

\COMPARISON OF ENERGY MINIMIZATION WITH
DIRECT STIFFNESS FOR LINEAR STRUCTURAL ANALYSIS /

by

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NOTATION

A	cross-sectional area
E	Young's modulus
I	moment of inertia
L	length
U	total potential energy
V	volume
$[\]$	square matrix
$\{ \}$	column vector
$[A]$	hessian matrix
$[\tilde{A}]$	approximation of hessian matrix
$[K]$	constrained stiffness matrix
$[\tilde{K}]^{-1}$	approximate inverse hessian of the total potential
$\{d^k\}$	k^{th} search direction used in minimization algorithms
$\{g^k\}$	gradient vector of total potential evaluated at $\{q^k\}$
$\{q\}$	generalized coordinates
$\{q^k\}$	k^{th} estimate of the deformation vector
$\{Q\}$	load vector
$\nabla f(x)$	gradient vector of $f(x)$ evaluated at x
$\nabla^2 f(x)$	hessian matrix of $f(x)$ evaluated at x
α_k	scalar steplength used in k^{th} 1-D minimization
ϵ	strain per unit length
ϵ_1, ϵ_2	limits on convergence criteria
Ω	potential energy of external forces

Π	strain energy
Π^*	strain energy density
σ	normal stress per unit area

Chapter 1

INTRODUCTION

This chapter contains the purpose and scope of this study. Included is a survey of the current literature on the variable metric and conjugate gradient methods of nonlinear function minimization. Emphasis has been placed on the minimization of quadratic functions. The effects of scaling on these algorithms has been included. Criteria for algorithm selection and the selection of the algorithms used in this study are also included.

1.1 Purpose and Scope

The purpose of this study is to compare the efficiency of two different approaches for finding the generalized displacement vector of a plane frame subject to static joint loads. The methods of analysis used are: the principle of minimum potential energy (the energy method) and the direct stiffness method of matrix structural analysis (stiffness method). The frames considered in this study are limited to small displacements and behave linearly. Evaluation is based on the amount of computational time required by each method to solve the same problem.

The energy method used in this study locates the generalized displacements of a structure by minimizing the total potential energy of that structure. The minimization algorithms used are iterative. The variable metric algorithms take information from a present iteration to improve the next iteration. Some of these algorithms exhibit

a special property: if there are no roundoff errors and the number of iterations required to find the solution is the same as the number of unknowns, the flexibility matrix of the structure is produced as a result of the minimization process. Because of roundoff errors only an approximation of the flexibility matrix can be expected. However, this approximation may be retained and used to reduce computational time when more than one load condition is applied to the same structure.

The stiffness method used in this study assembles the constrained stiffness matrix for a given structure and directly solves the resulting set of equilibrium equations. These equations are solved by Gaussian elimination. The algorithm used for the solution of the equilibrium equations requires a triangular decomposition of the stiffness matrix. When several load conditions are applied to the same structure the previously decomposed stiffness matrix may still be used.

Several frames have been considered to determine the efficiency of the energy method compared to the stiffness method. The effect of the number of degrees of freedom and configuration of a frame on the solution time required by both methods has been examined. A comparison of the rate of increase in computational time when additional load vectors are applied to the same structure is also given.

1.2 Literature Review

a. Variable Metric Algorithms

Variable metric is the name given to a large group of algorithms

which have been developed that will minimize a nonlinear function of n variables. These algorithms are also referred to as quasi-Newton algorithms because an attempt is made to simulate Newton's method [35]. Newton's method requires second derivative information about the function being minimized. This information is contained in an $(n \times n)$ matrix known as the hessian. In addition to calculating the hessian matrix, Newton's method also requires the hessian be inverted. Working under the assumption that evaluation and inversion of the hessian is impractical or costly, the idea underlying quasi-Newton algorithms is to use an approximation to the inverse hessian in place of the true inverse that is required in Newton's method [27]. The variable metric (quasi-Newton) algorithms are iterative and require only first derivative information about the function being minimized. The approximation of the inverse hessian is improved during each iteration by using the information obtained during that iteration and the previous iteration. This process will continue until some convergence criteria, which sufficiently defines a minimum value of the function, are satisfied.

