bmatrix} \text{x}(3) \\ \text{x}(4) \end{bmatrix}$$

$$\mathbf{F}^3 = \begin{bmatrix} \text{fx}(5) \\ \text{fx}(6) \end{bmatrix} \quad \mathbf{x}^3 = \begin{bmatrix} \text{x}(5) \\ \text{x}(6) \end{bmatrix}$$

$$\mathbf{H} = \begin{bmatrix} \text{fx}(7) \\ \text{fx}(8) \end{bmatrix} \quad \mathbf{z} = \begin{bmatrix} \text{z}(1) \\ \text{z}(2) \end{bmatrix}$$

$$\mathbf{G} = \begin{bmatrix} \text{fx}(9) \\ \text{fx}(10) \end{bmatrix} \quad \mathbf{u} = \begin{bmatrix} \text{u}(1) \\ \text{u}(2) \end{bmatrix}$$

The solution to the system is

$$\mathbf{x}^1 = \begin{bmatrix} 3 \\ 4 \end{bmatrix} \quad \mathbf{x}^2 = \begin{bmatrix} -2 \\ 2 \end{bmatrix} \quad \mathbf{x}^3 = \begin{bmatrix} 5 \\ -3 \end{bmatrix}$$

$$\mathbf{z} = \begin{bmatrix} -3 \\ -2 \end{bmatrix} \quad \mathbf{u} = \begin{bmatrix} 3 \\ 2 \end{bmatrix}$$

The matrix of equation (5.33) is

$$\mathbf{A}_{rr}^{-1} \mathbf{A}_{rs} \mathbf{A}_{ss}^{-1} \mathbf{A}_{sr} = \begin{bmatrix} -0.018 & 0.004 \\ 1.184 & 0.152 \end{bmatrix}$$

which has eigenvalues of

$$\lambda_1 = -0.04099$$

and

$$\lambda_2 = 0.17465$$

Since  $|\lambda_2| > |\lambda_1|$  then the convergence rate of the system is  $\lambda_2$ . This can be seen from the output of the Semi-Direct method for some chosen variables.

(The stopping criterion is  $e = 10^{-8}$ ).

x 1	deltax 1	x 2	deltax 2
0. 100000e+01	0. 204499e+01	0. 100000e+01	-0. 682876e+00
0. 304499e+01	-0. 940797e-01	0. 317124e+00	0. 376632e+01
0. 295091e+01	0. 450155e-01	0. 408344e+01	-0. 737360e-01
0. 299592e+01	0. 316198e-02	0. 400970e+01	-0. 767571e-02
0. 299909e+01	0. 762710e-03	0. 400203e+01	-0. 168599e-02
0. 299985e+01	0. 124398e-03	0. 400034e+01	-0. 281423e-03
0. 299997e+01	0. 220868e-04	0. 400006e+01	-0. 497403e-04
0. 300000e+01	0. 384271e-05	0. 400001e+01	-0. 866470e-05
0. 300000e+01	0. 671750e-06	0. 400000e+01	-0. 151429e-05
0. 300000e+01	0. 117299e-06	0. 400000e+01	-0. 264439e-06
0. 300000e+01	0. 204876e-07	0. 400000e+01	-0. 461868e-07
0. 300000e+01	0. 357820e-08	0. 400000e+01	-0. 806662e-08
0. 300000e+01	0. 624947e-09	0. 400000e+01	-0. 140887e-08
x 5	deltax 5	x 6	deltax 6
0. 100000e+01	0. 777409e+01	0. 100000e+01	-0. 385182e+01
0. 877409e+01	-0. 377328e+01	-0. 285182e+01	-0. 121813e+00
0. 500081e+01	-0. 967315e-02	-0. 297363e+01	-0. 244918e-01
0. 499114e+01	0. 787259e-02	-0. 299813e+01	-0. 143163e-02
0. 499901e+01	0. 792014e-03	-0. 299956e+01	-0. 370123e-03
0. 499981e+01	0. 160807e-03	-0. 299993e+01	-0. 595356e-04
0. 499997e+01	0. 270943e-04	-0. 299999e+01	-0. 106037e-04
0. 499999e+01	0. 477082e-05	-0. 300000e+01	-0. 184343e-05
0. 500000e+01	0. 831594e-06	-0. 300000e+01	-0. 322308e-06
0. 500000e+01	0. 145307e-06	-0. 300000e+01	-0. 562779e-07
0. 500000e+01	0. 253756e-07	-0. 300000e+01	-0. 982972e-08
0. 500000e+01	0. 443205e-08	-0. 300000e+01	-0. 171677e-08
0. 500000e+01	0. 774068e-09	-0. 300000e+01	-0. 299841e-09
x 9	deltax 9	x10	deltax10
0. 100000e+01	0. 199275e+01	0. 100000e+01	0. 119863e+01
0. 299275e+01	0. 830794e-02	0. 219863e+01	-0. 180298e+00
0. 300106e+01	-0. 100535e-02	0. 201833e+01	-0. 143212e-01
0. 300005e+01	-0. 368315e-04	0. 200401e+01	-0. 333959e-02
0. 300001e+01	-0. 118950e-04	0. 200067e+01	-0. 548953e-03
0. 300000e+01	-0. 184083e-05	0. 200012e+01	-0. 973105e-04
0. 300000e+01	-0. 330865e-06	0. 200002e+01	-0. 169375e-04
0. 300000e+01	-0. 573924e-07	0. 200000e+01	-0. 296060e-05
0. 300000e+01	-0. 100396e-07	0. 200000e+01	-0. 516981e-06
0. 300000e+01	-0. 175280e-08	0. 200000e+01	-0. 902966e-07
0. 300000e+01	-0. 306159e-09	0. 200000e+01	-0. 157705e-07
0. 300000e+01	-0. 534707e-10	0. 200000e+01	-0. 275438e-08
0. 300000e+01	-0. 933892e-11	0. 200000e+01	-0. 481061e-09

## Example 5.4:

Consider another system of equations in 10 equations and 10 unknowns

with the same partitions as example 5.3. The equations are:

```

fx(1) = x(1)**3 + 10*x(1) + x(2) - u(1)**2 + 2*u(2)**2 - 60
fx(2) = 2*(x(1) - 1)**3 - x(2) + 6*u(1)*u(2) - 16
fx(3) = x(3)**3 + 10*x(3) + x(4) - u(1)**2 + 2*u(2)**2 + 27
fx(4) = 2*(x(3) - 1)**3 - x(4) + 6*u(1)*u(2) + 216
fx(5) = x(5)**3 + 10*x(5) + x(6) - u(1)**2 + 2*u(2)**2 - 171
fx(6) = 2*(x(5) - 1)**3 - x(6) + 6*u(1)*u(2) - 725
fx(7) = z(1)**3 + 10*z(1) + z(2) - u(1)**2 + 2*u(2)**2 + 60
fx(8) = 2*(z(1) - 1)**3 - z(2) - 1**3 - z(2) + 6*u(1)*u(2) - 22
fx(9) = -16*x(1)**2 + x(3)**2 + x(6)**2 - u(1) + u(2)
fx(10) = -36*x(2)**3 + x(4)**2 - x(5)**2 + 2*u(1) - 4*u(2)
+z(1) + z(2)
*****

```

The matrix of equation (5.33) is

$$A^{-1}A^{TS}A^{-1}A^{SS}A^{-1}A^{SI} = \begin{bmatrix} 15.5 & 13.1 \\ 15.5 & 12.6 \end{bmatrix}$$

which has eigenvalues

$$\lambda_1 = 28.4 \quad \lambda_2 = -0.295$$

but  $|\lambda_1| > 1$  so the Semi-Direct method should diverge. A sample output for

some variables confirms that.

x 1	deltax 1	x 2	deltax 2
0. 100000e+01	0. 204499e+01	0. 100000e+01	-0. 682876e+00
0. 304499e+01	-0. 128632e+02	0. 317124e+00	0. 433097e+01
-0. 981824e+01	0. 523756e+02	0. 464810e+01	0. 976279e+02
0. 425574e+02	-0. 666501e+04	0. 102276e+03	0. 307951e+04

x 3	deltax 3	x 4	deltax 4
0. 100000e+01	-0. 307643e+01	0. 100000e+01	0. 717040e+00
-0. 207643e+01	-0. 802425e+01	0. 171704e+01	0. 280868e+01
-0. 101007e+02	0. 526421e+02	0. 452572e+01	0. 977447e+02
0. 425414e+02	-0. 666500e+04	0. 102270e+03	0. 307952e+04

x 5	deltax 5	x 6	deltax 6
0. 100000e+01	0. 397782e+01	0. 100000e+01	-0. 412236e+01
0. 497782e+01	-0. 144102e+02	-0. 312236e+01	0. 764576e+01
-0. 943236e+01	0. 520101e+02	0. 452340e+01	0. 977409e+02
0. 425777e+02	-0. 666503e+04	0. 102264e+03	0. 307952e+04

x 7	deltax 7	x 8	deltax 8
0. 100000e+01	-0. 395403e+01	0. 100000e+01	-0. 668195e+01
-0. 295403e+01	-0. 724920e+01	-0. 568195e+01	0. 994114e+01
-0. 102032e+02	0. 527385e+02	0. 425919e+01	0. 979945e+02
0. 425353e+02	-0. 666499e+04	0. 102254e+03	0. 307954e+04

x 9	deltax 9	x10	deltax10
0. 100000e+01	-0. 368239e+02	0. 100000e+01	-0. 355206e+02
-0. 358239e+02	0. 424696e+03	-0. 345206e+02	0. 226454e+03
0. 388873e+03	0. 567326e+06	0. 191934e+03	0. 553316e+06
0. 567715e+06	0. 162841e+11	0. 553508e+06	0. 161863e+11

## Example 5.5:

Consider the circuit of figure 4.6. Formulating the equations for the system produces the following equations:

```

fx(1) = 3*x(1) - u(1) - x(2)
fx(2) = x(2) - 2
fx(3) = x(2) - x(1) + x(3)
fx(4) = x(4) - u(1)**3 + u(1)
  jac(1,4,4) = 1
  jac(1,1,1) = 3
  jac(1,1,2) = -1
  jac(1,2,2) = 1
  jac(1,3,2) = 1
  jac(1,3,1) = -1
  jac(1,3,3) = 1
*****
fx(6) = 2*x(6) - u(2) - x(7)
fx(7) = x(7) - (x(5) - x(6))**3 + (x(5) - x(6))
  jac(2,3,3) = 1
  jac(2,3,1) = - 3*(x(5) - x(6))**2 + 1
  jac(2,3,2) = 3*(x(5) - x(6))**2 - 1
  jac(2,1,1) = 2
  jac(2,1,3) = 1
  jac(2,2,2) = 2
  jac(2,2,3) = -1
*****
fx(8) = 3.5*z(1) - 1.5*z(3) + z(2) - u(2)
fx(9) = z(2) - (z(1) - u(1))**3 + (z(1) - u(1))
fx(10) = z(3) - 2
fx(11) = z(3) - z(1) + z(4)
  jac(3,1,1) = 3.5
  jac(3,1,2) = 1
  jac(3,1,3) = -1.5
  jac(3,2,1) = -3*(z(1) - u(1))**2 + 1
  jac(3,2,2) = 1
  jac(3,3,3) = 1
  jac(3,4,1) = -1
  jac(3,4,3) = 1
  jac(3,4,4) = 1
*****
fx(12) = x(4) + 2*u(1) - x(1) - u(2) - z(2)
fx(13) = 5*u(2) - z(1) - u(1) - x(5) - x(6)
  jac(4,1,1) = 2
  jac(4,1,2) = -1
  jac(4,2,1) = -1
  jac(4,2,2) = 5
*****

```

The rate of convergence is 0.2728 and the solution is:

$$\begin{aligned}
 x_1 &= 0.9210 & x_2 &= 2.0 & x_3 &= -1.079 \\
 x_4 &= -0.3189 & x_5 &= 0.9441 & x_6 &= 0.1504 \\
 x_7 &= -0.2937 & z_1 &= 1.115 & z_2 &= -0.3085 \\
 z_3 &= 2.0 & z_4 &= -0.8848 & u_1 &= 0.7629 \\
 u_2 &= 0.5945
 \end{aligned}$$

A sample output looks like this.

x 3	deltax 3	x 4	deltax 4
0.100000e+01	-0.200000e+01	0.100000e+01	-0.100000e+01
-0.100000e+01	-0.833179e-01	0. e+00	-0.328093e+00
-0.108332e+01	0.491768e-02	-0.328093e+00	0.106387e-01
-0.107840e+01	-0.264129e-03	-0.317454e+00	-0.596618e-03
-0.107866e+01	-0.235310e-03	-0.318051e+00	-0.529096e-03
-0.107890e+01	-0.898942e-04	-0.318580e+00	-0.201525e-03
-0.107899e+01	-0.289776e-04	-0.318782e+00	-0.648911e-04
-0.107902e+01	-0.868616e-05	-0.318847e+00	-0.194447e-04
-0.107903e+01	-0.250601e-05	-0.318866e+00	-0.560933e-05
-0.107903e+01	-0.707341e-06	-0.318872e+00	-0.158323e-05
-0.107903e+01	-0.197058e-06	-0.318873e+00	-0.441068e-06
-0.107903e+01	-0.544608e-07	-0.318874e+00	-0.121897e-06
-0.107903e+01	-0.149766e-07	-0.318874e+00	-0.335215e-07
-0.107903e+01	-0.410570e-08	-0.318874e+00	-0.918961e-08
-0.107903e+01	-0.112333e-08	-0.318874e+00	-0.251429e-08
-0.107903e+01	-0.306960e-09	-0.318874e+00	-0.687055e-09
x11	deltax11	x12	deltax12
0.100000e+01	-0.180306e+01	0.100000e+01	-0.249954e+00
-0.803056e+00	-0.468189e-01	0.750046e+00	0.147530e-01
-0.849874e+00	-0.262227e-01	0.764799e+00	-0.792387e-03
-0.876097e+00	-0.646319e-02	0.764007e+00	-0.705929e-03
-0.882560e+00	-0.167506e-02	0.763301e+00	-0.269683e-03
-0.884235e+00	-0.442428e-03	0.763031e+00	-0.869327e-04
-0.884678e+00	-0.118137e-03	0.762944e+00	-0.260585e-04
-0.884796e+00	-0.317728e-04	0.762918e+00	-0.751804e-05
-0.884828e+00	-0.858639e-05	0.762911e+00	-0.212202e-05
-0.884836e+00	-0.232777e-05	0.762909e+00	-0.591175e-06
-0.884839e+00	-0.632356e-06	0.762908e+00	-0.163382e-06
-0.884839e+00	-0.172013e-06	0.762908e+00	-0.449298e-07
-0.884840e+00	-0.468306e-07	0.762908e+00	-0.123171e-07
-0.884840e+00	-0.127566e-07	0.762908e+00	-0.336998e-08
-0.884840e+00	-0.347612e-08	0.762908e+00	-0.920880e-09
-0.884840e+00	-0.947436e-09	0.762908e+00	-0.251440e-09



## Example 5.6:

Consider the two stage transistor circuits of figure 5.4. The two transistors are replaced by their Ebers-Moll dc model and the circuit is partitioned as in figure 5.5. The current variables  $x_4, x_5, x_9, x_{10}, z_2, z_4$  and  $z_6$  are all added optionally. We may choose not to include some or all of them in the formulation if there is not a need for their values as an output. Assuming the diodes are ideal, their current  $i_d$  can be expressed as

$$i_d \cong I_s e^{\frac{qv_d}{kT}} \quad (5.34)$$

where  $v_d$  is the voltage across the diode,  $q$  is the electron charge,  $k$  is Boltzmann's constant,  $T$  is the absolute temperature and  $I_s$  is the reverse saturation current. Using room temperature ( $T=300^\circ\text{K}$ ) and  $I_s = 10^{-14}$  A, equation (5.34) becomes

$$i_d \cong 10^{-14} e^{38.65V_d} \quad (5.35)$$

The equations for the circuit are:

```

F1: fx(1) = (x(1)-u(2))* .001 - x(4) - .5*x(5)
fx(2) = x(2)*.01 - x(5) + .98*x(4)
fx(3) = (x(3)-u(1))* .001 + .02*x(4) + .5*x(5)
fx(4) = x(4) - 1.e-14*exp(38.65*(x(3)-x(1)))
fx(5) = x(5) - 1.e-14*exp(38.65*(x(3)-x(2)))
*****
F2: fx(6) = (x(6)-u(2))* .001 - x(9) - .5*x(10)
fx(7) = x(7)*.01 - x(10) + .98*x(9)
fx(8) = (x(8)-u(1))* .001 + .02*x(9) + .5*x(10)
fx(9) = x(9) - 1.e-14*exp(38.65*(x(8)-x(6)))
fx(10) = x(10) - 1.e-14*exp(38.65*(x(8)-x(7)))
*****