The variables of a function may be considered as coordinates of a point in an n dimensional linear space. The set of variables for which the function has a constant value forms an $n-1$ dimensional surface in this space [8]. In Newton's method, the inverse hessian is a measure of distance in this space, a metric. A continual update of the approximate inverse hessian suggests referring to the iterative process as a variable metric algorithm.

The first variable metric algorithm was developed, and so named, in 1959 by Davidon [8]. The original method devised by Davidon was simplified by Fletcher and Powell [14] who also proved convergence and stability criteria for their simplified version of Davidon's original work. The modified method is known as the Davidon-Fletcher-Powell method, DFP. The convergence criteria proved by Fletcher and Powell for the DFP method was that of quadratic convergence. For a quadratic function, the method will locate the minimum of the function in at most n iterations. The stability criteria proved was that for each iteration the value of the function being minimized is reduced.

Since the first introduction of the variable metric method there have been numerous new algorithms developed to update the inverse hessian. There has also been the development of families of algorithms. These families have constants or parameters that may be changed to lead to new algorithms or demonstrate that most previously developed algorithms belong to a particular family. The first of these families was developed by Broyden [5] and another very important family was developed by Huang [21]. Dixon [10,11] has indicated the sequence of points generated in minimizing a general function by different members of Broyden's family are identical when the line search is exact and that Broyden's family is a subset of Huang's family. A survey on some of the methods used for construction of variable metric algorithms is given by Oren [35].

The construction of Huang's family illustrates the theory basic to many of the variable metric algorithms and uses four properties that

are essential to the theory:

- a) the algorithms use one dimensional search only
- b) for a quadratic function, the algorithms are capable of converging quadratically to the minimal point
- c) the algorithms employ the function and its gradient only
- d) the algorithms employ only information at the present iteration and the iteration immediately previous to the present

The requirement of one dimensional search by property (a) reduces the n dimensional minimization problem to a series of linear minimization problems, each of which is solved during each iteration. The search is carried out in the space defined by the variables of the function; for each iteration a new search direction is chosen. This is continued until a minimum of the function is located. Property (b) is of importance because even a nonquadratic function behaves approximately quadratically in the neighborhood of a minimal point [21]. Property (c) identifies the algorithms as only needing first derivative information and property (d) requires the only information that must be retained is that from the previous iteration. This takes advantage of previous information about the function being minimized to improve the next iteration.

The DFP method is probably the most widely known variable metric algorithm and one of the most successful which has the following

property. If for a positive definite quadratic function the convergence requires the full n iterations, then the n^{th} approximation of the inverse hessian is identically equal to the inverse hessian [31]. To guarantee the minimum will be located in no more than n iterations, quadratic convergence must be insured, which it is if the linear minimization problem or line search is done exactly [25]. Another variable metric method that has been introduced more recently is the Broyden-Fletcher-Goldfarb-Shanno, BFGS, algorithm. This algorithm is a member of Broyden's family and is considered to be the most successful member from Broyden's family in practice [4]. For general function minimization Brodliie [4] shows that for test functions in his study the BFGS algorithm was at least equivalent to or superior to the DFP algorithm.

There have been new algorithms proposed that eliminate the need for an accurate solution to the linear minimization problem. A symmetric rank one algorithm that avoids accurate line search was proposed by Fletcher [15]. In this algorithm quadratic convergence has been replaced by a property in which the approximate inverse hessian tends to the inverse hessian. A proof is given by Vial and Zang [39] that for a particular rank one algorithm without exact line search convergence will occur in at most $n+1$ iterations for a nonsingular quadratic function and if $n+1$ iterations are used the approximate inverse hessian will be the inverse hessian. Norris and Gerken [29] have presented a rank one method with a limited line search but are unable to prove convergence for quadratic functions

with eigenvalues both larger and smaller than one. However the numerical results given by Norris and Gerken indicate their method superior to the DFP algorithm for the nonlinear functions in their study.