```

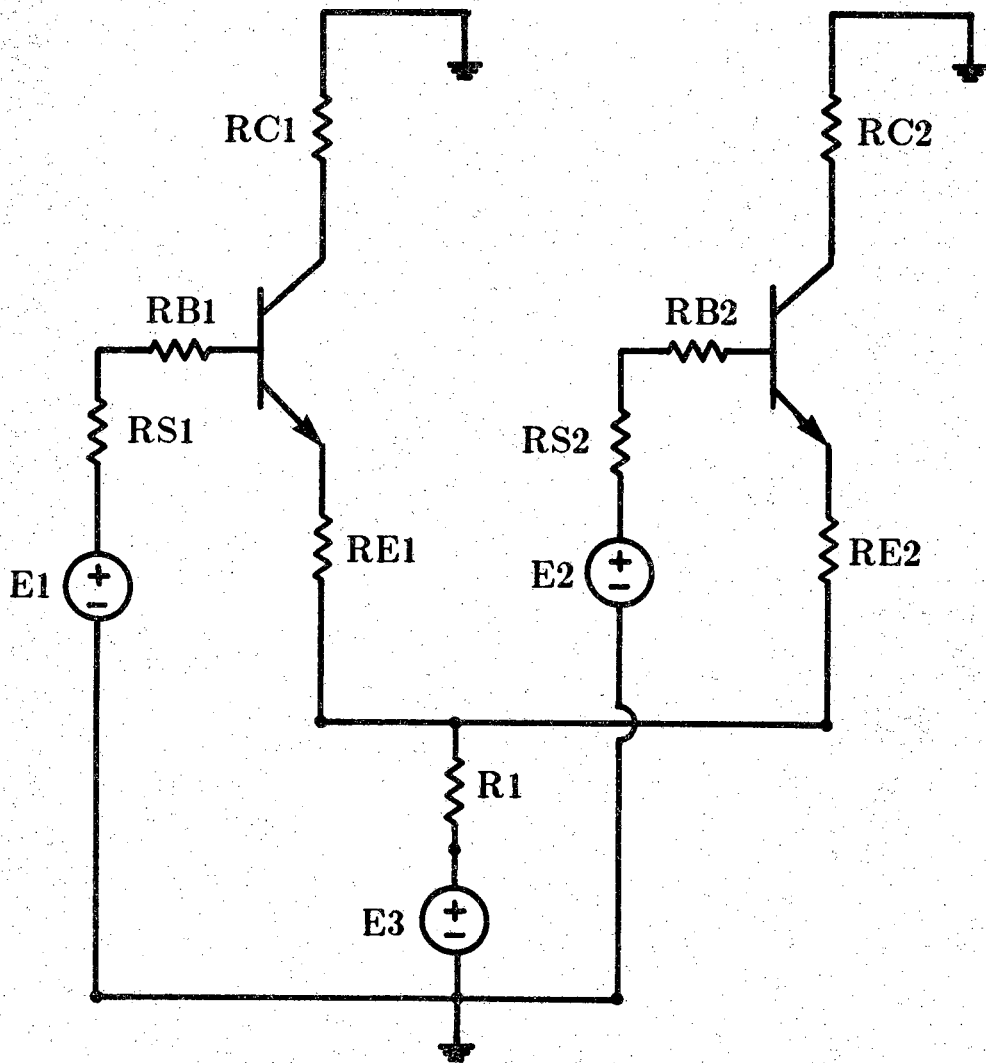


Figure 5.4: 2-stage transistor circuit

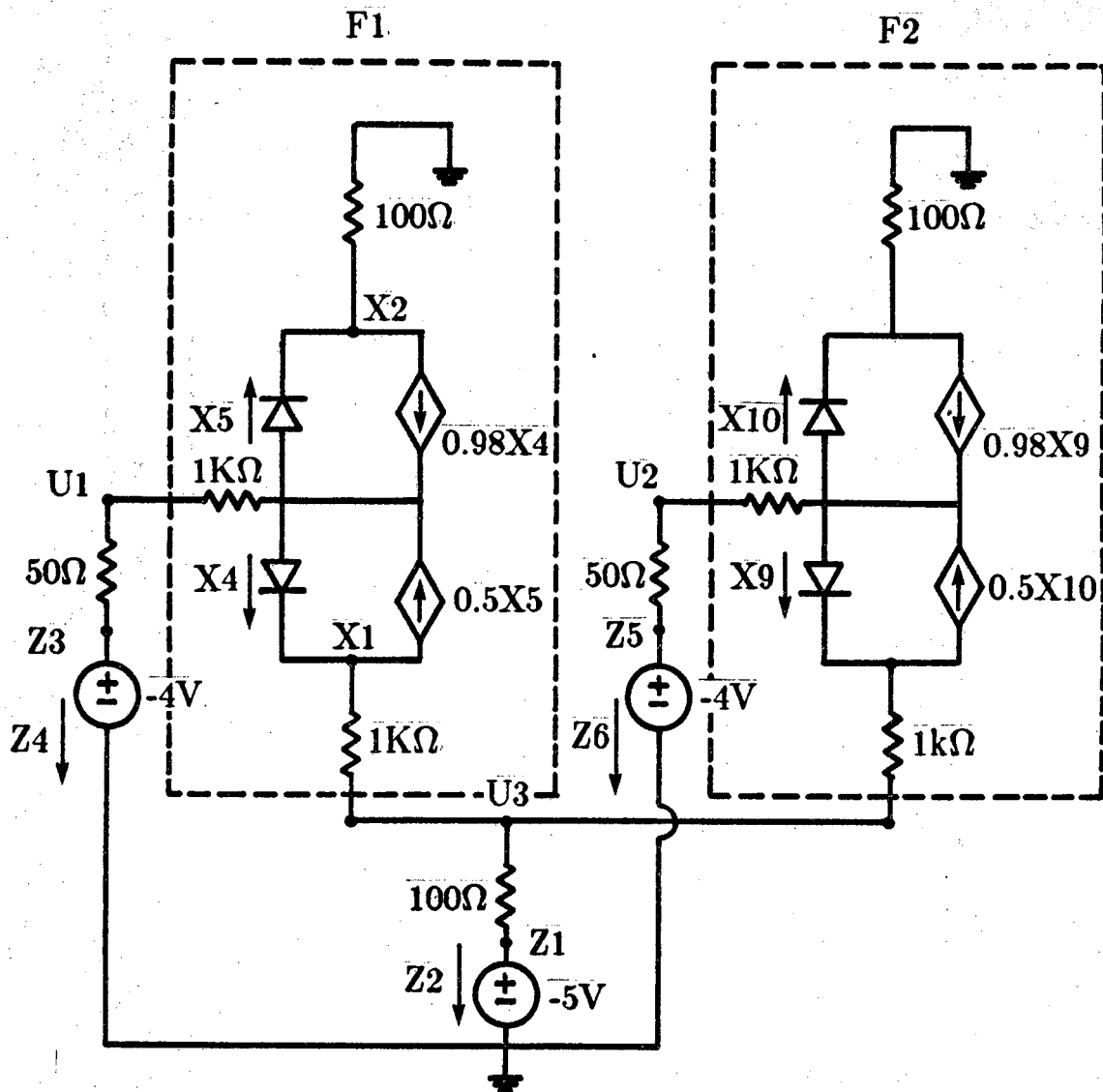


Figure 5.5: Labeled circuit

```

H : fx(11) = z(1) + 5
    fx(12) = (z(1)-u(3))/100. + z(2)
    fx(13) = z(3) + 4
    fx(14) = (z(3)-u(1))/50. + z(4)
    fx(15) = z(5) + 4
    fx(16) = (z(5)-u(2))/50. + z(6)
*****
G : fx(17) = (u(1)-x(3))/1000. + (u(1)-z(3))/50.
    fx(18) = (u(2)-x(8))/1000. + (u(2)-z(5))/50.
    fx(19) = (u(3)-x(1))/1000. + (u(3)-x(6))/1000. +
            (u(3)-z(1))/100.
*****

```

The analysis was done using a set of equations that combined the two resistors  $R_{B1}$  and  $R_{S1}$  as one 1050 ohm resistor, and the two resistors  $R_{B2}$  and  $R_{S2}$  as one 1050 ohm resistor. This is a case where an ideal voltage source is connected to a tearing node. This forces the currents through the source to be introduced as  $u$  variables. Figure 5.6 illustrates the new labeling. We now have 5  $u$  variables and 2  $z$  variables. The equations take the form:

```

F1: fx(1) = (x(1)-u(2))* .001 - x(4) - .5*x(5)
    fx(2) = x(2)*.01 - x(5) + .98*x(4)
    fx(3) = (x(3)-u(1))/1050. + .02*x(4) + .5*x(5)
    fx(4) = x(4) - 1.e-14*exp(38.65*(x(3)-x(1)))
    fx(5) = x(5) - 1.e-14*exp(38.65*(x(3)-x(2)))
*****
F1: fx(6) = (x(6)-u(2))* .001 - x(9) - .5*x(10)
    fx(7) = x(7)*.01 - x(10) + .98*x(9)
    fx(8) = (x(8)-u(3))/1050. + .02*x(9) + .5*x(10)
    fx(9) = x(9) - 1.e-14*exp(38.65*(x(8)-x(6)))
    fx(10) = x(10) - 1.e-14*exp(38.65*(x(8)-x(7)))
*****
H : fx(11) = z(1) +5
    fx(12) = (z(1)-u(2))* .01 +z(2)
*****
G : fx(13) = u(1) +4
    fx(14) = (u(2)-z(1))* .01 + (u(2)-x(1))* .001
            + (u(2)-x(6))* .001
    fx(15) = u(3) +4
    fx(16) = (u(1) - x(3))/1050. +u(4)
    fx(17) = (u(3) - x(8))/1050. + u(5)
*****

```

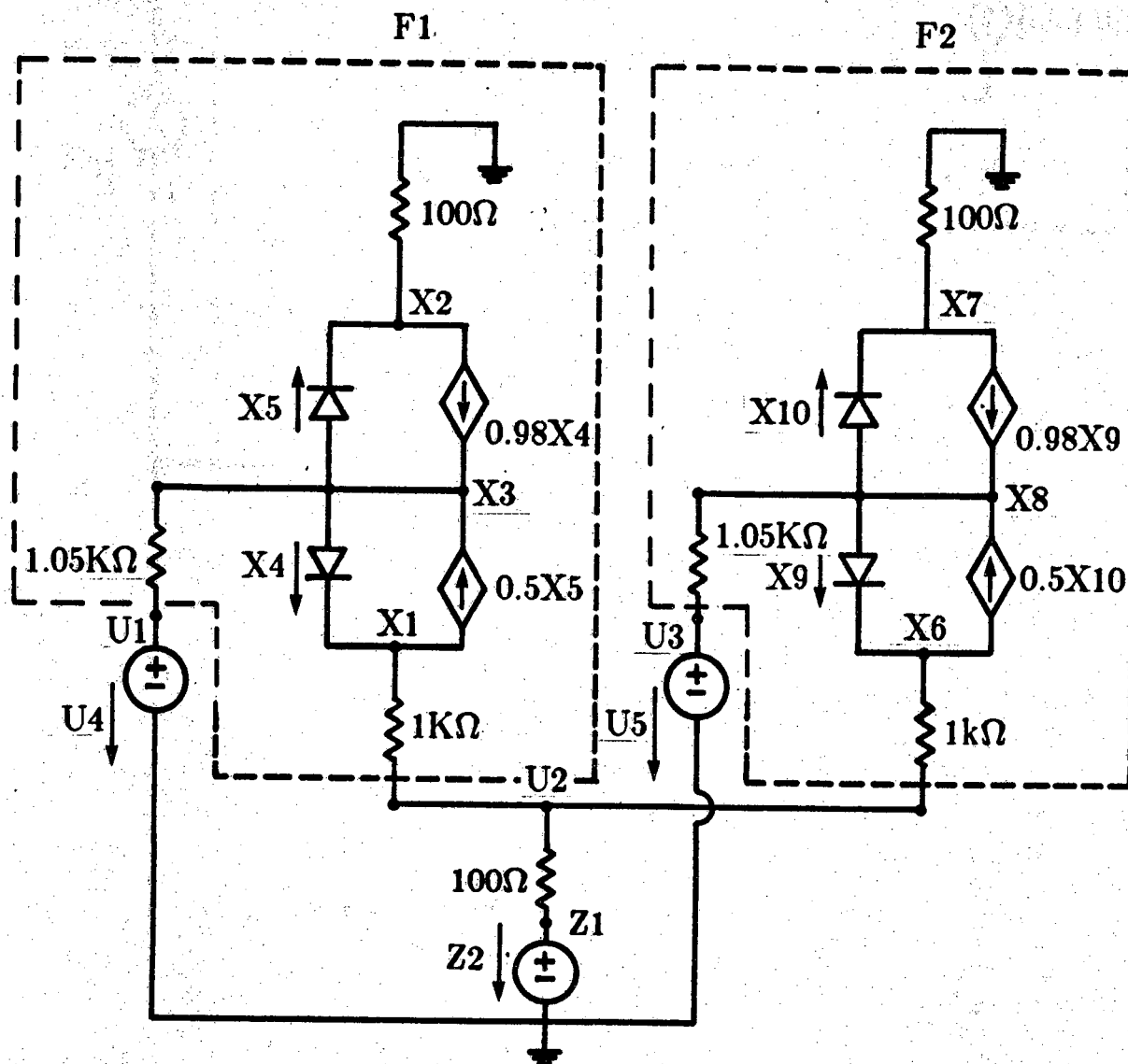


Figure 5.6: Model used in the analysis

The matrix equation (5.33) becomes

$$\mathbf{A}_{TR}^{-1} \mathbf{A}_{TS} \mathbf{A}_{SS}^{-1} \mathbf{A}_{ST} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0.01508 & 0.0159 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0.93 \times 10^{-3} & 0.16 \times 10^{-4} & 0 & 0 & 0 \\ 0.93 \times 10^{-3} & 0.18 \times 10^{-4} & 0 & 0 & 0 \end{bmatrix}$$

The only eigenvalue for the above matrix is

$$\lambda = 0.0158636$$

which has magnitude less than 1. The solution is as follows (apply to figure 5.6)

$$\begin{aligned} x_6 &= x_1 = -4.631 & x_7 &= x_2 = -0.0301 & x_8 &= x_3 = -4.006 \\ x_9 &= x_4 = 0.00031 & x_{10} &= x_5 = 0.0 \\ z_1 &= -5.0 & z_2 &= 0.000612 \\ u_1 &= -4.0 & u_2 &= -4.939 & u_3 &= -4.0 \\ u_5 &= u_4 = -0.615 \times 10^{-5} \end{aligned}$$

The output for a few selected variables are listed below.

x 6	deltax 6	x 7	deltax 7
0.100000e+01	0.287212e+00	0.100000e+01	-0.942558e+00
0.128721e+01	-0.107691e+02	0.574425e-01	0.484474e+00
-0.948189e+01	0.123014e+01	0.541917e+00	-0.296449e+00
-0.825176e+01	0.127127e+01	0.245468e+00	-0.104492e+00
-0.698049e+01	0.127141e+01	0.140976e+00	-0.103834e+00
-0.570907e+01	0.106323e+01	0.371414e-01	-0.834305e-01
-0.464584e+01	0.143581e-01	-0.462891e-01	0.159590e-01
-0.463148e+01	0.227182e-03	-0.303301e-01	0.212252e-03
-0.463126e+01	0.360390e-05	-0.301178e-01	0.335746e-05
-0.463125e+01	0.571726e-07	-0.301145e-01	0.532607e-07
-0.463125e+01	0.906994e-09	-0.301144e-01	0.844934e-09

x12	deltax12	x14	deltax14
0. 100000e+01	-0. 940000e+00	0. 100000e+01	-0. 495213e+01
0. 600000e-01	-0. 495213e-01	-0. 395213e+01	-0. 179485e+01
0. 104787e-01	-0. 179485e-01	-0. 574698e+01	0. 205023e+00
-0. 746982e-02	0. 205023e-02	-0. 554196e+01	0. 211878e+00
-0. 541959e-02	0. 211878e-02	-0. 533008e+01	0. 211902e+00
-0. 330081e-02	0. 211902e-02	-0. 511818e+01	0. 177206e+00
-0. 118179e-02	0. 177206e-02	-0. 494097e+01	0. 239302e-02
0. 590265e-03	0. 239302e-04	-0. 493858e+01	0. 378637e-04
0. 614195e-03	0. 378637e-06	-0. 493854e+01	0. 600649e-06
0. 614574e-03	0. 600649e-08	-0. 493854e+01	0. 952877e-08
0. 614580e-03	0. 952877e-10	-0. 493854e+01	0. 151166e-09

#### Example 5.7:

The transistor-switch circuit in figure 5.7 is considered in this example. This is a case where the convergence condition is marginally satisfied. So although convergence does occur, the number of sweeps it takes becomes very large because of the slow convergence rate. The transistor is replaced by its Ebers-Moll model, and the ideal diode equation (equation (5.35)) is used in the formulation. The circuit is partitioned as illustrated in figure 5.8. The equations extracted from the circuit are:

```

F1: fx(1) = x(1)/100. + 1. e-4*dxdt(1) + .5*x(5) -x(4)
     fx(2) = (x(2)-u(2))/1000. + .98*x(4) - x(5)
     fx(3) = (x(3)-u(1))/50. + .02*x(4) + .5*x(5)
     fx(4) = x(4) - 1. e-14*exp(38.65*(x(3)-x(1)))
     fx(5) = x(5) - 1. e-14*exp(38.65*(x(3)-x(2)))
     *****
H : fx(6) = 2. e-6*(dzdt(1)-dudt(1)) + (z(1)-z(2))/1000.
     fx(7) = z(2) - .01
     fx(8) = z(3) + (z(2)-z(1))/1000.
     *****
G : fx(9) = (u(1)-x(3))/50. + (u(1)-u(2))/100000.
     + u(1)/27000. + 2. e-6*(dudt(1)-dzdt(1))
     fx(10) = u(2) - 10
     fx(11) = (u(2)-u(1))/100000. + (u(2)-x(2))/1000.
     + u(3)
     *****

```

The matrix of equation (5.33) becomes (at  $t=0$ , dc solution)

$$\mathbf{A}_{TF}^{-1} \mathbf{A}_{TS} \mathbf{A}_{SS}^{-1} \mathbf{A}_{ST} = \begin{bmatrix} 0.9886 & 0 & 0 \\ 0 & 0 & 0 \\ -0.001 & 0.001 & 0 \end{bmatrix}$$

which has an eigenvalue

$$\lambda = 0.9886$$

The convergence rate of this circuit is very slow and reaching a dc-solution would take an access of 100 sweeps (where  $e = 10^{-8}$ ). The Semi-Direct method in this case is very impractical.



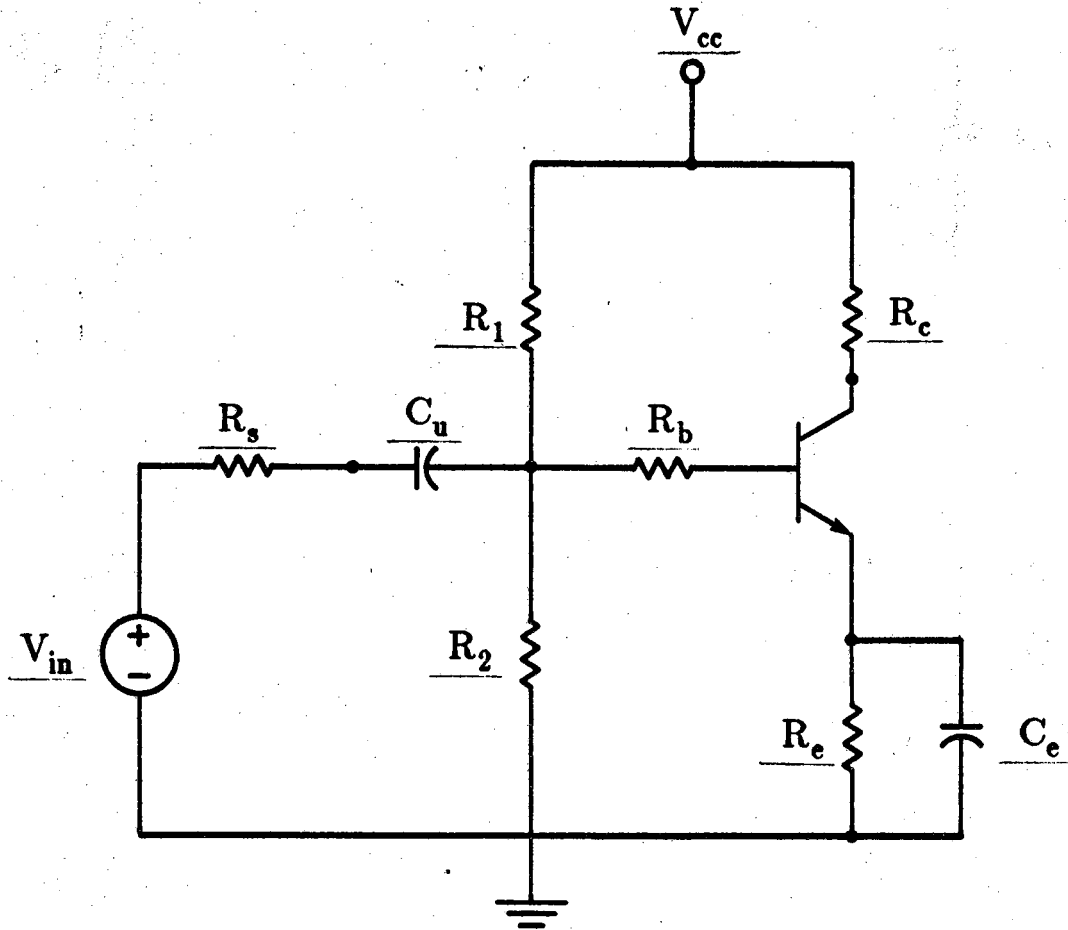


Figure 5.7: Transistor switch [4]

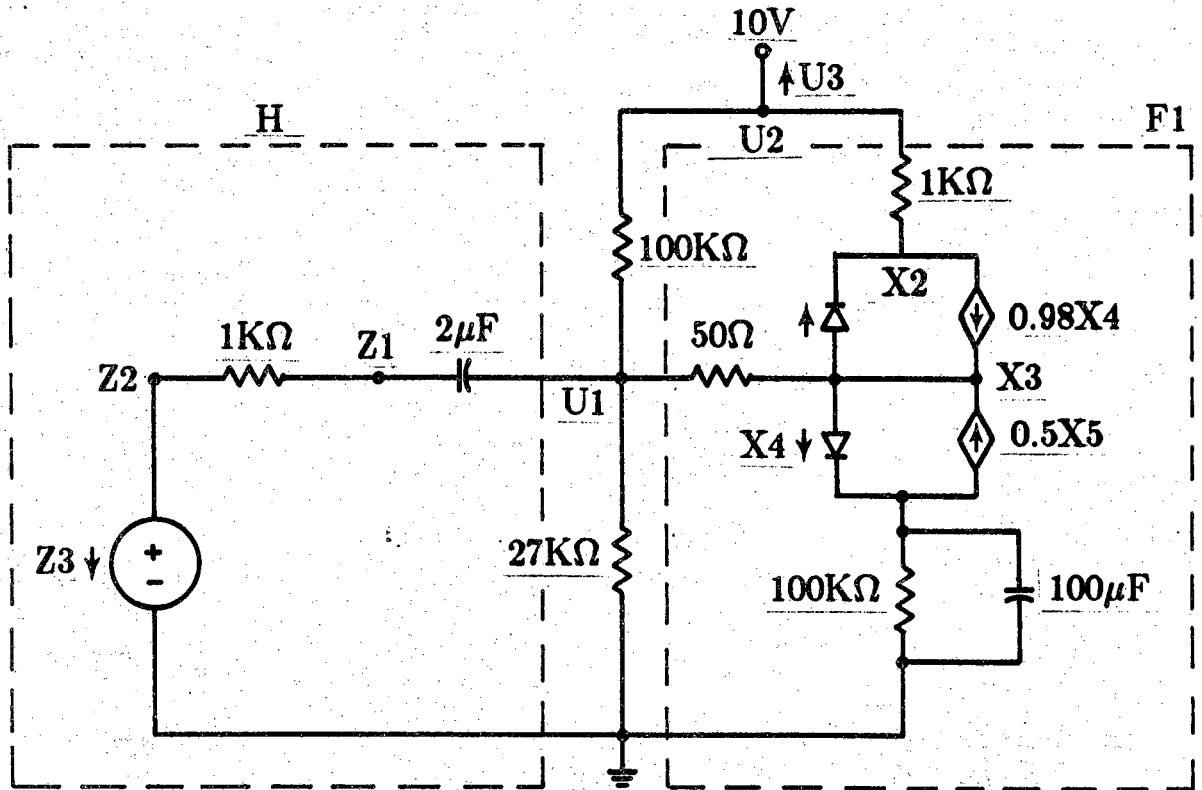


Figure 5.8: Labeled transistor switch circuit.