The most recent innovation in variable metric algorithms has been the development of self-scaling variable metric, SSVM, algorithms. A family introduced by Oren [31], in which the particular algorithm is dependent upon two parameters, produces the effect of scaling the function being minimized by scaling the update formula used to approximate the inverse hessian. The numerical results in [31] indicate promise for SSVM algorithms. Further studies by Oren and Luenberger [32], Oren [33], Brodlie [4], and Spedicato [38] indicate a SSVM algorithm superior to a conventional variable metric algorithm for a general function with a large number of variables. However, for some functions the SSVM algorithms have been shown to deteriorate with an increase in variables, suggesting there are particular functions to which they are best suited to minimize [4]. It was shown by Spedicato [38] that for a Hilbert quadratic, with the number of variables ranging from 5 to 80, the performance of a conventional variable metric algorithm and a SSVM algorithm was practically identical.

Theoretically the SSVM and DFP algorithms perform the same for an exact line search when minimizing a quadratic function [32]. However, if the scale factor is varied at each iteration there is no guarantee that the approximate inverse hessian will be the inverse

hessian for a positive definite quadratic function [33]. The performance of a SSVM algorithm critically depends upon the selection of parameters that scale the update formula. The selection of parameters reported by Oren and Spedicato [34] are heuristic in nature but appear to give good results.

b. Conjugate Gradient Algorithms

The conjugate gradient algorithms for minimization of nonlinear functions have developed from the introduction of a method for solving a system of linear equations developed by Hestenes and Stiefel [18] and later work done by Beckman [3]. Conjugate gradient algorithms applied to the minimization of nonlinear functions locate a minimum value of a function by solving a series of linear minimization problems. This is similar to the way the variable metric algorithms perform. In fact, Myers [28] proves that DFP algorithms and conjugate gradient algorithms, such as the Fletcher-Reeves algorithm, theoretically generate search directions that are positive scalar multiples of each other for a quadratic function if the initial search direction is the steepest descent. The difference in the algorithms is the way in which they generate the search directions.

The linear minimizations take place along a series of search directions which have been constructed such that they are A-conjugate for a positive definite quadratic function. A-conjugate directions require [19]:

$$\{d^i\}^T [A] \{d^j\} = 0 \quad (1.1)$$

where

$$1 \leq i \neq j \leq n$$

$\{d^i\}$ = search direction

$[A]$ = hessian matrix

The importance of a quadratic function is the same as mentioned for the variable metric algorithms.

The conjugate gradient method is iterative and the process is terminated when some convergence criteria are satisfied. The gradient at the previous iteration and the gradient at the present iteration are required to construct the A-conjugate directions. There is no need to compute the hessian or its inverse. The gradient is a vector whose negative identifies the direction of greatest decrease, locally, in the value of a function, the direction of steepest descent [17]. It has been shown by Allwright [1] that if the first search direction is the steepest descent, the conjugate gradient algorithms are superior to continuing to search in directions of steepest descent in minimizing a quadratic function.

The convergence properties of three conjugate gradient algorithms have been studied by Cohen [6]. The algorithms, Polak and Ribière, Daniel and Fletcher-Reeves all behave identically for a quadratic function. For a large class of nonlinear functions reinitializing the search direction periodically (when the number of iterations for each period is greater than or equal to the number of variables) they converge n-step quadratically [6]. Lenard [26] has also shown that theoretically the Fletcher-Reeves and Polak-Ribière algorithms exhibit

n-step quadratic convergence when restarted under certain conditions. The difference in the above algorithms is in the way they compute the conjugate directions. The Fletcher-Reeves method [13] is the simplest of the three to implement and appears quite frequently in the literature and texts [13,19,27] which demonstrate the properties of conjugate gradient methods.

To guarantee quadratic convergence the initial search direction of the conjugate gradient algorithms must be the steepest descent [37]. However for a poorly conditioned quadratic function it can take more than n iterations to reach the minimum, due fundamentally to the finite digit arithmetic in which all calculations must be performed [17]. This has been shown in the numerical experiences of Fox and Stanton [16].

c. Scaling Applications

The variable metric and conjugate gradient algorithms both search for a minimum in the space defined by the variables. The search directions make use of the curvature of the surface defined by the variables. The value of scaling can easily be illustrated by Fig. 1.1. Figure 1.1a is a series of ellipsoids which can be considered as contours formed by constant values of a quadratic function. Figure 1.1b is a representation of the same quadratic function that has undergone a scaling transformation to produce a series of contours which are circles.