## CHAPTER 6

### COMPARISON BETWEEN THE NEWTON-RAPHSON AND THE SEMI-DIRECT METHODS

The previous chapters were devoted to the explanation of the features and theoretical aspects of the Semi-Direct method. The application of the method in circuit analysis is explored in the next two chapters. The dc-case is studied first because, as explained earlier in chapter 1 the Semi-Direct method is an incremental in time method. A transient analysis is a collection of dc-analysis cases at successive time points. The comparison with respect to the conventional (Newton-Raphson) method, which is currently used in most computer-aided analysis programs, is made through the use of the Fortran programs we developed for this study (Appendix). The comparison is made in two categories, computer storage requirements and execution time (CPU time).

#### 6.1 Storage

The main storage requirement is storing the Jacobian matrix elements that result from tearing the circuit (Chapter 4). The matrix has the bordered block-diagonal form of figure 4.1. To solve the system using the Newton-Raphson algorithm for bordered block-diagonal dependency matrices (section 4.4), which is used throughout this thesis, we need only store the elements of the submatrices  $\mathbf{A}_{ssi}$  ( $1 \leq i, \leq m+1$ ),  $\mathbf{A}_{rr}$ ,  $\mathbf{A}_{rs}$  and  $\mathbf{A}_{sr}$ . To solve the system

using the Semi-Direct method we only need to store the  $A_{ssi}$  and  $A_{tr}$  submatrices. Each  $A_{ssi}$  submatrix corresponds to a subcircuit and  $A_{tr}$  corresponds to the tearing node variables which can be considered as a subcircuit with no internal nodes and will be in the next discussion.

Assume we have  $m$   $F^i$  subcircuits. The total number of subcircuits (including  $H$  and  $G$ , see figure 4.2) is then

$$k = m + 2 \quad (6.1)$$

At this point let us consider equal size subcircuits each with  $n$  variables for a total number of variables for the torn circuit of  $kn$ . The dimensions of the Jacobian matrix would then be  $(kn)^2$ . The number of elements that are needed for the Semi-Direct method would be  $kn^2$ . For the Newton-Raphson method we would need to store the same  $kn^2$  elements in addition to the elements of the submatrices  $A_{rs}$  and  $A_{sr}$  each of size  $n(kn-n)$ . So the total number of elements needed for the Newton-Raphson method is

$$\begin{aligned} & kn^2 + 2n(kn-n) \\ &= kn^2 + 2n^2(k-1) \\ &= n^2(k + 2k-2) \\ &= n^2(3k-2) \text{ elements} \end{aligned}$$

The savings ratio that the Semi-Direct method exhibits over the Newton-Raphson method is calculated from

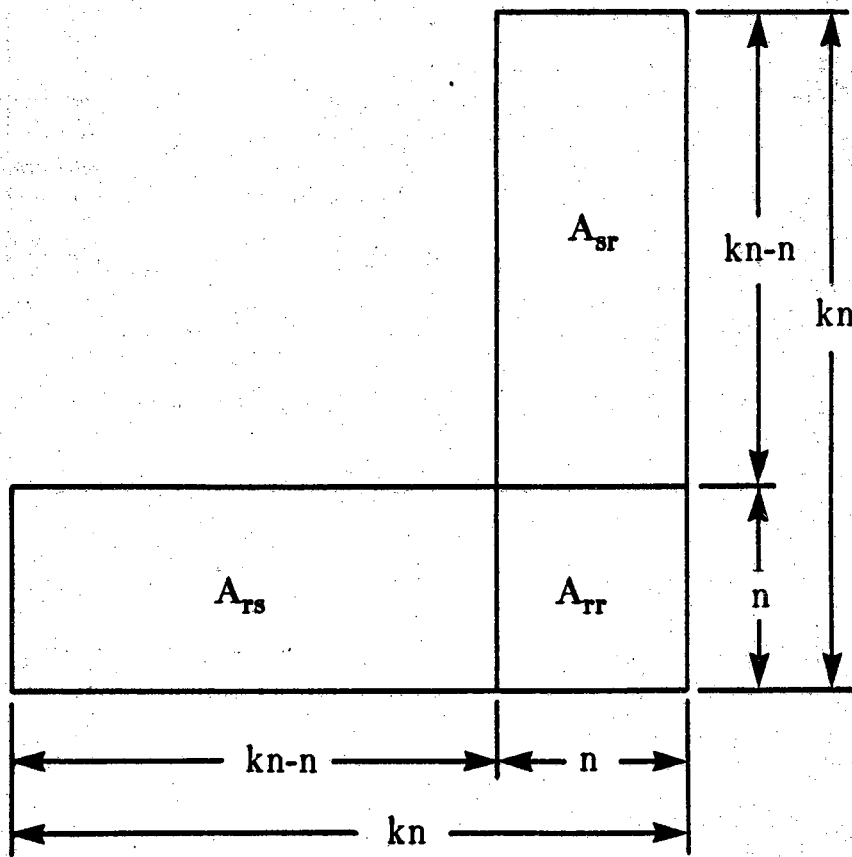


Figure 6.1:  $A_{sr}$  and  $A_{rs}$  dimensions.

$$\text{savings ratio} = \left( 1 - \frac{\text{number of elements in Semi-Direct}}{\text{number of elements in Newton-Raphson}} \right) \quad (6.2)$$

So

$$\text{savings ratio} = 1 - \frac{kn^2}{n^2(3k-2)}$$

which can be written

$$\text{savings ratio} = 1 - \frac{k}{3k-2} \quad (6.3)$$

The savings for a large scale circuit where it is torn into a large number of subcircuits so that  $3k \gg 2$  we have

$$\text{savings ratio} \simeq 1 - \frac{1}{3} = 0.6667 \quad (6.4)$$

or 66.67%.

Now let us do an analysis on the savings ratio for a more general case where the number of variables per subcircuit varies. Let  $n_{\max}$  be the number of variables in the largest subcircuit and  $n_{\min}$  the number of variables in the smallest subcircuit. So for the Semi-Direct method we have

$$\text{Total number of elements to be stored} \leq kn_{\max}^2 \quad (6.5)$$

and for the Newton-Raphson method we need to find the minimum size for the submatrices  $A_{rs}$  and  $A_{sr}$ . From figure 6.1 we see that the size is minimal when  $A_{rr}$  is  $n_{\min} \times n_{\min}$  because we have in the case of equal size subcircuits

$$\text{size of } A_{rs} = (kn-n)n$$

taking the derivative of the above expression we get

$$\frac{d(kn^2 - n^2)}{dn} = 2n(k-1) \quad (6.6)$$

from equation (6.1) we know  $k \geq 2$ , so equation (6.6) is always positive for positive  $n$ . Which means the size of  $A_{rs}$  increases as  $n$  increases. So the minimum size of  $A_{rs}$  occurs when  $n$  is minimal. The same argument applies to  $A_{sr}$  since they always have the same dimensions. So for the Newton-Raphson method we have

$$\text{Total number of elements to be stored} \geq kn_{\max}^2 + 2n_{\min}^2(k-1) \quad (6.7)$$

So the savings ratio for a certain circuit can be approximated by

$$\text{Savings Ratio} \cong 1 - \frac{kn_{\max}^2}{kn_{\max}^2 + 2n_{\min}^2(k-1)} \quad (6.8)$$

for the case where  $k \gg 1$  we have

$$\text{Savings Ratio} \cong 1 - \frac{n_{\max}^2}{n_{\max}^2 + 2n_{\min}^2}$$

or

$$\text{Savings Ratio} \cong \frac{2n_{\min}^2}{n_{\max}^2 + 2n_{\min}^2} \quad (6.9)$$

Equation (6.9) is optimized when  $n_{\min} = n_{\max}$  where the savings ratio is 0.6667 which is the same case where all subcircuits are of the same size. For the application in a computer program we have to dimension the arrays that store the elements of the submatrices of the dependency matrix. These arrays have a fixed dimension that is equal for all the submatrices (subcircuits). So the users instructions would include a maximum subcircuit size (number of variables/subcircuit) that can be inputted. The storage savings ratio is then

fixed for a certain computer program and approaches 66.67% as the number of subcircuits becomes large.

for a certain computer program to implement the above algorithms a constant number of variables should be declared to store the values of the functions in equations (4.5), (4.6) and (4.7). In addition to some intermediate result variables and loop counters. This constant number of variables is approximately equal for implementation of both methods. The effect of the constant on the savings ratio decreases as the programs are designed to solve large circuits, but it will have a significant effect in decreasing it for programs designed for smaller circuits.

The following examples will illustrate the above. The discussions are applied to IBM 360 series computers [8,16].

#### Example 6.1.

First, let us consider a program designed to handle a maximum of 10 subcircuits at a maximum of 5 variables per subcircuit for a total of 50 variables. Using double precision floating point operations, each floating point variable would need 64-bits to store, that is 8-bytes. The integers would require 32-bits that is 4-bytes.

The storage space needed, that is common in both programs can be approximated as follows:

50 circuit variables at 8-bytes for a total of	400-bytes
50 function values at 8-bytes for a total of	400-bytes
50 error variables at 8-bytes for a total of	400-bytes



20 miscellaneous at 8-bytes for a total of	160-bytes
--	-----------

40 integers at 4-bytes each	160-bytes
-----------------------------	-----------

---

Total	1520-bytes
-------	------------

Including Jacobian matrix elements:

The Semi-Direct method needs

10 x 5 <sup>2</sup> function values at 8-bytes for a total of	2200-bytes
---	------------

So total bytes needed	3520-bytes
-----------------------	------------

The Newton-Raphson method needs:

5 <sup>2</sup> (3 x 10 <sup>-2</sup> ) function values at 8-bytes for a total of	5600-bytes
--	------------

So Total bytes needed	7120-bytes
-----------------------	------------

which gives us a savings ratio of

$$1 - \frac{3520}{7120} = 0.5056$$

instead of 0.6667 as expected earlier due to the 1520-bytes added to both computations. The programs developed for this thesis, (see Appendix), has the limitations described in the above example. The actual storage the programs reserve for the data are as follows:

Semi-Direct	3772-bytes
Newton-Raphson	7212-bytes

So the savings ratio is

$$\text{savings ratio} = 1 - \frac{3772}{7212} = 0.4770$$

which is very close to the value predicted above.

#### Example 6.2:

Now let us increase the maximum number of subcircuits allowed to 1000 and the number of variables per subcircuit allowed to 100 for a total of 100,000 variables. The storage space needed can be approximated as follows:

100,000	circuit variables	800,000-bytes
100,000	function values	800,000-bytes
100,000	error variables	800,000-bytes
20	miscellaneous	160-bytes
100,030	integers	400,120-bytes
	Total	<u>2,800,280-bytes</u>

Including the Jacobian matrix elements:

The Semi-Direct methods needs:

1,000 × 100 <sup>2</sup> function values	80,000,000-bytes
Total needed	82,800,280-bytes

The Newton-Raphson method needs:

$100^2 (3 \times 1000 - 2)$ function values	239,840,000-bytes
Total needed	242,640,280-bytes

which gives us a savings ratio of

$$1 - \frac{82,800,280}{242,640,280} = 0.6588$$

This figure is a lot closer to 0.6667 as predicted earlier.

The two examples above illustrate the savings advantage that the Semi-Direct would have in an ideal case. From a more practical point of view we can study the results of analyzing the circuits of figures 6.1, 6.2 and 6.3 in section 6.3 using the programs developed during this study.

## 6.2 Execution Time

There are two criteria to be considered when studying execution time. One that depends on the circuit properties and the other on the computer program structure. They are:

- 1) The number of iterations or sweeps, and
- 2) Execution time of each iteration or sweep, respectively.

In the dc case the number of iterations or sweeps depends on the convergence rate of the method and the initial guess. For the Newton-Raphson method the rate of convergence is quadratic for almost all practical circuits as long as the initial guess is within a certain range of the solution. If the initial

guess is somewhat far from the solution quadratic convergence will not take effect until the iteration reach some local range of the solution. An example of that is the circuit of figure 5.6. Results from the Newton-Raphson solution is illustrated in example 6.3. Examining the exponent of the delta x column we noticed that the quadratic convergence starts taking effect at the 17th iteration, (initial guess is 0 for all variables). The Semi-Direct method has a linear convergence rate determined by the eigenvalue of the matrix  $\mathbf{P}^{-1}\mathbf{Q}$  (see section 5.2). Looking at example 6.3 the convergence rate is 0.01572 and takes effect at the 4th sweep of the Semi-Direct method. In general the convergence rate we have discussed for both methods is a local one and takes effect when  $\Delta x^i$  became less than 0.01 where  $\Delta x^i = x^{i+1} - x^i$  and  $x^i$  is the value of the slowest convergent variable of a given system. So the main consideration is how close does the initial guess have to be in order that the linearly convergent Semi-Direct method take as many sweeps (or even less) as the quadratically convergent Newton-Raphson method would take in iterations? The answer depends on the circuit and its rate of convergence. For the case of example 6.3 the Semi-Direct method converges in 8 sweeps while the Newton-Raphson takes 20 iterations to reach the same solution. For the case of example 6.4 the Semi-Direct method converges in 17 sweeps while the Newton-Raphson converges in 13 iterations. For local convergence the Newton-Raphson method is a faster convergent method than the Semi-Direct, but they can be compatible if we start at the very close initial guess where only one or two iterations are needed to reach a solution within an error limit of the true solution. This is the case in transient analysis, where for a small enough time step the solution at one time point is within the local area of the solution at the next time point. This criterion is illustrated through examples 6.3 and 6.4.

The time that each iteration takes depends more on the structure of the algorithm and the problem size and is independent of the convergence rate.

We have to note that the time the Semi-Direct method consumes during one sweep could vary from sweep to sweep in the same problem. The reason is in steps 2 and 3 of the algorithm (see section 5.1), we use the Newton-Raphson method to solve for the variables the subcircuits. These subiterations could vary depending on the closeness of the initial guess. It was found that in general a Semi-Direct sweep and a Newton-Raphson iterations take the same amount of execution time when steps 2 and 3 of the Semi-Direct method take on the average 1.5 subiterations. So if the Semi-Direct method takes the same number of sweeps as the Newton-Raphson would take in iterations, with only one subiterations per sweep, the Semi-Direct method would have a time savings advantage, because of the added calculations associated with  $\mathbf{A}_{rs}$  and  $\mathbf{A}_{sr}$  (see section 4.4).

### Example 6.3:

Consider the 2-stage transistor circuit of figure 5.6. If we start at an initial guess of 0 for all the variables, the Semi-Direct sweeps would converge to the solution ( $e=10^{-8}$ ) after 8 sweeps. On the other hand it would take the Newton-Raphson method 20 iterations with the same initial guess. Each Newton-Raphson iteration takes  $\sim 0.0966$  seconds. A Semi-Direct sweep takes  $\sim 0.1625$  seconds with no limit on the number of subiterations. So for this case

Total CPU time Semi-Direct $\simeq$	1.300 seconds
Newton-Raphson $\simeq$	1.932 seconds

For the case where we allow only 2 subiterations per sweep, each sweep would take  $\sim 0.1167$  seconds, but now it takes 12 sweeps to converge to the solution.

So

Total CPU time, Semi-Direct  $\simeq$  1.400 seconds

For the case where we allow only 1 subiteration per sweep, each sweep would take  $\sim 0.0582$  seconds, but it takes 18 sweeps to converge to the solution.

Total CPU time, Semi-Direct  $\simeq$  1.0476 seconds

If we choose an initial guess close enough to the true solution so that both methods start their local convergence rate properties. The initial guess in this case is 0.1% away from the true solution. The Semi-Direct method results are listed in table 6.1 below.

Table 6.1: Semi-Direct results (1).

# substitutions	# sweeps	Total time (seconds)
unlimited	6	0.9750
2	6	0.7002
1	6	0.3492

The Newton-Raphson method on the other hand takes 3 iterations to converge, and the

Total CPU time, Newton-Raphson  $\simeq$  0.2898 seconds

which is less than any of the time figures for the Semi-Direct method.

Now we examine another aspect. Let us reduce the incremental stopping criterion from  $e = 10^{-8}$  to  $e = 10^{-4}$ , which for most analysis purposes is a sufficient figure. The initial guess is still 0.1% away from the time solution. The Semi-Direct results are listed in table 6.2 below.

Table 6.2: Semi-Direct results (2).

# substitutions	# sweeps	Total time (seconds)
unlimited	3	0.4875
2	3	0.3501
1	3	0.1746

The Newton-Raphson method takes 2 iterations in this case for a total CPU time of 0.1932 seconds. In this case the Semi-Direct method is faster.

A summary of the results for example 6.3 are listed in table 6.3. The local convergence rate does not take effect for either method until the initial guess is within  $\sim 0.2\%$  of the true solution.

For an initial guess outside the local area of convergence for a system, either method could have the speed advantage. That depends very much on the problem itself. In the case of example 6.3 the Semi-Direct method had the edge while in the next example the Newton-Raphson method will be faster. This thesis is concerned with the convergence in a local area of the solution, since that is the case in transient analysis. Let us study another example.

Table 6.3: CPU times for example 6.3

Initial Guess (app)	Method	Incremental stopping criterion		
		$10^{-8}$	$10^{-6}$	$10^{-4}$
1%	S-D	0.3492	0.2910	0.2328
	N-R	0.3864	0.2898	0.2898
0.1%	S-D	0.3492	0.2910	0.1746
	N-R	0.2989	0.2898	0.1932

## Example 6.4:

Consider the following 10 equation in 10 unknowns.

```

fx(1)= x(1)**3 + 10*x(1) + x(2) -u(1)**2+2*u(2)**2-60
fx(2)= 2*(x(1)-x(2)-1)**3 -x(2) +6*u(1)*u(2) -16
*****
fx(3)=x(3)**3+10*x(3)+x(4) -u(1)**2+2*u(2)**2+27
fx(4)= 2*(x(3)-x(4)-1)**3 -x(4) +6*u(1)*u(2) +216
*****
fx(5)= x(5)**3 + 10*x(5) + x(6) -u(1)**2+2*u(2)**2-171
fx(6)= 2*(x(5)-x(6)-1)**3 -x(6) +6*u(1)*u(2) -725
*****
fx(7)= z(1)**3 + 10*z(1) + z(2) -u(1)**2+2*u(2)**2+60
fx(8)= 2*(z(1)-z(2)-1)**3 -z(2) +6*u(1)*u(2) -22
*****
fx(9)=281+x(1)**2 + x(3)**2 + x(6)**2-100*u(1)+u(2)
      +z(1)+z(2)
fx(10)=156+x(2)**3 + x(4)**2-x(5)**2+2*u(1)-100*u(2)
      +z(1)+z(2)
*****

```

The system is partitioned as illustrated in example 5.3.



For the case where  $e = 10^{-8}$  and we start at a far initial guess (0's), the Semi-Direct method converges in 17 sweeps while the Newton-Raphson method converges in 13 iterations.

Total CPU time, Semi-Direct  $\simeq 1.5$  seconds

Newton Raphson  $\simeq 0.4$  seconds

Any attempt to reduce the number of subiterations did not improve the time for the Semi-Direct method. The first two sweeps needed at least 3 subiterations in order to reach convergence. Let us consider a local area of the solution, where the Semi-Direct method only needs 1 subiteration during a sweep. CPU times are

CPU time/sweep  $\simeq 0.0281$

CPU time/iteration  $\simeq 0.0332$

The results from this example are listed in table 6.4. For the Semi-Direct method to exhibit faster convergence, we needed an initial guess and an incremental criterion where it would only take both methods only one iteration or sweep to converge to the true solution.

We know that the Newton-Raphson method has, in general, quadratic convergence. Then for an initial guess  $10^{-q}$  away from the solution, the  $i$ th iteration will be  $k^{(2^i-1)} \cdot 10^{-2^i q}$  away from the solution, (see Section 2.3). The convergence rate for the Semi-Direct method is the magnitude of the largest eigenvalue (in magnitude) of the matrix of equation (5.33), call it  $\lambda$ . Then for an initial guess  $10^{-q}$  away from the solution the  $j$ th sweep will be  $|\lambda|^j 10^{-q}$  away from the true solution. Assuming a specified increment  $e=10^{-q}$ , the iterations or sweeps will stop when

Table 6.4: CPU times for example 6.4.

Initial Guess (app)	Method	Incremental stopping criterion		
		$10^{-8}$	$10^{-5}$	$10^{-4}$
1%	S-D	0.3653	0.2529	0.1967
	N-R	0.1328	0.0996	0.0996
0.1%	S-D	0.3372	0.1967	0.1405
	N-R	0.0996	0.0996	0.0664
0.01%	S-D	0.2810	0.1405	0.0843
	N-R	0.0996	0.0664	0.0064
0.001%	S-D	0.2810	0.0281	0.0281
	N-R	0.0332	0.0332	0.0332

$$k^{(2^l-1)} \cdot 10^{-2^l q} \leq 10^{-t} \quad (6.10)$$

and

$$|\lambda|^j \cdot 10^{-q} \leq 10^{-t} \quad (6.11)$$

respectively. If each iteration takes  $t_i$  seconds and each sweep takes  $t_j$  seconds of CPU time to run, then for the Semi-Direct method to be faster than the Newton-Raphson method we need

$$t_j < t_i \quad (6.12)$$

where  $j$  = number of sweeps and  $i$  = number of iterations. We can rewrite this requirement as

$$j < \frac{t_i}{t_j} i \quad (6.13)$$

Since we don't want to give up any accuracy we have to require that

$$|\lambda|^j 10^{-q} \leq k^{(2^j-1)} 10^{-2^j q} \quad (6.14)$$

that is

$$|\lambda|^j \leq \frac{k^{(2^j-1)} 10^{-2^j q}}{10^{-q}} \quad (6.15)$$

which finally reduces to

$$|\lambda|^j \leq k^{(2^j-1)} 10^{(1-2^j)q} \quad (6.16)$$

If equations (6.13) and (6.16) are satisfied, and the initial guess is within the local convergence area, the Semi-Direct method will converge faster than the Newton-Raphson method.

Equations (6.13) and (6.16) involve variables that are related to the Newton-Raphson method. An expression that only involves Semi-Direct method variables may be derived.

Assume we have an absolute maximum error requirement of  $10^{-l}$ , and an initial guess that is  $10^{-q}$  away from the true solution. If we require that

- 1) the initial guess is within the local convergence area for the Semi-Direct method,
- 2) only one subiteration per block in each sweep is allowed, and
- 3) the method converges to the solution in only one sweep,

the Semi-Direct method guarantees a faster convergence than the Newton-Raphson method. The reason is the time one Semi-Direct sweep takes is less than the time of one Newton-Raphson iteration, and either method needs at least one sweep or iteration to reach the solution if  $10^{-q} > 10^{-l}$ . After one sweep the absolute error becomes  $|\lambda| \cdot 10^{-q}$ , which has to be within the error limit  $10^{-l}$ , that is

$$|\lambda| \cdot 10^{-q} < 10^{-f} \quad (6.17)$$

or

$$|\lambda| < 10^{q-f} \quad (6.18)$$

As an easy test, we choose to use the Semi-Direct method, if the initial guess is such that  $10^{q-f}$  is in the order of magnitude of  $|\lambda|$ . An example case is when  $q-f = -1$ , that is when equation's (5.33) largest (in magnitude) eigenvalue has a magnitude in the order of  $10^{-1}$ .

## CHAPTER 7

### TRANSIENT ANALYSIS

For performing a transient analysis on a circuit we need to model the dynamic elements (capacitors and inductors) of the circuit at each time point. Two approaches can be taken:

- 1) Replacing each of the dynamic elements by a model that incorporates static elements (resistors and sources). The values of these elements are then updated at each successive time point. Section 4.2 and figures 4.3 and 4.4 explain and show the models used for capacitors and inductors.
- 2) Expressing the inductor voltages and the capacitor currents in the equations using

$$v_L = L \frac{di_L}{dt} \quad (7.1)$$

and

$$i_c = C \frac{dv_c}{dt} \quad (7.2)$$

Then the computer algorithm would incorporate some numerical integration formula to replace the two derivatives in equations (7.1) and (7.2). This approach is more user oriented and is implemented in

the programs developed for this thesis.

### 7.1 Integration Methods

The numerical integration formulae used are the first order and second order backward differentiation formulae (BDF). A predictor formula is also used to improve the initial guess at the next time point, and a truncation error estimation formula [1].

So for a system characterized by

$$\mathbf{f}(\mathbf{x}, \dot{\mathbf{x}}, t) = 0 \quad (7.3)$$

$\dot{\mathbf{x}}$  can be approximated using the BDF. The equation to be solved at a certain time point  $t_n$  then becomes

$$\mathbf{f}(\mathbf{x}(t_n)) = 0 \quad (7.4)$$

A suitable numerical analysis method like the Newton-Raphson method or the Semi-Direct method could then be used to solve equation (7.4) for  $\mathbf{x}(t_n)$ .

The first order BDF, sometime referred to as backward Euler formula, estimates  $\dot{\mathbf{x}}(t)$  at some time point  $t_n$  as

$$\dot{\mathbf{x}}(t_n) \simeq \frac{1}{t_n - t_{n-1}} \left[ \mathbf{x}(t_n) - \mathbf{x}(t_{n-1}) \right] \quad (7.5)$$

where  $t_{n-1}$  is the previous time point.  $(t_n - t_{n-1})$  is the time step "h" taken.

The second order BDF has the form

$$\dot{\mathbf{x}}(t_n) \simeq \left[ \frac{1}{t_n - t_{n-1}} + \frac{1}{t_n - t_{n-2}} \right] \mathbf{x}(t_n)$$

$$\begin{aligned}
& - \left[ \frac{t_n - t_{n-2}}{(t_n - t_{n-1})(t_{n-1} - t_{n-2})} \right] x(t_{n-1}) \\
& + \left[ \frac{t_n - t_{n-1}}{(t_n - t_{n-2})(t_{n-1} - t_{n-2})} \right] x(t_{n-2})
\end{aligned} \tag{7.6}$$

For the case where we are taking uniform time steps, that is,  $t_n - t_{n-1} = t_{n-1} - t_{n-2} = h$ , equation (7.6) becomes

$$\dot{x}(t_n) \simeq \frac{1}{h} \left[ 1.5x(t_n) - 2x(t_{n-1}) + 0.5x(t_{n-2}) \right] \tag{7.7}$$

To help the numerical analysis algorithm used to solve equation (7.4) a predictor formula can be used to predict the value of  $x(t_{n+1})$ . This would produce a closer initial guess which implies a faster convergence.

The first order BDF predictor formula can be written as

$$x^p(t_n) = \frac{t_n - t_{n-2}}{t_{n-1} - t_{n-2}} x(t_{n-1}) + \frac{t_n - t_{n-1}}{t_{n-2} - t_{n-1}} x(t_{n-2}) \tag{7.8}$$

For the uniform time step case this becomes.

$$x^p(t_n) = 2x(t_{n-1}) - x(t_{n-2}) \tag{7.9}$$

The second order BDF predictor formula is

$$\begin{aligned}
x^p(t_n) &= \frac{(t_n - t_{n-2})(t_n - t_{n-3})}{(t_{n-1} - t_{n-2})(t_{n-1} - t_{n-3})} x(t_{n-1}) \\
&+ \frac{(t_n - t_{n-1})(t_n - t_{n-3})}{(t_{n-2} - t_{n-1})(t_{n-2} - t_{n-3})} x(t_{n-2}) \\
&+ \frac{(t_n - t_{n-1})(t_n - t_{n-2})}{(t_{n-3} - t_{n-1})(t_{n-3} - t_{n-2})} x(t_{n-3})
\end{aligned} \tag{7.10}$$

which reduces, for uniform time steps, to

$$x'(t_n) = 3x(t_{n-1}) - 3x(t_{n-2}) + x(t_{n-3}) \quad (7.11)$$

The truncation error may be estimated using first order BDF as

$$e(t_n) \cong \frac{t_n - t_{n-1}}{t_n - t_{n-2}} \left[ x(t_n) - x'(t_n) \right] \quad (7.12)$$

or for uniform time steps as

$$e(t_n) \cong \frac{1}{2} \left[ x(t_n) - x'(t_n) \right] \quad (7.13)$$

For the second order BDF, the truncation error estimate is

$$e(t_n) \cong \frac{t_n - t_{n-1}}{t_n - t_{n-3}} \left[ x(t_n) - x'(t_n) \right] \quad (7.14)$$

or for the uniform time step

$$e(t_n) \cong \frac{1}{3} \left[ x(t_n) - x'(t_n) \right] \quad (7.15)$$

This estimation of the error at a time point  $n$  is very helpful in getting a better estimate of the derivative using the BDF formulae. The aspect to notice in these formula is that the smaller the time step is the better the estimate is.

## 7.2 Applications of the Semi-Direct Method

The transient analysis algorithm developed using the Semi-Direct method implements the above formula to estimate the capacitor currents and the inductor voltages.



### Example 7.1:

Consider the RC circuit in figure 7.1. The circuit has essentially two constants, one effective for the rise part and one for the fall part. Figure 7.2 illustrates the labeled variables and the values of the elements. The capacitor currents are expressed using equation (7.2). The derivative is approximated at each time point by the 2nd order BDF as in equation (7.7). The equations extracted from the circuit are:

```

F1: fx(1) = 3. e-9*dxdt(1)+x(1)/500. +2. e-6*(dxdt(1)-dxdt(2))
fx(2) = 2. e-6*(dxdt(2)-dxdt(1)) + (x(2)-u(1))/1500.
*****
H : fx(3) = z(1) - .1
fx(4) = .02*(z(1)-u(1)) + z(2)
*****
G : fx(5) = .02*(u(1) - z(1)) +(u(1) - x(1))/1500.
*****

```

The rise time constant is determined using

$$R_2C_2 = 1.5 \text{ ms}$$

while the fall time constant is approximated using

$$(R_1+R_s)C_1 = 3.1 \text{ ms}$$

The output for the transient analysis of this circuit using both, the Newton-Raphson method and the Semi-Direct method are listed in the appendix. The rise analysis is made from  $t = 0$  up to  $t = 10 \mu\text{s}$  using a time step  $h = 0.1 \mu\text{s}$ . The fall analysis is made from  $t = 0$  up to  $t = 20 \text{ ms}$  using a time step  $h = 0.2$

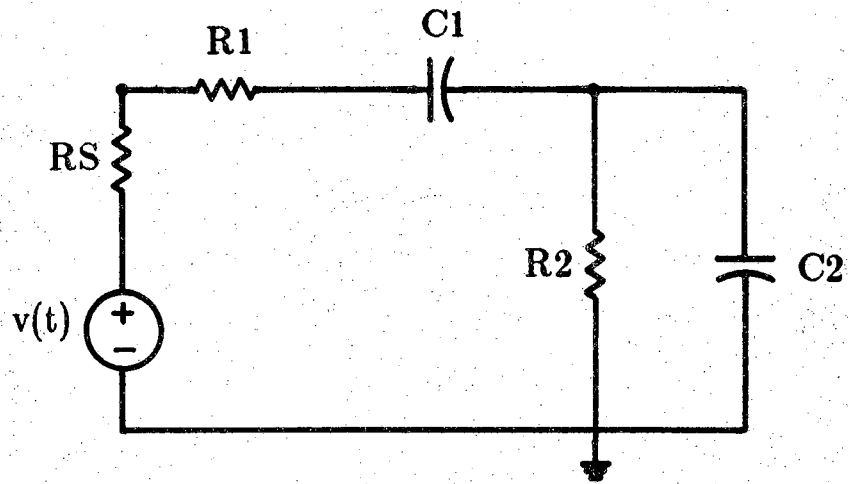


Figure 7.1. 2-time constant RC circuit.

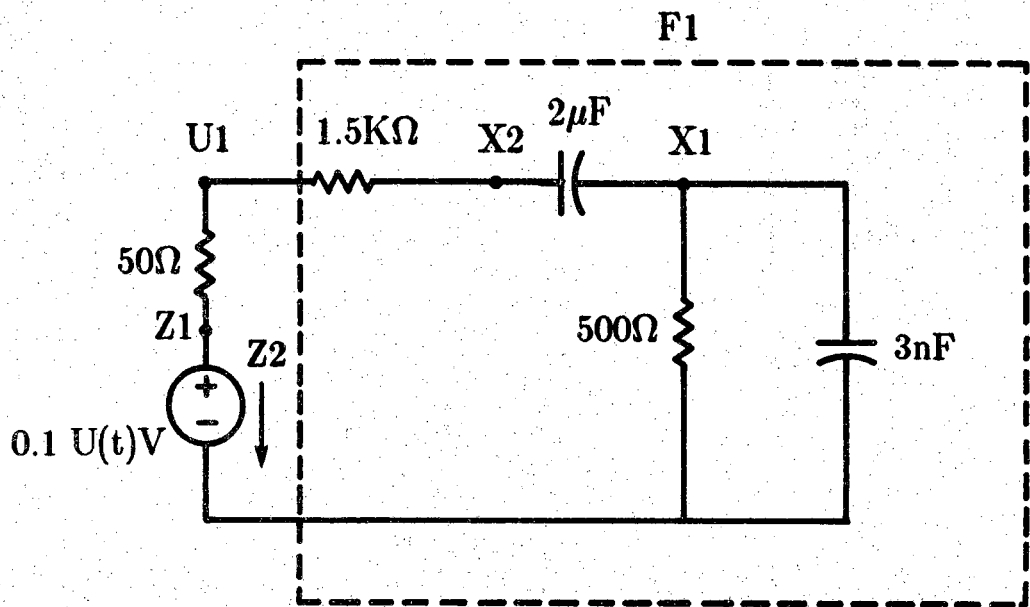
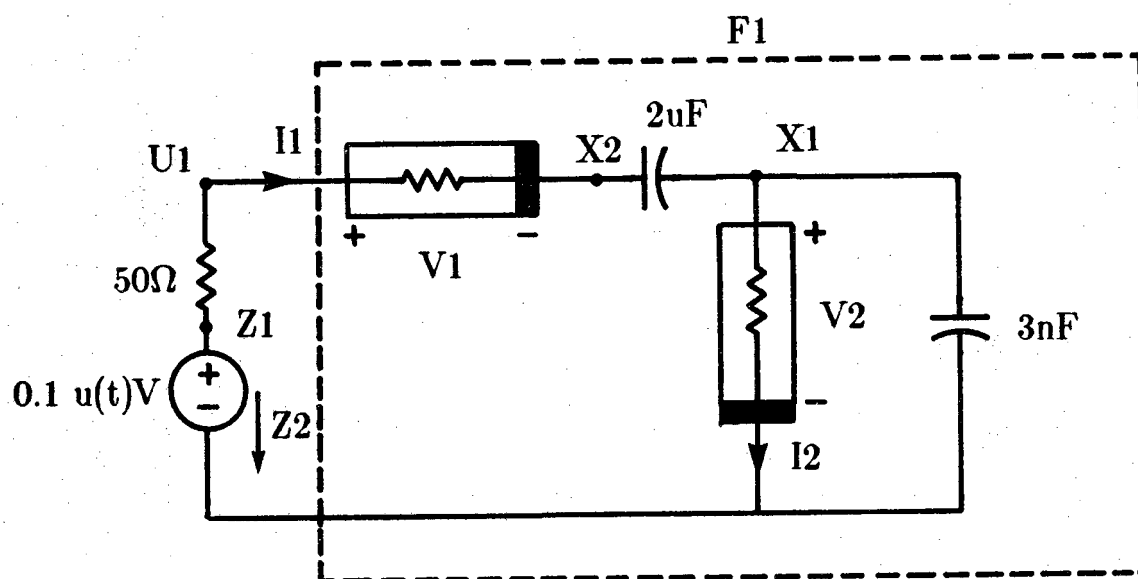


Figure 7.2. RC circuit with variables labeled and element values



$$I_1 = (1500)^{-1}(V_1 - V_1^3)$$

$$I_2 = (500)^{-1}(V_2 - V_2^3)$$

Figure 7.3. RC circuit with nonlinear elements

ms. Since the equations are linear at any time point, the Semi-Direct method takes less time to execute than the Newton-Raphson method. Only one sweep is needed at each time point and one subiteration internally. Only one iteration is needed, also, but a sweep takes less time than an iteration (1 subiteration/sweep is the case here).

### Example 7.2:

Now let us introduce some nonlinearity in the RC circuit of figure 7.1. The new nonlinear circuit is introduced in figure 7.3. The currents through the nonlinear resistors are given by

$$i = R^{-1}(v_i - v_i^3).$$

The element values are illustrated in figure 7.3. The output using both, the Newton-Raphson method and the Semi-Direct method are listed in the appendix. The equations for the circuit are:

---

```

F1: fx(1) = 3. e-9*dxdt(1) + (x(1)-x(1)**3)/500
      + 2. e-6*(dxdt(1)-dxdt(2))
fx(2) = 2. e-6*(dxdt(2)-dxdt(1)) - ((u(1)-x(2))
      - (u(1)-x(2))**3)/1500.
*****
H : fx(3) = z(1) - .1
      fx(4) = .02*(z(1)-u(1)) + z(2)
*****
G : fx(5) = .02*(u(1)-z(1)) + ((u(1)-x(2))
      - (u(1)-x(2))**3)/1500.
*****

```

The time step for which the Semi-Direct method takes as many sweeps as the

Newton-Raphson iterations per time point is  $h \leq 0.15 \mu\text{s}$  for the rise part of the response (1 subiteration/sweep). We can assume our time step guarantees that the solution at  $(t-h)$  is within the local convergence area of the solution at  $t$ . The time step would have to become very large in order to contradict the above assumption. For example 7.2 the time step could be 3 times the time constant and we still would be within the local convergence area.

The constraint on the time step is as follows: We want  $h$  such that  $|x'(t_n) - x(t_n)| \leq 10^{-q}$ , so that  $10^{q-f}$  is in the order of  $|\lambda(t_n)|$ , (see section 3.2 and equation (6.20)), where  $10^{-f}$  is the incremental stopping criterion for the sweeps or iterations at certain time point. If we assume  $e = 10^{-f}$  we would require a prediction at  $t_n$  that is at most  $10^{-q}$  away from the solution at  $t_n$ . From equations (7.12) and (7.14) we want for 1st order BDF

$$|e(t_n)| \leq 10^{-q} \frac{t_n - t_{n-1}}{t_n - t_{n-2}} \quad (7.16)$$

and for 2nd order BDF.

$$|e(t_n)| \leq 10^{-q} \frac{t_n - t_{n-1}}{t_n - t_{n-3}} \quad (7.17)$$

In Example 7.2 the value of  $h$  for which the Semi-Direct method would do the transient analysis faster than the Newton-Raphson method was experimentally determined to be  $\sim 0.15 \mu\text{s}$  for the rise time response of the circuit.

## CHAPTER 8

### CONCLUSIONS

We have studied in this thesis the algorithm and the properties of the Semi-Direct method. Its application in computer-aided circuit analysis was illustrated using several examples. It was found that the method has a linear convergence rate. The method was then compared to the Newton-Raphson method which is widely used in most computer analysis programs nowadays. The Semi-Direct method has computer-storage advantages over the Newton-Raphson method. As the circuits get larger the savings ratio approaches ~66.67%. Therefore, the method is most suitable in the analysis of large scale circuits. The execution time comparison revealed that the Semi-Direct method can be faster than the Newton-Raphson method under certain conditions. These conditions are usually satisfied in transient analysis applications. Therefore, the Semi-Direct method would be very applicable in the transient analysis of large scale circuits. The Semi-Direct method can be studied further in these areas:

- 1) The local convergence condition of the Semi-Direct method is that the eigenvalues of the matrix of equation (5.33) all have magnitudes less than unity. The matrices  $\mathbf{A}_{rr}$ ,  $\mathbf{A}_{rs}$ ,  $\mathbf{A}_{ss}$  and  $\mathbf{A}_{sr}$ , in the case of linear circuits are submatrices of the modified nodal analysis matrix, equation (4.4). How is the matrix of equation (5.33) and its eigenvalues related to the circuit parameters?

That is, can we write the convergence condition in terms of the physical properties of the circuit?

2) The Semi-Direct method will converge faster than the Newton-Raphson method if the initial guess satisfies equations (6.14) and (6.16). In transient analysis, the initial guess at time  $t_{n+1}$  is the solution at time  $t_n$  (or a predicted value based on it). What size time step can be taken in order to guarantee the comparable or faster convergence of the Semi-Direct method? An equation to compute the time step in terms of the other parameters could then be included in the transient analysis program. A time step that would guarantee a faster convergence could then be computed before the analysis at each time point.

3) Modify the programs developed in this thesis to accommodate larger circuits and experiment with transient analysis of some large-scale circuits.

## **LIST OF REFERENCES**



**LIST OF REFERENCES**

- [1] "Advanced Statistical Analysis Program (ASTAP)," reference guide, IBM, 1973.
- [2] R. K. Brayton, F. Gustavson and G. D. Hachtel, "A new efficient algorithm for solving differential-algebraic systems using implicit backward differentiation formulas," in Proc. IEEE, Vol. 60, pp. 98-108, Jan. 1972.
- [3] R. L. Burden, J. D. Faires, et al., Numerical Analysis, Weber and Schmidt, Inc., 1978.
- [4] L. O. Chua and P. M. Lin, Computer-Aided Analysis of Electronic Circuits, Prentice-Hall, Inc., Englewood Cliffs, NJ, 1975.
- [5] C. F. Gerald, Applied Numerical Analysis, Addison-Wesley Publishing Co., 1978.
- [6] G. Hachtel and A. L. Gangiovanni-Vincentelli, "A Survey of Third Generation Simulation Techniques," Proc. IEEE, Vol. 69, pp. 1264-1280, Oct. 1981.
- [7] C-W. Ho, A. E. Ruehli and P. A. Brennan, "The Modified Nodal Approach to Network Analysis," IEEE Trans. Circuits Syst., Vol. CAS-25, pp. 504-509, June 1975.
- [8] K. Hwang and F. A. Briggs, Computer Architecture and Parallel Processing, McGraw-Hill, Inc., 1984.

- [9] G. Kron, *Diakoptics: The Piecewise Solution of Large-Scale Systems*, MacDonald, London, 1963.
- [10] E. L. Lelarasmee, A. E. Ruehli, and A. L. Sangiovanni-Vincentelli, "The Waveform Relaxation Method for Time-Domain Analysis of Large-Scale Integrated Circuits," *IEEE Trans. on Computer-Aided Design of Integrated Circuits and Systems*, Vol. CAD-1, pp. 131-145, July 1982.
- [11] P. M. Lin and A. W. Nordsieck, "A Study of the Convergence Rate of a Multilevel Newton Algorithm," TR-EE 82-24, Purdue University, Nov. 1982.
- [12] P. M. Lin, A. W. Nordsieck, and H. Y. Hsieh, "A Convergence Rate Investigation of a Multilevel Newton Algorithm for Large-Scale Analysis," *Proc. 1983 Midwest Symp. on Circuits and Systems*, August 1983.
- [13] B. Nobel and J. W. Daniel, *Applied Linear Algebra*, Prentice-Hall, Inc., Englewood Cliffs, NJ, 1977.
- [14] A. W. Nordsieck and P. M. Lin, "Exploitation of Latency and Near-Latency in a Multilevel Newton Algorithm for Transient Analysis of Large-Scale Circuits," TR-EE 83-41, Purdue University, November 1983.
- [15] F. Odeh and D. Zein, "A Semi-Direct method for Modular Circuits," *Proc. 1983 Int'l. Symp. on Circuits and Systems*, pp. 226-229, May 1983.
- [16] W. G. Rudd, *Assembly Language Programming and the IBM 360 and 370 Computers*, Prentice-Hall, Inc., Englewood Cliffs, NJ, 1976.
- [17] P. A. Stark, *Introduction to Numerical Methods*, The Macmillan Company, 1970.
- [18] A. Sangiovanni-Vincentelli, L-K. Chen and L. Chua, "A New Tearing Approach -- Node-Tearing Nodal Analysis," *Proc. 1977 Int'l. Symp. on Circuits and Systems*, pp. 143-147, 1977.

- [19] W. A. Smith, *Elementary Numerical Analysis*, Harper and Row, Publishers, 1979.
- [20] J. Todd (editor), *Survey of Numerical Analysis*, McGraw-Hill Book Company, Inc., 1962.
- [21] F. F. Wu, "Solution of Large-Scale Networks by Tearing," *IEEE Trans. on Circuits and Systems*, Vol. CAS-23, pp. 706-713, Dec. 1976.

## **APPENDICES**

**APPENDIX A**  
**Program Listings**

```

*****
*****      USERS' INSTRUCTIONS      *****
*****
* For "semi-direct. dc. f" and "semi-direct. transient. f":
* The equations:
* Limit: 50 equations (10 blocks at 5 equations/block)
* Write in a file "out2" as FORTRAN statements (all Fortran
* rules apply) in the form:
*   fx(i) = ... (all listed sequentially, Fi, H then G equations)
*   jac(a,b,c)=... (jac is db/dc where b and c are the equation #
*                   and variable # within the block a)
*
* Program Parameters:
* Create a file "initial2" with the following FORTRAN
* statements (all FORTRAN rules apply):
*   nblks = .. # of blocks (10 max)
*   nequ = .. total # of equations (50 max)
*   nf(i) = .. # of equations/block (5 max)
*   nu = .. # of u variables
*   nz = .. # of z variables
*   msteps = .. max # of sweeps (default 20)
*   ssteps = .. max # of subiterations (default 20)
*   merror = .. sweep increment, for termination (default 1e-8)
*   serror = .. subiteration termination (default 1e-8)
*   miter = 1 or 0 sweep print control (yes or no)
*   siter = 1 or 0 subiteration print control (yes or no)
*   x(i) = .. initial guess for ith x (default 0)
*   z(i) = .. initial guess for ith x (default 0)
*   u(i) = .. initial guess for ith x (default 0)
* (for "semi-direct. transient. f" only)
*   h = .. time step
*   limit = .. upper time limit
*   subout= 1 or 0 print sweeps or only time point result
*   order = 1 or 2 1st or 2nd order BDF
*   predict= 1 or 0 use predictor formula or not
*
* Results:
* Final result is always in file "result". Other requested
* data are in files "result1", "result2", ..., "result6")
*
*****
* For "newton. dc. f" and "newton. transient. f":
* The equations:
* Limit: 50 equations (10 blocks at 5 equations/block)
* Write in a file "out" as FORTRAN statements (all Fortran
* rules apply). Same as "out2" above plus
*   asr(p,q) = .. asr is d(fx(p))/du(q)
*   ars(q,p) = .. ars is d(fx(nvar-nu+q))/dx(p)
*
* Program Parameters:
* Create a file "initial" with the following FORTRAN
* statements (all FORTRAN rules apply):
*   nblks = .. # of blocks (10 max)
*   nvar = .. total # of equations (50 max)
*   nf(i) = .. # of equations/block (5 max)
*   nu = .. # of u variables

```

```
*   nz = ..      # of z variables
*   steps = ..   max # of sweeps (default 20)
*   error = ..   iteration termination (default 1e-8)
*   iter = 1 or 0 iteration print control (yes or no)
*   x(i) = ..    initial guess for ith x (default 0)
*   z(i) = ..    initial guess for ith x (default 0)
*   u(i) = ..    initial guess for ith x (default 0)
* (for "newton.transient.f" only)
*   Same as for "semi-direct.transient.f" above.
```

```
*
```

```
* Results:
```

```
*   Final result is always in file "res". Other requested
*   data are in files "res1", "res2", ..., "res6")
```

```
*
```

```
*****
```

```
* For "convergence.f":
```

```
* The equations:
```

```
*   File "out2" from above and file solution that is
*   created by program "newton.dc.f". The eigenvalues of
*   the matrix of equation (5.33) are computed. The matrix
*   elements are printed, too.
```

```
*****
```

semi-direct. dc. f

```

1 *****
2 * This is a program that implements the Semi-Direct method *
3 * to solve a set of nonlinear (or linear) equations. *
4 * INPUT: files out2 that contains the equations and their *
5 * derivatives, and initial2 that contains the *
6 * partitioning information and the initial guess. *
7 *
8 * OUTPUT: final solution in a file called result. The sweep*
9 * are in files result1,result2,.. (4 variables/file)*
10 *****
11 c
12     double precision norm,merror,serror,x(50),u(5),z(5),
13     +             xi(50),sum,fx(50)
14     integer miter,siter,msteps,ssteps
15     +             ,nblks,nequ,nf(10),nz,nu,pos
16 c
17     common /data/nequ,nu,nz
18 c
19 c This is to set the default values for the print control
20 c and the initial guesses.
21     data miter,siter/1,0/
22     data msteps,ssteps,merror,serror/2*20,2*1e-8/
23     data x,u,z/60*0/
24 c
25 cThe file "initial2" includes the initial print control
26 c variables, the initial guesses and the partitions.
27 c
28     include "initial2"
29     nf(nblks-1) = nz
30     nf(nblks) = nu
31 c
32 cxi saves the previous sweep values for error and
33 cnorm calculation purposes.
34     nn = nequ - nu - nz
35     do 13 i=1,nn
36     13     xi(i) = x(i)
37 c Concatenate u's and z's to the end of xi array
38     do 14 j=1,nz
39     xi(i) = z(j)
40     x(i) = z(j)
41     14     i = i + 1
42     do 16 j=1,nu
43     xi(i) = u(j)
44     x(i) = u(j)
45     16     i = i + 1
46 c
47 c The title for the final result.
48     open ( unit=11,file="result",status="new")
49     write(11,800)
50     write(11,301) nequ
51     write(11,302) msteps
52     write(11,303)merror
53     write (11,310)
54     write(11,305) ( i,x(i),i=1,nequ )
55     write(11,307)
56     800 format(/'The Semi-Direct Method (dc analysis)')

```



```

57 301 format(/'Number of Equations: ',i2)
58 302 format(/'Max Number of Iterations: ',i2)
59 303 format(/'Error Criterion: ',e10.4)
60 310 format(/'Initial Conditions: ')
61 c
62 c The headings of the sweep results
63 c
64     if (miter.eq.1) then
65 c
66         open(unit=2, file="result1", status="new")
67         write(2,309)(i, i, i=1, 4)
68     if (nequ.gt.4) then
69         open(unit=3, file="result2", status="new")
70         write(3,309)(i, i, i=5, 8)
71     end if
72     if (nequ.gt.8) then
73         open(unit=4, file="result3", status="new")
74         write(4,309)(i, i, i=9, 12)
75     end if
76     if (nequ.gt.12) then
77         open(unit=7, file="result4", status="new")
78         write(7,309)(i, i, i=13, 16)
79     end if
80     if (nequ.gt.16) then
81         open(unit=8, file="result5", status="new")
82         write(8,309)(i, i, i=17, 20)
83     end if
84     if (nequ.gt.20) then
85         open(unit=9, file="result6", status="new")
86         write(9,309)(i, i, i=21, 24)
87     end if
88     end if
89 c
90 309 format(/" i ",2x,4(" x",i2,7x," deltax",i2,6
91 c
92     nsave=ssteps
93     do 700 i=1,msteps
94 c
95 c This to control the number of Newton subiterations
96     if (ni.eq.1) then
97         if (i.le.n2) then
98             ssteps=nsteps
99         else
100            ssteps=nsave
101        end if
102    end if
103 c
104 cThis is to solve each block using the Newton method
105     pos = i
106     do 710 j=1,nblks
107         call newton(j, x, fx, nf(j), serror, ssteps, siter, pos, u
108 710     pos = pos + nf(j)
109 c
110 c This calculatates the 2nd norm of the vector x
111     sum = 0
112     do 720 j=1,nequ

```

```

113         fx(j) = x(j) - xi(j)
114     720         sum = sum + fx(j)**2
115                 norm = sqrt(sum)
116     c
117     c Sweep print statements
118     c
119         if (miter.eq.1) then
120     c
121         if (nequ.gt.4) then
122             write(2,110) i, (xi(j), fx(j), j=1,4)
123             if (nequ.gt.8) then
124                 write(3,110) i, (xi(j), fx(j), j=5,8)
125                 if (nequ.gt.12) then
126                     write(4,110) i, (xi(j), fx(j), j=9,12)
127                     if (nequ.gt.16) then
128                         write(7,110) i, (xi(j), fx(j), j=13,16)
129                         if (nequ.gt.20) then
130     3                 write(8,110) i, (xi(j), fx(j), j=17,20)
131                             if (nequ.gt.24) then
132                                 write(9,110) i, (xi(j), fx(j), j=21,24)
133                                 else
134                                     write(9,110) i, (xi(j), fx(j), j=21,nequ)
135                                 end if
136                             else
137                                 write(8,110) i, (xi(j), fx(j), j=17,nequ)
138                             end if
139                         else
140                             write(7,110) i, (xi(j), fx(j), j=13,nequ)
141                         end if
142                     else
143                         write(4,110) i, (xi(j), fx(j), j=9,nequ)
144                     end if
145                 else
146                     write(3,110) i, (xi(j), fx(j), j=5,nequ)
147                 end if
148             else
149                 write(2,110) i, (xi(j), fx(j), j=1,nequ)
150             end if
151     c
152     c
153     110     format(i2,2x,4(e13.6,2x,e13.6,3x))
154     c
155         end if
156     c
157     c Check if increment stopping criterion has been acheived
158         if (norm.lt.merror) go to 900
159         do 910 j=1,nequ
160     910         xi(j) = x(j)
161     700     continue
162     c
163     c This is to print the final solution
164     c
165     900         write(11,307)
166                 write(11,300)
167                 write(11,305) (i,x(i),i=1,nequ)
168     307         format(//"*****")

```

```

169      +*****")
170      300      format(// "Solution: ")
171      305      format(/4("      x", i2, "=", e10.4))
172      end
173      c
174      c
175      c
176      c
177      c
178      subroutine newton (num, x, fx, nvar, error, steps, iter, pos
179      +          u, z)
180      c
181      common /data/nequ, nu, nz
182      double precision jac(10, 5, 5), fx(50), error, norm, temp(2
183      +          , sum, z(nz), u(nu), x(nequ)
184      integer nvar, steps, count, nu, nz, nequ, c1, c2, pos
185      c
186      if (iter.eq.1) then
187      write(6, 320) num
188      320      format (// "Block Number ", i2)
189      c
190      end if
191      c
192      c
193      do 10 count=1, steps
194      c
195      c here we insert the equations and their derivatives
196      include "out2"
197      c
198      c Transfer the jacobian of a block to lu subroutine.
199      c2 = 1
200      do 500 i=1, nvar
201      do 500 j=1, nvar
202      temp(c2)=jac(num, j, i)
203      500      c2 = c2+1
204      c
205      call lu(fx(pos), temp, nvar)
206      c
207      c this will output the subiterations
208      if (iter.eq.1) then
209      write(6, 110) count, (x(i), fx(i), i=pos, nn)
210      110      format(i2, 2x, 4(e13.6, 2x, e13.6, 3x), 5(/4x, 4(e13.6
211      +, 2x, e13.6, 3x)))
212      end if
213      c
214      c
215      c
216      c Compute second norm of x and calculate new x
217      nn=pos+nvar-1
218      sum = 0
219      do 100 i=pos, nn
220      sum = sum+fx(i)**2
221      100      x(i) = x(i) + fx(i)
222      norm = sqrt(sum)
223      c
224      c this is to compensate for the u's and z's in the original

```

```

225 c equations in the file out2
226     nn = nequ - nu - nz + 1
227     if (pos.eq.nn) then
228         c1 = pos
229         do 311 i=1,nz
230             z(i) = x (c1)
231     311     c1 = c1 + 1
232         end if
233         if (pos.eq.nn+nz) then
234             c1=pos
235             do 312 i=1,nu
236                 u(i) = x (c1)
237     312     c1 = c1 + 1
238         end if
239 c
240 c Check for increment stopping criterion
241     if (norm.lt.error) go to 200
242 c     otherwise go do another subiteration
243     10     continue
244     200     end
245 c
246 c
247 c this is the LU subroutine called once each subiteration
248 c It factors the jacobian into lower and upper triangular
249 c matrices and then solves for delta x. (result returned
250 c in fx vector).
251 c.
252     subroutine lu(fx,jac,nvar)
253 c
254     double precision sumlu1,sumlu2,jac(nvar,nvar),fx(nvar)
255     +           ,l(5,5),u(5,5)
256     equivalence(l,u)
257     integer s,nvar
258     do 11 i=1,nvar
259         fx(i)=-fx(i)
260     11     continue
261     s=1
262     15     j1=s
263     do 30 i1=s,nvar
264         sumlu1=0
265         do 20 k=1,j1-1
266     20         sumlu1= sumlu1+l(i1,k)*u(k,j1)
267     30         l(i1,j1)=jac(i1,j1) - sumlu1
268 c
269     if (j1.ge.nvar) go to 55
270 c
271     i2=s
272     s = s + 1
273     do 50 j2=s,nvar
274         sumlu2 = 0
275         do 40 k=1,i2-1
276     40         sumlu2 = sumlu2 + l(i2,k)*u(k,j2)
277     50         u(i2,j2) = (jac(i2,j2) - sumlu2) / l(i2,i2)
278     go to 15
279     55     do 70 i=1,nvar
280         fx(i) = fx(i) / l(i,i)

```

```
281         do 70 j=1,i-1
282     60         l(i,j) = l(i,j) / l(i,i)
283     70         continue
284 c solve for y answer stored in fx
285         do 80 j=i,nvar
286     80         do 80 i=j+1,nvar
287                 fx(i) = fx(j) * (-l(i,j)) + fx(i)
288     80         continue
289 c solve for delta x answer is in fx
290         do 90 js=1,nvar
291     90         j = nvar - js + 1
292                 do 90 k=js+1,nvar
293                     i = nvar - k + 1
294                     fx(i) = fx(j) * (-u(i,j)) + fx(i)
295     90         continue
296 c
297     end
```

semi-direct. transient. f

```

1 *****
2 # This is a program that implements the Semi-Direct method #
3 # to perform a transient analysis on a set of time varying #
4 # set of equations #
5 # INPUT: files out2 that contains the equations and their #
6 # derivatives, and initial2 that contains the #
7 # partitioning information and the dc solution. #
8 # #
9 # OUTPUT: Solutions for the whole time interval are in the #
10 # files result1,result2,.. (7 variables/file) #
11 *****
12 c
13     double precision norm,merror,serror,x(50),u(5),z(5),
14     +xi(50),sum,time,h,secd,limit,x1(50),x2(50),xp(50)
15     integer uniform,miter,siter,eq,incon,msteps,ssteps
16     + ,flag,nblks,nequ,nf(10),nz,nu,pos,order,reads,predict
17     + ,subout
18 c
19     common /data/nequ,nu,nz,secd
20     common order,x,x2,x1,h,flag
21 c
22 c This is to set the default values for the print control
23 c and program options.
24     data subout,siter,miter/2*0,1/
25     data msteps,ssteps,merror,serror/2*20,2*1e-16/
26     data x,reads,predict/50*0,2*1/
27     data u,z/10*0/
28     data x2/50*0/
29 c
30 cThe file "initial2" includes the initial print control
31 c variables plus the initial guesses.
32 c
33     include "initial2"
34 c
35 c This is to read the solution at t=0 (dc solution) stored is
36 c a file called "solution" on unit 10. We get solution from
37 c running the original dc program once with capacitors replaced
38 c by voltage sources.
39     if (reads.eq.1) then
40         nn = nequ - nu - nz
41         open(unit=10,file="solution",status="old")
42         read(10,43) (x(i),i=1,nn),(z(i),i=1,nz),(u(i),i=1,nu)
43         read(10,43) h,limit
44         read(10,44) subout,order,predict
45         read(10,45) ssteps
46         read(10,43) merror,serror
47     end if
48     45     format(i2)
49     44     format(i1)
50     43     format(e13.6)
51         nf(nblks-1) = nz
52         nf(nblks) = nu
53 c
54 c xi saves the previous main iterations values for error and
55 c norm calculation purposes. x2 and x1 are used for the
56 c calculation of the derivatives using BDF formulas.

```

```

57  c
58      do 13 i=1,nn
59          xp(i) = x(i)
60          x1(i) = x(i)
61          x2(i) = x(i)
62      13      xi(i) = x(i)
63  c Concatenate u's and z's to the end of xi array
64      do 14 j=1,nz
65          xi(i) = z(j)
66          x(i) = z(j)
67          x2(i) = x(i)
68          xp(i) = x(i)
69          x1(i) = x(i)
70      14      i = i + 1
71      do 16 j=1,nu
72          xi(i) = u(j)
73          x(i) = u(j)
74          x2(i) = x(i)
75          xp(i) = x(i)
76          x1(i) = x(i)
77      16      i = i + 1
78  c
79  c The program parameters used in file result
80  c
81  c
82  c
83      open ( unit=11,file="result",status="new")
84          write(11,800)
85          if(order.eq.1) then
86              write(11,801)
87          else
88              write(11,802)
89          end if
90          write(11,301) nequ
91          write(11,302) msteps
92          write(11,303)merror
93          write(11,304)limit
94          write(11,314) h
95          write (11,310)
96          write(11,305) ( i, x(i), i=1, nequ )
97          write(11,307)
98      800  format('/The Time Solution Using The Semi-Direct Meth
99      801  format('/Transient Analysis (using First Order BDF)')
100     802  format('/Transient Analysis (using Second Order BDF)')
101     301  format('/Number of Equations: ',i2)
102     302  format('/Max Number of Iterations: ',i2)
103     303  format('/Error Criterion: ',e10.4)
104     304  format('Time Limit: ',e10.4)
105     314  format('Time Step: ',e10.4,' (uniform time step)')
106     310  format('/Initial Conditions:')
107  c
108      if (miter.eq.1) then
109          if (subout.eq.1) then
110              open(unit=2,file="result1",status="new")
111                  write(2,309)(i,i,i=1,4)
112          if (nequ.gt.4) then

```

```

113         open(unit=3, file="result2", status="new")
114             write(3, 309)(i, i, i=5, 8)
115     end if
116     if (nequ. gt. 8) then
117         open(unit=4, file="result3", status="new")
118             write(4, 309)(i, i, i=9, 12)
119     end if
120     if (nequ. gt. 12) then
121         open(unit=7, file="result4", status="new")
122             write(7, 309)(i, i, i=13, 16)
123     end if
124     if (nequ. gt. 16) then
125         open(unit=8, file="result5", status="new")
126             write(8, 309)(i, i, i=17, 20)
127     end if
128     if (nequ. gt. 20) then
129         open(unit=9, file="result6", status="new")
130             write(9, 309)(i, i, i=21, 24)
131     end if
132     else
133         open(unit=2, file="result1", status="new")
134             write(2, 333)(i, i=1, 7)
135     if (nequ. gt. 7) then
136         open(unit=3, file="result2", status="new")
137             write(3, 333)(i, i=8, 14)
138     end if
139     if (nequ. gt. 14) then
140         open(unit=4, file="result3", status="new")
141             write(4, 333)(i, i=15, 21)
142     end if
143     if (nequ. gt. 21) then
144         open(unit=7, file="result4", status="new")
145             write(7, 333)(i, i=22, 28)
146     end if
147     end if
148     end if
149 c
150 309 format(/"t#h ", 2x, 4(" x", i2, 7x, " deltax", i2, 6x))
151 333 format(/6x, " time ", 7x, 7(" x", i2, 8x))
152 c
153 c The Time loop starts here.
154     flag=1
155     time =h
156 c Compute the derivative of the BDF
157 701 if ((order. eq. 1). or. (flag. eq. 1)) then
158     secd = 1. /h
159     else
160     secd = 1. 5/h
161     end if
162 c
163 c This is the Semi-Direct method to solve the equations at
164 c a certain time point. (dc program).
165 c
166     do 700 i=1, msteps
167         pos = 1
168         do 710 j=1, nblks

```



```

169      call newton(j, x, nf(j), serror, ssteps, siter, pos, u, z, h)
170      710      pos = pos + nf(j)
171      c
172      sum = 0
173      do 720 j=1, nequ
174          xp(j) = x(j) - xi(j)
175      720      sum = sum + xp(j)**2
176          norm = sqrt(sum)
177      c
178      if (subout.eq.1) then
179          if (miter.eq.1) then
180      c
181      c
182      c
183      c      print statements
184      if (nequ.gt.4) then
185          write(2,110) i, (xi(j), xp(j), j=1,4)
186          if (nequ.gt.8) then
187              write(3,110) i, (xi(j), xp(j), j=5,8)
188              if (nequ.gt.12) then
189                  write(4,110) i, (xi(j), xp(j), j=9,12)
190                  if (nequ.gt.16) then
191                      write(7,110) i, (xi(j), xp(j), j=13,16)
192                      if (nequ.gt.20) then
193                          write(8,110) i, (xi(j), xp(j), j=17,20)
194                          if (nequ.gt.24) then
195                              write(9,110) i, (xi(j), xp(j), j=21,24)
196                              else
197                                  write(9,110) i, (xi(j), xp(j), j=21,nequ)
198                                  end if
199                              else
200                                  write(8,110) i, (xi(j), xp(j), j=17,nequ)
201                                  end if
202                              else
203                                  write(7,110) i, (xi(j), xp(j), j=13,nequ)
204                                  end if
205                              else
206                                  write(4,110) i, (xi(j), xp(j), j=9,nequ)
207                                  end if
208                              else
209                                  write(3,110) i, (xi(j), xp(j), j=5,nequ)
210                                  end if
211                              else
212                                  write(2,110) i, (xi(j), xp(j), j=1,nequ)
213                                  end if
214      c
215      c
216      110      format(i2,2x,4(e13.6,2x,e13.6,3x))
217      c
218      c
219      end if
220      end if
221      if (norm.lt.merror) go to 900
222      do 910 j=1,nequ
223      910      xi(j) = x(j)
224      700      continue

```

```

225 c
226 900 if (subout.ne.1) then
227 write(11,307)
228 write(11,300) time
229 write(11,305) (i,x(i),i=1,nequ)
230 write(11,307)
231 else
232 if (nequ.gt.7) then
233 write(2,111) time,(x(j),j=1,7)
234 if (nequ.gt.14) then
235 write(3,111) time,(x(j),j=8,14)
236 if (nequ.gt.21) then
237 write(4,111) time,(x(j),j=15,21)
238 if (nequ.gt.28) then
239 write(7,111) time,(x(j),j=22,28)
240 else
241 write(7,111) time,(x(j),j=22,nequ)
242 end if
243 else
244 write(4,111) time,(x(j),j=15,nequ)
245 end if
246 else
247 write(3,111) time,(x(j),j=8,nequ)
248 end if
249 else
250 write(2,111) time,(x(j),j=1,nequ)
251 end if
252 end if
253 111 format(4x,8(e13.6,2x))
254 307 format(//"*****")
255 +*****")
256 300 format(//"Solution at t= ",e14.9," :")
257 305 format(/4(" x",i2,"=",e10.4))
258 if (time.gt.limit) go to 703
259 time = time + h
260 c
261 c Update the initial guess for the next time step by
262 c using the solution obtained or use of a predictor
263 c formula xh
264 if ((order.eq.1).or.(flag.eq.1)) then
265 flag = 0
266 do 569 i=1,nequ
267 xp(i) = 2*x(i) - x2(i)
268 x1(i) = x2(i)
269 x2(i) = x(i)
270 if (predict.eq.1) x(i) = xp(i)
271 xi(i) = x(i)
272 569 continue
273 else
274 do 571 i=1,nequ
275 xp(i) = 3*x(i) - 3*x2(i) + x1(i)
276 x1(i) = x2(i)
277 x2(i) = x(i)
278 if (predict.eq.1) x(i) = xp(i)
279 xi(i) = x(i)
280 571 continue

```

```

281      end if
282      nn = nequ-nu-nz+1
283      do 311 i=1,nz
284          z(i) = x(nn)
285      311  nn = nn + 1
286          do 312 i=1,nu
287              u(i) = x(nn)
288      312  nn = nn + 1
289      go to 701
290      703  end
291      c
292      c
293      c
294      c
295      c
296      subroutine newton(num, x, nvar, error, steps, iter, pos, u, z,
297      c
298      c
299      common /data/nequ, nu, nz, secd
300      double precision jac(10, 5, 5), fx(50), error, norm, temp(25
301      +          , h, secd, dxdt, sum, z(nz), u(nu), x(nequ)
302      integer nvar, steps, count, nu, nz, nequ, c1, c2, pos
303      if (iter.eq.1) then
304      write(6,320)num
305      320  format(//"Block Number",i2)
306      end if
307      c
308      c this is to compensate for the u's and z's in the original
309      c equations in the file out2
310      c
311      do 10 count=1, steps
312      nn =nequ - nu - nz +1
313      if (pos.eq.nn) then
314      c1 = pos
315      do 311 i=1,nz
316          z(i) = x(c1)
317      311  c1 = c1 + 1
318      end if
319      if (pos.eq.nn+nz) then
320      c1=pos
321      do 312 i=1,nu
322          u(i) = x(c1)
323      312  c1 = c1 + 1
324      end if
325      c
326      c
327      c here we insert the equations and their derivatives
328      include "out2"
329      c
330      c
331      c2 = 1
332      do 500 i=1,nvar
333          do 500 j=1,nvar
334              temp(c2)=jac(num, j, i)
335      500  c2 = c2+1
336      c

```

```

337      call lu(fx(pos), temp, nvar)
338 c
339 c
340      nn=pos+nvar-1
341      sum = 0
342      do 100 i=pos, nn
343          sum = sum+fx(i)**2
344      100      x(i) = x(i) + fx(i)
345      norm = sqrt(sum)
346 c  this will output the data
347      if (iter. eq. 1) then
348          write(6, 110) count, (x(i), fx(i), i=pos, nn)
349      110      format(/12, 2x, 4(e13.6, 2x, e13.6, 3x),
350          end if          5(/4x, 4(x, 4(e13.6, 2x, e13.6, 3x)))
351 c
352      if (norm. lt. error) go to 200
353 c  otherwise go do another iteration
354      10      continue
355      200      end
356 c
357 c
358 c  Soluion of blocks using LU factorization.
359 c
360 c.
361      subroutine lu(fx, jac, nvar)
362 c
363      double precision sumlu1, sumlu2, jac(nvar, nvar), fx(nvar)
364      +, l(5, 5), u(5, 5)
365      equivalence(l, u)
366      integer s, nvar
367      do 11 i=1, nvar
368          fx(i)=-fx(i)
369      11      continue
370      s=1
371      15      j1=s
372      do 30 i1=s, nvar
373          sumlu1=0
374          do 20 k=1, j1-1
375      20          sumlu1= sumlu1+l(i1, k)*u(k, j1)
376      30      l(i1, j1)=jac(i1, j1) - sumlu1
377 c
378      if (j1. ge. nvar) go to 55
379 c
380      i2=s
381      s = s + 1
382      do 50 j2=s, nvar
383          sumlu2 = 0
384          do 40 k=1, i2-1
385      40          sumlu2 = sumlu2 + l(i2, k)*u(k, j2)
386      50          u(i2, j2) = (jac(i2, j2) - sumlu2) / l(i2, i2)
387      go to 15
388      55      do 70 i=1, nvar
389          fx(i) = fx(i) / l(i, i)
390          do 70 j=1, i-1
391      60          l(i, j) = l(i, j) / l(i, i)
392      70          continue

```

```

393 c solve for y answer stored in fx
394 do 80 j=1,nvar
395 do 80 i=j+1,nvar
396     fx(i) = fx(j) * (-l(i,j))+ fx(i)
397 80 continue
398 c solve for delta x answer is in fx
399 do 90 js=1,nvar
400     j = nvar - js + 1
401 do 90 k=js+1,nvar
402     i = nvar - k + 1
403     fx(i) = fx(j) * (-u(i,j)) + fx(i)
404 90 continue
405 c
406     end
407 c
408 c
409 c this function is to evaluate the derivatives using BDF of
410 c order 1 or 2 .
411 c
412     function dxdt(i)
413     double precision x(50), x2(50), x1(50), h, dxdt
414     integer flag, order
415     common order, x, x2, x1, h, flag
416 c
417     if ((order.eq.1).or.(flag.eq.1)) then
418     dxdt = (x(i) - x2(i) )/h
419     else
420     dxdt = (1.5*x(i) - 2*x2(i) + .5*x1(i) )/h
421     end if
422     return
423     end

```

newton. dc. f

```

1 *****
2 * This is a program that implements the Newton-Raphson method*
3 * to solve a set of nonlinear (or linear) equations.          *
4 * INPUT: files out that contains the equations and their     *
5 * derivatives, and initial that contains the                 *
6 * partitioning information and the initial guess.            *
7 *
8 * OUTPUT: final solution in file called res. The iterations *
9 * in files res1, res2, ... (4 variables per file).          *
10 *****
11 c
12     double precision norm, sum, b(5), phi(25), error, x(50), u(5), z
13     +, ars(5, 45), asr(45, 5), move(25), fx(50), jac(10, 5, 5)
14     integer k, pos, c, nblks, nvar, steps, nu, nf(10)
15 c
16 c
17 c
18 c This is to set the default values for the print control
19 c and the initial guesses.
20     data steps, error, iter/20, 1. e-8, 1/
21     data x, ars, asr, jac/50*0, 450*0, 250*0/
22     data z, u/10*0/
23 c
24 c The file "initial" includes the initial print control
25 c variables, the initial guesses and the partitions.
26 c
27     include "initial"
28     nf(nblks-1) = nz
29     nf(nblks) = nu
30 c
31 c Concatenate u's and z's to the x array.
32     k=nvar -nu - nz+1
33     do 13 j=1, nz
34         x(k) = z(j)
35     13     k=k+1
36     do 16 j=1, nu
37         x(k) = u(j)
38     16     k=k+1
39 c
40 c The title for the main result
41     open ( unit=11, file="res", status="new")
42     write(11, 800)
43     write(11, 301) nvar
44     write(11, 302) steps
45     write(11, 303) error
46     write (11, 310)
47     write(11, 305) ( i, x(i), i=1, nvar )
48     write(11, 307)
49     800 format(/'Modified Newton-Raphson Method (block diagonal)
50     301 format(/'Number of Equations: ', i2)
51     302 format(/'Max Number of Iterations: ', i2)
52     303 format(/'Error Criterion: ', e10.4)
53     310 format(/'Initial Conditions: ')
54 c
55 c Headings for the iteration results
56     if (iter. eq. 1) then

```

```

57         open(unit=2, file="res1", status="new")
58           write(2,309)(i, i, i=1, 4)
59         if (nvar.gt. 4) then
60           open(unit=3, file="res2", status="new")
61             write(3,309)(i, i, i=5, 8)
62           end if
63         if (nvar.gt. 8) then
64           open(unit=4, file="res3", status="new")
65             write(4,309)(i, i, i=9, 12)
66           end if
67         if (nvar.gt. 12) then
68           open(unit=7, file="res4", status="new")
69             write(7,309)(i, i, i=13, 16)
70           end if
71         if (nvar.gt. 16) then
72           open(unit=8, file="res5", status="new")
73             write(8,309)(i, i, i=17, 20)
74           end if
75         if (nvar.gt. 20) then
76           open(unit=9, file="res6", status="new")
77             write(9,309)(i, i, i=21, 24)
78           end if
79         end if
80       c
81       309   format(/" i ", 2x, 4("   x", i2, 7x, "   deltax", i2, 6x
82       c
83       c This is the iteration loop
84       c
85         do 700 i=1, steps
86       c
87       c these do loops zero the arrays jac, asr and ars because t
88       c are used for storage purposes
89       c.
90         do 702 j=1, nblks
91           do 701 k=1, nf(j)
92             do 701 l=1, nf(j)
93       701   jac(j, k, l)=0
94           do 702 k=1, nvar
95             asr(k, j)=0
96       702   ars(j, k)=0
97       c
98       c the file out contains the equations and their derivative
99       include "out"
100      c
101        do 777 j=1, nvar
102      777   fx(j) = -fx(j)
103      c
104      c This part makes use of the boarded block diagonal form
105      c of the jacobian. The algorithm is explained in section 4.
106      c
107        pos = 1
108        do 70 j =1, nblks-1
109          c=i
110          do 330 l=1, nf(j)
111            do 330 k=1, nf(j)
112              move(c) = jac(j, k, l)

```

```

113 330      c=c+1
114          call lu(nf(j),move)
115          c=1
116          do 331 l=1,nf(j)
117              lzz=l+pos-1
118              b(l) = fx(lzz)
119              do 331 k=1,nf(j)
120                  jac(j,k,l) = move(c)
121 331      c=c+1
122          call lsolve(move,b,nf(j),1)
123          c=1
124          do 345 l=1,nu
125              do 345 k=pos,pos+nf(j)-1
126                  phi(c)=ars(l,k)
127 345      c=c+1
128          c=1
129          do 344 l=1,nf(j)
130              do 344 k=1,nf(j)
131                  if(k.eq.1) then
132                      move(c) = 1
133                  else
134                      move(c) = jac(j,l,k)
135                  end if
136 344      c=c+1
137          call lsolve(move,phi,nf(j),nu)
138          c=1
139          do 668 l=1,nu
140              do 668 k=1,nf(j)
141                  ars(l,k) = phi(c)
142 668      c=c+1
143          c=1
144              do 320 l=1,nu
145                  do 320 k=pos,pos+nf(j)-1
146                      phi(c)=asr(k,l)
147 320      c=c+1
148          c=1
149          do 667 l=1,nf(j)
150              do 667 k=1,nf(j)
151                  move(c)=jac(j,k,l)
152 667      c=c+1
153          call lsolve(move,phi,nf(j),nu)
154          do 888 l=1,nu
155              lzz= l+nvar-nu
156              do 889 k=1,nu
157                  do 889 m=1,nf(j)
158                      jac(nblks,l,k)=jac(nblks,l,k) - ars(l,m)
159 889                      *phi(m+(k-1)*nf(j))
160                  do 888 k=1,nf(j)
161                      fx(lzz)=fx(lzz)-ars(l,k)*b(k)
162 888          continue
163 70      pos=pos+nf(j)
164          c=1
165          do 910 l=1,nu
166              do 910 k=1,nu
167                  move(c)=jac(nblks,k,l)

```



```

169      call lu(nu,move)
170      call lusolve(move,fx(nvar-nu+1),nu)
171      pos=1
172      do 950 j=1,nblks-1
173          c=1
174          do 920 l=1,nf(j)
175              do 920 k=1,nf(j)
176                  move(c)=jac(j,k,l)
177          c=c+1
178          do 921 l=pos,pos+nf(j)-1
179              do 921 k=1,nu
180                  ku=k+nvar-nu
181                  fx(l)=fx(l)-asr(l,k)*fx(ku)
182          continue
183          call lusolve(move,fx(pos),nf(j))
184      950      pos = pos+nf(j)
185      c
186      c      Iteration print statement.
187      c
188          if (iter.eq.1) then
189      c
190      if (nvar.gt.4) then
191          write(2,110) i,(x(j),fx(j),j=1,4)
192          if (nvar.gt.8) then
193              write(3,110) i,(x(j),fx(j),j=5,8)
194              if (nvar.gt.12) then
195                  write(4,110) i,(x(j),fx(j),j=9,12)
196                  if (nvar.gt.16) then
197                      write(7,110) i,(x(j),fx(j),j=13,16)
198                      if (nvar.gt.20) then
199                          write(8,110) i,(x(j),fx(j),j=17,20)
200                          if (nvar.gt.24) then
201                              write(9,110) i,(x(j),fx(j),j=21,24)
202                              else
203                                  write(9,110) i,(x(j),fx(j),j=21,nvar)
204                              end if
205                          else
206                              write(8,110) i,(x(j),fx(j),j=17,nvar)
207                          end if
208                      else
209                          write(7,110) i,(x(j),fx(j),j=13,nvar)
210                      end if
211                  else
212                      write(4,110) i,(x(j),fx(j),j=9,nvar)
213                  end if
214              else
215                  write(3,110) i,(x(j),fx(j),j=5,nvar)
216              end if
217          else
218              write(2,110) i,(x(j),fx(j),j=1,nvar)
219          end if
220      c
221      c
222      110      format(i2,2x,4(e13.6,2x,e13.6,3x))
223      c
224          end if

```

```

225 c
226 c Calculate the second norm of the vector x
227 c and update the value of x
228     sum = 0
229     do 720 j=1,nvar
230         sum = sum + fx(j)**2
231     720     x(j) = x(j) + fx(j)
232     norm = sqrt(sum)
233 c     Update u and z.
234         k=nvar -nu - nz+1
235         do 14 j=1,nz
236             z(j) = x(k)
237     14         k=k+1
238         do 17 j=1,nu
239             u(j) = x(k)
240     17         k=k+1
241 c Check if error stopping criterion has been acheived
242     if (norm.lt.error) go to 900
243     700 continue
244 c
245 c This is to print the final solution
246     900     write(11,307)
247             write(11,300)
248             write(11,305) (i,x(i),i=1,nvar)
249     307     format(//"*****")
250             +*****")
251     300     format(//"Solution:")
252     305     format(/4("      x",i2,"=",e10.4))
253 c the file solution contains the solution for the use of the
254 c program convergance. f
255     open ( unit=10,file="solution",status="new")
256     nn= 1
257     write(10,332)nn,nvar,nu,nblks,(nf(i),i=1,nblks)
258     332     format(i2)
259     write(10,333)(x(i),i=1,nvar)
260     333     format(e13.6)
261     end
262 c
263 c
264 c
265 c
266 c
267 c     LU factorization
268 c
269     subroutine lu(nvar,jac)
270 c
271     double precision sumlu1,sumlu2,jac(nvar,nvar),l(5,5)
272     equivalence(l,u) ,u(5,5)
273     integer s,k,nvar
274     s=1
275     15     j1=s
276     do 30 i1=s,nvar
277         sumlu1=0
278         do 20 k=1,j1-1
279     20         sumlu1=sumlu1+l(i1,k)*u(k,j1)
280     30         l(i1,j1)=jac(i1,j1) - sumlu1

```

```

281 c
282 c   if (j1.ge.nvar) go to 55
283 c
284 c   i2=s
285 c   s = s + 1
286 c   do 50 j2=s,nvar
287 c     sumlu2 = 0
288 c     do 40 k=1,i2-1
289 40       sumlu2 = sumlu2 +1(i2,k)*u(k,j2)
290 50       u(i2,j2) = (jac(i2,j2) - sumlu2) /1(i2,i2)
291 c   go to 15
292 55     do 1 i=1,nvar
293 c       do 1 j=1,nvar
294 1       jac(i,j)=1(i,j)
295 c     end
296 c
297 c
298 c   Solve an LU factorized jacobian for deltax.
299 c
300 c     subroutine lusolve(jac,fx,nvar)
301 c
302 c     double precision jac(nvar,nvar),fx(nvar)
303 c
304 c   solve LY = FX for Y storing it in fx
305 c   normalize pivot
306 55   do 70 i=1,nvar
307 c     fx(i) = fx(i) / jac(i,i)
308 c     do 70 j=1,i-1
309 c       jac(i,j) = jac(i,j) / jac(i,i)
310 70   continue
311 c   solve for y answer stored in fx
312 c   do 80 j=1,nvar
313 c   do 80 i=j+1,nvar
314 c     fx(i) = fx(j) * (-jac(i,j)) + fx(i)
315 80   continue
316 c   solve for x answer is in fx
317 c   do 90 js=1,nvar
318 c     j = nvar - js + 1
319 c     do 90 k=js+1,nvar
320 c       i = nvar - k + 1
321 c       fx(i) = fx(j) * (-jac(i,j)) + fx(i)
322 90   continue
323 c   end
324 c
325 c   Solve a jacobian that is in lower triangular form.
326 c
327 c     subroutine lsolve(jac,fx,nvar,nu)
328 c
329 c     double precision jac(nvar,nvar),fx(nvar,nu)
330 c   solve LY = FX for Y storing it in fx
331 c   normalize pivot
332 55   do 70 i=1,nvar
333 c     take care of whole row in fx
334 c     do 56 k=1,nu
335 56   fx(i,k) = fx(i,k) / jac(i,i)
336 c     do 70 j=1,i-1

```

```
337         jac(i,j) = jac(i,j) / jac(i,i)
338     70     continue
339 c       solve for y answer stored in fx
340         do 80 j=1,nvar
341         do 80 i=j+1,nvar
342         do 80 k=i,nu
343             fx(i,k) = fx(j,k) * (-jac(i,j))+ fx(i,k)
344     80     continue
345 c
346     end
```

newton.transient.f

```

1 *****
2 * This is a program that implements the Newton-Raphson method
3 * to perform a transient analysis on a set of time varying
4 * set of equations.
5 * INPUT: files out that contains the equations and their
6 * derivatives, and initial that contains the
7 * partitioning information and the dc solution.
8 *
9 * OUTPUT: Solutions for the whole time interval are in the
10 * files res1,res2,... (7 variables per file).
11 *****
12 c
13     double precision norm,sum,b(5),phi(25),error,x(50),x1(50)
14     + ,x2(50),limit,secd,h,time, xp(50),u(5),z(5),jac(10,5,5)
15     + ars(5,45),asr(45,5),move(25),fx(50)
16     integer k,pos,c,nblks,nvar,steps,nu,nf(10),order,uniform
17     + predict,subout
18     common order,x,x2,flag,x1,h
19 c
20 c
21 c
22 c This is to set the default values for the print control
23 c and the initial guesses.
24     data steps,error,iter/20,1.e-16,0/
25     data x,asr,ars,jac/50*1,450*0,250*0/
26     data reads,predict/2*1/
27 c
28 cThe file "initial" includes the initial print control
29 c variables plus the initial guesses.
30 c
31     include "initial"
32     nf(nblks) = nu
33     nf(nblks-1) = nz
34 c This is to read the soluiton at t=0 (dc solution) stored in
35 c a file called "solution" on unit 10.
36 c
37     if (reads.eq.1) then
38     open ( unit=10,file="solution",status="old")
39     read(10,43)(x(i),i=1,nvar)
40     read(10,43)h,limit
41     read(10,44) subout,order,predict
42     read(10,44) i
43     read(10,43) error
44     end if
45     44     format(i1)
46     43     format(e13.6)
47 c
48 c Initial x1 and x2 that are used to store the previous
49 c values of x for the use in BDF.
50     do 13 i=1,nvar
51     xp(i) = x(i)
52     x1(i) = x(i)
53     13     x2(i) = x(i)
54 c
55 c Write program parameters used in file res
56 c

```

```

57      open ( unit=11, file="res", status="new")
58          write(11,800)
59      if(order. eq. 1) then
60          write(11,801)
61      else
62          write(11,802)
63      end if
64          write(11,301) nvar
65          write(11,302) steps
66      write(11,303)error
67      write(11,304) limit
68          write(11,314) h
69      write (11,310)
70      write(11,305) ( i, x(i), i=1, nvar )
71          write(11,307)
72      800 format(/'Newton-Raphson Method (block diagonal)')
73      801 format(/'Transient Analysis (using First Order BDF)')
74      802 format(/'Transient Analysis (using Second Order BDF)')
75      301 format(/'Number of Equations: ', i2)
76      302 format(/'Max Number of Iterations: ', i2)
77      303 format(/'Error Criterion: ', e10.4)
78      304 format(/'Time Limit : ', e10.4)
79      314 format(/'Time Step : ', e10.4)
80      310 format(/'Initial Conditions:')
81  c
82      if (iter. eq. 1) then
83          if (subout. eq. 1) then
84              open(unit=2, file="res1", status="new")
85                  write(2,309)(i, i, i=1, 4)
86          if (nvar. gt. 4) then
87              open(unit=3, file="res2", status="new")
88                  write(3,309)(i, i, i=5, 8)
89          end if
90          if (nvar. gt. 8) then
91              open(unit=4, file="res3", status="new")
92                  write(4,309)(i, i, i=9, 12)
93          end if
94          if (nvar. gt. 12) then
95              open(unit=7, file="res4", status="new")
96                  write(7,309)(i, i, i=13, 16)
97          end if
98          if (nvar. gt. 16) then
99              open(unit=8, file="res5", status="new")
100                  write(8,309)(i, i, i=17, 20)
101          end if
102          if (nvar. gt. 20) then
103              open(unit=9, file="res6", status="new")
104                  write(9,309)(i, i, i=21, 24)
105          end if
106      else
107          open(unit=2, file="res1", status="new")
108              write(2,333)(i, i=1, 7)
109          if (nvar. gt. 7) then
110              open(unit=3, file="res2", status="new")
111                  write(3,333)(i, i=8, 14)
112          end if

```

```

113         if (nvar.gt.14) then
114             open(unit=4, file="res3", status="new")
115             write(4, 333)(i, i=15, 21)
116         end if
117         if (nvar.gt.21) then
118             open(unit=7, file="res4", status="new")
119             write(7, 333)(i, i=22, 28)
120         end if
121     end if
122 end if
123 c
124 309 format(/" j ", 2x, 4(" x", i2, 7x, " deltax", i2, 6x)
125 333 format(/6x, " time ", 7x, 7(" x", i2, 8x))
126 c
127 c The time loop starts here
128     flag=1
129     time = h
130 c Compute the derivative of the BDF
131 766 if ((order.eq.1).or.(flag.eq.1)) then
132     secd=1./h
133     else
134     secd = 1.5/h
135     end if
136 c This is the Newton method to solve the equations at
137 c a certain time point (dc program).
138 c
139     do 700 i=1, steps
140 c
141 c these do loops zero the arrays jac.asr and ars because th
142 c are used for storage purposes
143 c.
144     do 702 j=1, nblks
145     do 701 k=1, nf(j)
146     do 701 l=1, nf(j)
147 701 jac(j, k, l)=0
148     do 702 k=1, nvar
149     asr(k, j)=0
150 702 ars(j, k)=0
151 c
152     k=nvar -nu - nz+1
153     do 14 j=1, nz
154     z(j) = x(k)
155 14 k=k+1
156     do 17 j=1, nu
157     u(j) = x(k)
158 17 k=k+1
159 c the file out contains the equations and their derivatives
160 include "out"
161 c
162     do 777 j=1, nvar
163 777 fx(j) = -fx(j)
164 c
165 c Steps 1 and 2 are executed using the subroutine sums
166 c
167     pos = 1
168     do 70 j =1, nblks-1

```

```

169          c=1
170          do 330 l=1,nf(j)
171            do 330 k=1,nf(j)
172              move(c) = jac(j,k,l)
173      330          c=c+1
174          call lu(nf(j),move)
175          c=1
176          do 331 l=1,nf(j)
177            lzz=l+pos-1
178            b(l) = fx(lzz)
179            do 331 k=1,nf(j)
180              jac(j,k,l) = move(c)
181      331          c=c+1
182          call lsolve(move,b,nf(j),1)
183          c=1
184          do 345 l=1,nu
185            do 345 k=pos,pos+nf(j)-1
186              phi(c)=ars(l,k)
187      345          c=c+1
188          c=1
189          do 344 l=1,nf(j)
190            do 344 k=1,nf(j)
191              if(k.eq.1) then
192                move(c) = 1
193              else
194                move(c) = jac(j,l,k)
195              end if
196      344          c=c+1
197          call lsolve(move,phi,nf(j),nu)
198          c=1
199          do 668 l=1,nu
200            do 668 k=1,nf(j)
201              ars(l,k) = phi(c)
202      668          c=c+1
203          c=1
204            do 320 l=1,nu
205              do 320 k=pos,pos+nf(j)-1
206                phi(c)=asr(k,l)
207      320          c=c+1
208          c=1
209          do 667 l=1,nf(j)
210            do 667 k=1,nf(j)
211              move(c)=jac(j,k,l)
212      667          c=c+1
213          call lsolve(move,phi,nf(j),nu)
214          do 888 l=1,nu
215            lzz= l+nvar-nu
216            do 889 k=1,nu
217              do 889 m=1,nf(j)
218                jac(nblks,l,k)=jac(nblks,l,k)-ars(l,m)*phi(m+(k-1)*nf(j)
219      889          continue
220            do 888 k=1,nf(j)
221              fx(lzz)=fx(lzz)-ars(l,k)*b(k)
222      888          continue
223      70          pos=pos+nf(j)
224          c=1

```





```

281         write(2,110) i, (x(j), fx(j), j=1, nvar)
282     end if
283 c
284 c
285 110     format(i2, 2x, 4(e13. 6, 2x, e13. 6, 3x))
286 c
287 c
288         end if
289         end if
290         sum = 0
291         do 720 j=1, nvar
292             sum = sum + fx(j)**2
293 720     x(j) = x(j) + fx(j)
294         norm = sqrt(sum)
295 c Check if error stopping criterion has been acheived
296         if (norm.lt.error) go to 900
297 700     continue
298 c
299 900     if (subout.eq.1) then
300         write(11,307)
301         write(11,300) time
302         write(11,305) (i, x(i), i=1, nvar)
303         write(11,307)
304     else
305     if (nvar.gt.7) then
306         write(2,111) time, (x(j), j=1, 7)
307         if (nvar.gt.14) then
308             write(3,111) time, (x(j), j=8, 14)
309             if (nvar.gt.21) then
310                 write(4,111) time, (x(j), j=15, 21)
311                 if (nvar.gt.28) then
312                     write(7,111) time, (x(j), j=22, 28)
313                 else
314                     write(7,111) time, (x(j), j=22, nvar)
315                 end if
316             else
317                 write(4,111) time, (x(j), j=15, nvar)
318             end if
319         else
320             write(3,111) time, (x(j), j=8, nvar)
321         end if
322     else
323         write(2,111) time, (x(j), j=1, nvar)
324     end if
325     end if
326 111     format(4x, 8(e13. 6, 2x))
327 307     format(//"*****")
328     +*****")
329 300     format(//"Solution at t= ", e14. 9, " : ")
330 305     format(/4("      x", i2, "=", e10. 4))
331         if (time.gt.limit) go to 703
332         time = time + h
333 c
334 c Update the initial guess for the next time point
335 c by using the solution obtained or a predictor
336 c formula.

```

```

337 c
338     if ((order.eq.1).or.(flag.eq.1)) then
339         flag = 0
340         do 569 i=1,nvar
341             xp(i) = 2*x(i) - x2(i)
342             x1(i) = x2(i)
343             x2(i) = x(i)
344             if (predict.eq.1) x(i) = xp(i)
345 569         continue
346         else
347             do 571 i=1,nvar
348                 xp(i) = 3*x(i) - 3*x2(i) + x1(i)
349                 x1(i) = x2(i)
350                 x2(i) = x(i)
351             if (predict.eq.1) x(i) = xp(i)
352 571         continue
353         end if
354         go to 766
355 703     end
356 c
357 c
358 c
359 c
360 c
361 c
362 c LU factorization
363 c
364     subroutine lu(nvar, jac)
365 c
366         double precision sumlu1, sumlu2, jac(nvar, nvar),
367 + l(5,5), u(5,5)
368         equivalence(l, u)
369         integer s, k, nvar
370         s=1
371 15     j1=s
372         do 30 i1=s, nvar
373             sumlu1=0
374             do 20 k=1, j1-1
375 20         sumlu1= sumlu1+l(i1, k)*u(k, j1)
376 30     l(i1, j1)=jac(i1, j1) - sumlu1
377 c
378         if (j1.ge.nvar) go to 55
379 c
380         i2=s
381         s = s + 1
382         do 50 j2=s, nvar
383             sumlu2 = 0
384             do 40 k=1, i2-1
385 40         sumlu2 = sumlu2 +l(i2, k)*u(k, j2)
386 50     u(i2, j2) = (jac(i2, j2) - sumlu2) /l(i2, i2)
387         go to 15
388 55     do 1 i=1, nvar
389             do 1 j=1, nvar
390 1         jac(i, j)=l(i, j)
391         end
392 c

```

```

393 c
394 c      Solve lu factorized jacobian
395 c
396 c      subroutine lusolve(jac,fx,nvar)
397 c
398 c      double precision jac(nvar,nvar),fx(nvar)
399 c
400 c      solve LY = FX for Y storing it in fx
401 c      normalize pivot
402 55  do 70 i=1,nvar
403     fx(i) = fx(i) / jac(i,i)
404     do 70 j=1,i-1
405     jac(i,j) = jac(i,j) / jac(i,i)
406 70  continue
407 c      solve for y answer stored in fx
408     do 80 j=1,nvar
409     do 80 i=j+1,nvar
410     fx(i) = fx(j) * (-jac(i,j))+ fx(i)
411 80  continue
412 c      solve for x answer is in fx
413     do 90 js=1,nvar
414     j = nvar - js + 1
415     do 90 k=js+1,nvar
416     i = nvar - k + 1
417     fx(i) = fx(j) * (-jac(i,j)) + fx(i)
418 90  continue
419     end
420 c
421 c      Solve a lower triangular jacobian
422 c
423 c      subroutine lsolve(jac,fx,nvar,nu)
424 c
425 c      double precision jac(nvar,nvar),fx(nvar,nu)
426 c      solve LY = FX for Y storing it in fx
427 c      normalize pivot
428 55  do 70 i=1,nvar
429 c      take care of whole row in fx
430     do 56 k=1,nu
431 56  fx(i,k) = fx(i,k) / jac(i,i)
432     do 70 j=1,i-1
433     jac(i,j) = jac(i,j) / jac(i,i)
434 70  continue
435 c      solve for y answer stored in fx
436     do 80 j=1,nvar
437     do 80 i=j+1,nvar
438     do 80 k=1,nu
439     fx(i,k) = fx(j,k) * (-jac(i,j))+ fx(i,k)
440 80  continue
441     end
442 c
443 c      this function is to evaluate the dirivatives using BDF of
444 c      order 1 or 2 .
445 c
446 c      function dxdt(i)
447 c      double precision x(50),x2(50),x1(50),h,dxdt
448 c      integer order

```

```
449 c
450     common order, x, x2, flag, x1, h
451     if ((order.eq.1).or.(flag.eq.1)) then
452         dxdt = (x(i) - x2(i))/h
453     else
454         dxdt = (1.5*x(i) - 2*x2(i) + .5*x1(i))/h
455     end if
456     return
457     end
```

conversance.f

```

1 *****
2 * This program computes the eigenvalues of the matrix *
3 *      inv(Arr). Asr. inv(Ass). Asr *
4 * The input is the file out and the the file solution. *
5 * The file solution is set by the program newton.dc.f. *
6 * The output is the eigenvalues and optionally the above *
7 * matrix element. IMSL (International Mathematical and *
8 * Statistical Library) routines are used. *
9 *****
10 *
11      double precision jac(10,5,5), x(50), fx(50), arr(5,5)
12      +, z(5), u(5), ans(5,5), ars(5,20), ass(5,5), assinv(5,5)
13      +, asr(20,5), eigen(10)
14      integer nf(10)
15      data ans, jac/275*0/
16      open(unit=10, file="solution", status="old")
17      read(10,10) n, nvar, nu, nblks, (nf(i), i=1, nblks)
18      write(6,10) nvar, nu, nblks, (nf(i), i=1, nblks)
19      10      format(i2)
20      nn=nvar-nu-nz+1
21      read(10,20)(x(i), i=1, nvar)
22      do 22 i=1, nz
23          z(i) = x(nn)
24      22      nn=nn+1
25      do 23 i=1, nu
26          u(i) = x(nn)
27      23      nn=nn+1
28      c      write(6,11)(x(i), i=1, nvar)
29      11      format(e13.6)
30      20      format(e13.6)
31      include "out"
32      c
33      pos = 1
34      do 1 i=1, nblks-1
35          do 15 l=1, nf(i)
36              ll=l+pos-1
37              do 25 k=1, nf(i)
38      25          ass(1,k)=jac(i, l, k)
39              do 15 k=1, nu
40                  asr(1,k)=asr(ll, k)
41                  ars(k,1)=ars(k, ll)
42      15          continue
43              call linvlf(ass, nf(i), 5, assinv, 0, arr, ier)
44              call vmulff(ars, assinv, nu, nf(i), nf(i), 5, 5, ass, 5, ier)
45              call vmulff(ass, asr, nu, nf(i), nu, 5, 20, arr, 5, ier)
46              do 35 l=1, nu
47                  do 35 k=1, nu
48      35          ans(1,k)=ans(1,k)+arr(1,k)
49              write(6,343)
50      343      format("ok")
51              1      pos = pos+nf(i)
52              do 40 i=1, nu
53                  do 40 j=1, nu
54      40          arr(i,j)=jac(nblks, i, j)
55              call linvlf(arr, nu, 5, assinv, 0, asr, ier)
56              call vmulff(assinv, ans, nu, nu, nu, 5, 5, ass, 5, ier)

```

```
57 c this statement write the resulting matrix from the
58 c product inv(Arr).Ars. inv(Ass).Asr.
59 if (n. eq. 1) write(6,600)((ass(i, j), j=1, nu), i=1, nu)
60 600 format(4e13.6)
61 call eigrf(ass, nu, 5, 0, eigen, assinv, 5, asr, ier)
62 70 format(/"eigenvalue #", i2, " =", e13.6, " + j ", e13.6)
63 do 43 i=2, 2*nu, 2
64     write(6,70) i/2, eigen(i-1), eigen(i)
65     eigen(i)=sqrt(eigen(i-1)**2+eigen(i)**2)
66     write(6,71) eigen(i)
67 71 format("Magnitude = ", e13.6)
68 43 continue
69 end
```

**APPENDIX B**

**Results for Examples**

**7.1 and 7.2**

**(Semi-Direct and Newton-Raphson  
have identical listings, therefore  
only one version is listed)**



example 7.1 (rise)

time	x 1	x 2	x 5
0.100000e-06	0.135468e-02	0.135680e-02	0.967742e-01
0.200000e-06	0.305937e-02	0.306429e-02	0.968179e-01
0.300000e-06	0.478035e-02	0.478824e-02	0.968729e-01
0.400000e-06	0.641075e-02	0.642165e-02	0.969284e-01
0.500000e-06	0.792205e-02	0.793593e-02	0.969810e-01
0.600000e-06	0.931190e-02	0.932872e-02	0.970297e-01
0.700000e-06	0.105863e-01	0.106060e-01	0.971157e-01
0.800000e-06	0.117536e-01	0.117762e-01	0.971533e-01
0.900000e-06	0.128222e-01	0.128477e-01	0.971878e-01
0.100000e-05	0.138005e-01	0.138288e-01	0.972194e-01
0.120000e-05	0.146960e-01	0.147270e-01	0.972483e-01
0.130000e-05	0.155157e-01	0.155494e-01	0.972747e-01
0.140000e-05	0.162659e-01	0.163023e-01	0.972989e-01
0.150000e-05	0.169526e-01	0.169917e-01	0.973211e-01
0.160000e-05	0.175811e-01	0.176229e-01	0.973413e-01
0.170000e-05	0.181564e-01	0.182008e-01	0.973599e-01
0.180000e-05	0.186829e-01	0.187300e-01	0.973769e-01
0.190000e-05	0.191649e-01	0.192145e-01	0.973924e-01
0.200000e-05	0.196060e-01	0.196582e-01	0.974066e-01
0.210000e-05	0.200097e-01	0.200645e-01	0.974197e-01
0.220000e-05	0.203792e-01	0.204366e-01	0.974316e-01
0.230000e-05	0.207173e-01	0.207773e-01	0.974425e-01
0.240000e-05	0.210268e-01	0.210894e-01	0.974525e-01
0.250000e-05	0.213101e-01	0.213752e-01	0.974616e-01
0.260000e-05	0.215693e-01	0.216370e-01	0.974700e-01
0.270000e-05	0.218066e-01	0.218767e-01	0.974776e-01
0.280000e-05	0.220237e-01	0.220964e-01	0.974846e-01
0.290000e-05	0.222224e-01	0.222976e-01	0.974910e-01
0.300000e-05	0.224042e-01	0.224819e-01	0.974969e-01
0.310000e-05	0.225706e-01	0.226508e-01	0.975023e-01
0.320000e-05	0.227228e-01	0.228055e-01	0.975072e-01
0.330000e-05	0.228621e-01	0.229473e-01	0.975117e-01
0.340000e-05	0.229896e-01	0.230772e-01	0.975158e-01
0.350000e-05	0.231062e-01	0.231964e-01	0.975196e-01
0.360000e-05	0.232129e-01	0.233055e-01	0.975230e-01
0.370000e-05	0.233106e-01	0.234056e-01	0.975261e-01
0.380000e-05	0.233999e-01	0.234974e-01	0.975290e-01
0.390000e-05	0.234816e-01	0.235816e-01	0.975317e-01
0.400000e-05	0.235563e-01	0.236588e-01	0.975341e-01
0.410000e-05	0.236247e-01	0.237296e-01	0.975363e-01
0.420000e-05	0.236872e-01	0.237946e-01	0.975383e-01
0.430000e-05	0.237444e-01	0.238542e-01	0.975401e-01
0.440000e-05	0.237967e-01	0.239090e-01	0.975418e-01
0.450000e-05	0.238445e-01	0.239592e-01	0.975434e-01
0.460000e-05	0.238882e-01	0.240054e-01	0.975448e-01
0.470000e-05	0.239281e-01	0.240478e-01	0.975461e-01
0.480000e-05	0.239647e-01	0.240868e-01	0.975472e-01
0.490000e-05	0.239981e-01	0.241226e-01	0.975483e-01
0.500000e-05	0.240286e-01	0.241556e-01	0.975493e-01
0.510000e-05	0.240564e-01	0.241859e-01	0.975502e-01
0.520000e-05	0.240819e-01	0.242138e-01	0.975510e-01
0.530000e-05	0.241051e-01	0.242395e-01	0.975518e-01
0.540000e-05	0.241264e-01	0.242632e-01	0.975525e-01



example 7.1 (fall)

time	x 1	x 2	x 5
0. 200000e-03	0. e+00	0. e+00	0. 967742e-01
0. 400000e-03	0. 233962e-01	0. 265508e-01	0. 975289e-01
0. 600000e-03	0. 226451e-01	0. 298578e-01	0. 975047e-01
0. 800000e-03	0. 213323e-01	0. 327404e-01	0. 974623e-01
0. 100000e-02	0. 204702e-01	0. 360055e-01	0. 974345e-01
0. 120000e-02	0. 194843e-01	0. 389921e-01	0. 974027e-01
0. 140000e-02	0. 185219e-01	0. 418226e-01	0. 973717e-01
0. 160000e-02	0. 176122e-01	0. 445246e-01	0. 973423e-01
0. 180000e-02	0. 167464e-01	0. 470946e-01	0. 973144e-01
0. 200000e-02	0. 159225e-01	0. 495383e-01	0. 972878e-01
0. 220000e-02	0. 151393e-01	0. 518620e-01	0. 972626e-01
0. 240000e-02	0. 143945e-01	0. 540714e-01	0. 972385e-01
0. 260000e-02	0. 136864e-01	0. 561722e-01	0. 972157e-01
0. 280000e-02	0. 130131e-01	0. 581696e-01	0. 971940e-01
0. 300000e-02	0. 123729e-01	0. 600688e-01	0. 971733e-01
0. 320000e-02	0. 117642e-01	0. 618745e-01	0. 971537e-01
0. 340000e-02	0. 111855e-01	0. 635914e-01	0. 971350e-01
0. 360000e-02	0. 106352e-01	0. 652238e-01	0. 971173e-01
0. 380000e-02	0. 101120e-01	0. 667759e-01	0. 971004e-01
0. 400000e-02	0. 961453e-02	0. 682517e-01	0. 970843e-01
0. 420000e-02	0. 914154e-02	0. 696549e-01	0. 970691e-01
0. 440000e-02	0. 869182e-02	0. 709890e-01	0. 970546e-01
0. 460000e-02	0. 826423e-02	0. 722575e-01	0. 970408e-01
0. 480000e-02	0. 785767e-02	0. 734636e-01	0. 970277e-01
0. 500000e-02	0. 747111e-02	0. 746104e-01	0. 970152e-01
0. 520000e-02	0. 710357e-02	0. 757007e-01	0. 970033e-01
0. 540000e-02	0. 675411e-02	0. 767374e-01	0. 969921e-01
0. 560000e-02	0. 642184e-02	0. 777231e-01	0. 969813e-01
0. 580000e-02	0. 610592e-02	0. 786604e-01	0. 969712e-01
0. 600000e-02	0. 580554e-02	0. 795515e-01	0. 969615e-01
0. 620000e-02	0. 551993e-02	0. 803987e-01	0. 969523e-01
0. 640000e-02	0. 524838e-02	0. 812043e-01	0. 969435e-01
0. 660000e-02	0. 499018e-02	0. 819703e-01	0. 969352e-01
0. 680000e-02	0. 474469e-02	0. 826986e-01	0. 969272e-01
0. 700000e-02	0. 451128e-02	0. 833910e-01	0. 969197e-01
0. 720000e-02	0. 428934e-02	0. 840494e-01	0. 969126e-01
0. 740000e-02	0. 407833e-02	0. 846754e-01	0. 969058e-01
0. 760000e-02	0. 387770e-02	0. 852706e-01	0. 968993e-01
0. 780000e-02	0. 368693e-02	0. 858365e-01	0. 968931e-01
0. 800000e-02	0. 350555e-02	0. 863746e-01	0. 968873e-01
0. 820000e-02	0. 333310e-02	0. 868862e-01	0. 968817e-01
0. 840000e-02	0. 316913e-02	0. 873727e-01	0. 968764e-01
0. 860000e-02	0. 301322e-02	0. 878352e-01	0. 968714e-01
0. 880000e-02	0. 286498e-02	0. 882749e-01	0. 968666e-01
0. 900000e-02	0. 272404e-02	0. 886930e-01	0. 968621e-01
0. 920000e-02	0. 259003e-02	0. 890906e-01	0. 968577e-01
0. 940000e-02	0. 246262e-02	0. 894686e-01	0. 968536e-01
0. 960000e-02	0. 234147e-02	0. 898280e-01	0. 968497e-01
0. 980000e-02	0. 222628e-02	0. 901697e-01	0. 968460e-01
0. 100000e-01	0. 211676e-02	0. 904946e-01	0. 968425e-01
0. 102000e-01	0. 201262e-02	0. 908035e-01	0. 968391e-01
0. 104000e-01	0. 191361e-02	0. 910973e-01	0. 968359e-01
0. 106000e-01	0. 181947e-02	0. 913765e-01	0. 968329e-01
0. 108000e-01	0. 172996e-02	0. 916421e-01	0. 968300e-01

0. 110000e-01	0. 164486e-02	0. 918946e-01	0. 968273e-01
0. 112000e-01	0. 156394e-02	0. 921346e-01	0. 968246e-01
0. 114000e-01	0. 148700e-02	0. 923629e-01	0. 968222e-01
0. 116000e-01	0. 141385e-02	0. 925799e-01	0. 968198e-01
0. 118000e-01	0. 134429e-02	0. 927862e-01	0. 968176e-01
0. 120000e-01	0. 127816e-02	0. 929824e-01	0. 968154e-01
0. 122000e-01	0. 121528e-02	0. 931689e-01	0. 968134e-01
0. 124000e-01	0. 115549e-02	0. 933463e-01	0. 968115e-01
0. 126000e-01	0. 109865e-02	0. 935149e-01	0. 968096e-01
0. 128000e-01	0. 104460e-02	0. 936753e-01	0. 968079e-01
0. 130000e-01	0. 993212e-03	0. 938277e-01	0. 968062e-01
0. 132000e-01	0. 944351e-03	0. 939727e-01	0. 968047e-01
0. 134000e-01	0. 897894e-03	0. 941105e-01	0. 968032e-01
0. 136000e-01	0. 853722e-03	0. 942415e-01	0. 968017e-01
0. 138000e-01	0. 811723e-03	0. 943661e-01	0. 968004e-01
0. 140000e-01	0. 771790e-03	0. 944846e-01	0. 967991e-01
0. 142000e-01	0. 733822e-03	0. 945972e-01	0. 967979e-01
0. 144000e-01	0. 697721e-03	0. 947043e-01	0. 967967e-01
0. 146000e-01	0. 663397e-03	0. 948062e-01	0. 967956e-01
0. 148000e-01	0. 630761e-03	0. 949030e-01	0. 967945e-01
0. 150000e-01	0. 599731e-03	0. 949950e-01	0. 967935e-01
0. 152000e-01	0. 570227e-03	0. 950826e-01	0. 967926e-01
0. 154000e-01	0. 542175e-03	0. 951658e-01	0. 967917e-01
0. 156000e-01	0. 515502e-03	0. 952449e-01	0. 967908e-01
0. 158000e-01	0. 490142e-03	0. 953201e-01	0. 967900e-01
0. 160000e-01	0. 466030e-03	0. 953917e-01	0. 967892e-01
0. 162000e-01	0. 443103e-03	0. 954597e-01	0. 967885e-01
0. 164000e-01	0. 421305e-03	0. 955243e-01	0. 967878e-01
0. 166000e-01	0. 400579e-03	0. 955858e-01	0. 967871e-01
0. 168000e-01	0. 380872e-03	0. 956443e-01	0. 967865e-01
0. 170000e-01	0. 362135e-03	0. 956999e-01	0. 967859e-01
0. 172000e-01	0. 344320e-03	0. 957527e-01	0. 967853e-01
0. 174000e-01	0. 327381e-03	0. 958030e-01	0. 967848e-01
0. 176000e-01	0. 311275e-03	0. 958508e-01	0. 967842e-01
0. 178000e-01	0. 295962e-03	0. 958962e-01	0. 967837e-01
0. 180000e-01	0. 281402e-03	0. 959394e-01	0. 967833e-01
0. 182000e-01	0. 267559e-03	0. 959805e-01	0. 967828e-01
0. 184000e-01	0. 254396e-03	0. 960195e-01	0. 967824e-01
0. 186000e-01	0. 241881e-03	0. 960566e-01	0. 967820e-01
0. 188000e-01	0. 229982e-03	0. 960919e-01	0. 967816e-01
0. 190000e-01	0. 218668e-03	0. 961255e-01	0. 967812e-01
0. 192000e-01	0. 207910e-03	0. 961574e-01	0. 967809e-01
0. 194000e-01	0. 197682e-03	0. 961877e-01	0. 967806e-01
0. 196000e-01	0. 187957e-03	0. 962166e-01	0. 967803e-01
0. 198000e-01	0. 178711e-03	0. 962440e-01	0. 967800e-01
0. 200000e-01	0. 169919e-03	0. 962701e-01	0. 967797e-01

## examples 7.2

time	x 1	x 2	x 5
0. 100000e-06	0. 195933e-02	0. 196247e-02	0. 968651e-01
0. 200000e-06	0. 381049e-02	0. 381672e-02	0. 969233e-01
0. 300000e-06	0. 552536e-02	0. 553464e-02	0. 969774e-01
0. 400000e-06	0. 710259e-02	0. 711487e-02	0. 970272e-01
0. 500000e-06	0. 854935e-02	0. 856458e-02	0. 970728e-01
0. 600000e-06	0. 987510e-02	0. 989323e-02	0. 971147e-01
0. 700000e-06	0. 110895e-01	0. 111105e-01	0. 971531e-01
0. 800000e-06	0. 122017e-01	0. 122255e-01	0. 971883e-01
0. 900000e-06	0. 132202e-01	0. 132469e-01	0. 972206e-01
0. 100000e-05	0. 141530e-01	0. 141824e-01	0. 972502e-01
0. 110000e-05	0. 150072e-01	0. 150393e-01	0. 972773e-01
0. 120000e-05	0. 157894e-01	0. 158242e-01	0. 973021e-01
0. 130000e-05	0. 165057e-01	0. 165432e-01	0. 973249e-01
0. 140000e-05	0. 171616e-01	0. 172018e-01	0. 973457e-01
0. 150000e-05	0. 177623e-01	0. 178051e-01	0. 973648e-01
0. 160000e-05	0. 183123e-01	0. 183578e-01	0. 973823e-01
0. 170000e-05	0. 188160e-01	0. 188641e-01	0. 973983e-01
0. 180000e-05	0. 192772e-01	0. 193279e-01	0. 974130e-01
0. 190000e-05	0. 196995e-01	0. 197528e-01	0. 974265e-01
0. 200000e-05	0. 200862e-01	0. 201421e-01	0. 974388e-01
0. 210000e-05	0. 204403e-01	0. 204987e-01	0. 974501e-01
0. 220000e-05	0. 207646e-01	0. 208255e-01	0. 974605e-01
0. 230000e-05	0. 210614e-01	0. 211249e-01	0. 974700e-01
0. 240000e-05	0. 213333e-01	0. 213992e-01	0. 974787e-01
0. 250000e-05	0. 215821e-01	0. 216506e-01	0. 974867e-01
0. 260000e-05	0. 218100e-01	0. 218810e-01	0. 974940e-01
0. 270000e-05	0. 220187e-01	0. 220922e-01	0. 975007e-01
0. 280000e-05	0. 222097e-01	0. 222857e-01	0. 975068e-01
0. 290000e-05	0. 223846e-01	0. 224631e-01	0. 975124e-01
0. 300000e-05	0. 225447e-01	0. 226256e-01	0. 975176e-01
0. 310000e-05	0. 226912e-01	0. 227747e-01	0. 975223e-01
0. 320000e-05	0. 228254e-01	0. 229114e-01	0. 975267e-01
0. 330000e-05	0. 229482e-01	0. 230367e-01	0. 975306e-01
0. 340000e-05	0. 230607e-01	0. 231516e-01	0. 975343e-01
0. 350000e-05	0. 231636e-01	0. 232569e-01	0. 975376e-01
0. 360000e-05	0. 232578e-01	0. 233536e-01	0. 975407e-01
0. 370000e-05	0. 233440e-01	0. 234423e-01	0. 975435e-01
0. 380000e-05	0. 234229e-01	0. 235237e-01	0. 975461e-01
0. 390000e-05	0. 234952e-01	0. 235983e-01	0. 975485e-01
0. 400000e-05	0. 235613e-01	0. 236669e-01	0. 975507e-01
0. 410000e-05	0. 236217e-01	0. 237298e-01	0. 975526e-01
0. 420000e-05	0. 236771e-01	0. 237876e-01	0. 975545e-01
0. 430000e-05	0. 237277e-01	0. 238406e-01	0. 975562e-01
0. 440000e-05	0. 237740e-01	0. 238894e-01	0. 975577e-01
0. 450000e-05	0. 238163e-01	0. 239342e-01	0. 975591e-01
0. 460000e-05	0. 238551e-01	0. 239754e-01	0. 975604e-01
0. 470000e-05	0. 238905e-01	0. 240132e-01	0. 975616e-01
0. 480000e-05	0. 239229e-01	0. 240481e-01	0. 975628e-01
0. 490000e-05	0. 239525e-01	0. 240801e-01	0. 975638e-01
0. 500000e-05	0. 239796e-01	0. 241096e-01	0. 975647e-01
0. 510000e-05	0. 240044e-01	0. 241368e-01	0. 975656e-01
0. 520000e-05	0. 240270e-01	0. 241619e-01	0. 975664e-01
0. 530000e-05	0. 240476e-01	0. 241850e-01	0. 975671e-01
0. 540000e-05	0. 240665e-01	0. 242063e-01	0. 975678e-01

0. 550000e-05	0. 240837e-01	0. 242259e-01	0. 975684e-01
0. 560000e-05	0. 240995e-01	0. 242441e-01	0. 975690e-01
0. 570000e-05	0. 241138e-01	0. 242609e-01	0. 975695e-01
0. 580000e-05	0. 241269e-01	0. 242764e-01	0. 975700e-01
0. 590000e-05	0. 241389e-01	0. 242908e-01	0. 975705e-01
0. 600000e-05	0. 241498e-01	0. 243041e-01	0. 975709e-01
0. 610000e-05	0. 241597e-01	0. 243165e-01	0. 975713e-01
0. 620000e-05	0. 241687e-01	0. 243279e-01	0. 975716e-01
0. 630000e-05	0. 241770e-01	0. 243386e-01	0. 975720e-01
0. 640000e-05	0. 241845e-01	0. 243485e-01	0. 975723e-01
0. 650000e-05	0. 241913e-01	0. 243578e-01	0. 975726e-01
0. 660000e-05	0. 241974e-01	0. 243664e-01	0. 975729e-01
0. 670000e-05	0. 242031e-01	0. 243744e-01	0. 975731e-01
0. 680000e-05	0. 242082e-01	0. 243819e-01	0. 975734e-01
0. 690000e-05	0. 242128e-01	0. 243890e-01	0. 975736e-01
0. 700000e-05	0. 242169e-01	0. 243956e-01	0. 975738e-01
0. 710000e-05	0. 242207e-01	0. 244018e-01	0. 975740e-01
0. 720000e-05	0. 242241e-01	0. 244076e-01	0. 975742e-01
0. 730000e-05	0. 242272e-01	0. 244131e-01	0. 975743e-01
0. 740000e-05	0. 242300e-01	0. 244183e-01	0. 975745e-01
0. 750000e-05	0. 242325e-01	0. 244232e-01	0. 975747e-01
0. 760000e-05	0. 242347e-01	0. 244279e-01	0. 975748e-01
0. 770000e-05	0. 242367e-01	0. 244323e-01	0. 975750e-01
0. 780000e-05	0. 242384e-01	0. 244365e-01	0. 975751e-01
0. 790000e-05	0. 242400e-01	0. 244405e-01	0. 975752e-01
0. 800000e-05	0. 242414e-01	0. 244443e-01	0. 975753e-01
0. 810000e-05	0. 242426e-01	0. 244479e-01	0. 975755e-01
0. 820000e-05	0. 242437e-01	0. 244514e-01	0. 975756e-01
0. 830000e-05	0. 242446e-01	0. 244548e-01	0. 975757e-01
0. 840000e-05	0. 242454e-01	0. 244580e-01	0. 975758e-01
0. 850000e-05	0. 242461e-01	0. 244611e-01	0. 975759e-01
0. 860000e-05	0. 242467e-01	0. 244641e-01	0. 975760e-01
0. 870000e-05	0. 242472e-01	0. 244670e-01	0. 975761e-01
0. 880000e-05	0. 242476e-01	0. 244698e-01	0. 975761e-01
0. 890000e-05	0. 242479e-01	0. 244726e-01	0. 975762e-01
0. 900000e-05	0. 242481e-01	0. 244752e-01	0. 975763e-01
0. 910000e-05	0. 242483e-01	0. 244778e-01	0. 975764e-01
0. 920000e-05	0. 242484e-01	0. 244804e-01	0. 975765e-01
0. 930000e-05	0. 242484e-01	0. 244828e-01	0. 975766e-01
0. 940000e-05	0. 242484e-01	0. 244852e-01	0. 975766e-01
0. 950000e-05	0. 242484e-01	0. 244876e-01	0. 975767e-01
0. 960000e-05	0. 242483e-01	0. 244899e-01	0. 975768e-01
0. 970000e-05	0. 242481e-01	0. 244922e-01	0. 975769e-01
0. 980000e-05	0. 242479e-01	0. 244944e-01	0. 975769e-01
0. 990000e-05	0. 242477e-01	0. 244967e-01	0. 975770e-01
0. 100000e-04	0. 242475e-01	0. 244988e-01	0. 975771e-01