Consider a search made in the direction of steepest descent initially in both Figs. 1.1a and 1.1b. In Fig. 1.1a the first search

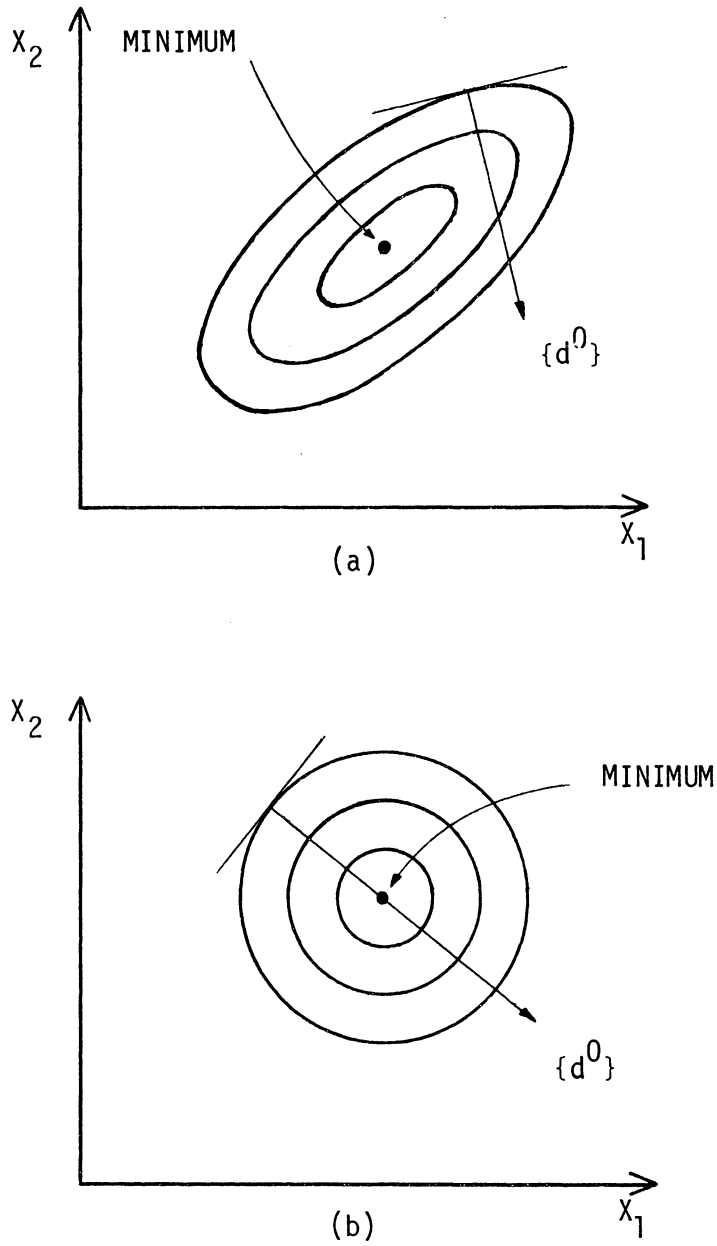


FIGURE 1.1 OPTIMALLY SCALED 2 VARIABLE QUADRATIC FUNCTION

direction will not lead to the minimum unless it should happen to be along a principle axis. While in Fig. 1.1b the first search direction will find the minimum regardless of where it originates from. Figure 1.1b is the result of optimally scaling the function represented by Fig. 1.1a by minimizing its eccentricities (the contours defined by ellipses were transformed to circles). However, in practice proper scaling of a function with many variables can be a difficult task since there is no set of rules to follow for all functions.

A method of reducing the condition number of the hessian of a positive definite quadratic function to being near optimally scaled is presented by Fox and Stanton [16]. A low condition number will reduce roundoff error and improve stability [34]. This method is easy to implement but requires the hessian of the function be known. The numerical results of [16] showed a poorly scaled function that could not be minimized by the Fletcher-Reeves conjugate gradient algorithm was minimized in less than n iterations by the same algorithm after scaling. The DFP algorithm used did however minimize the poorly scaled function, but did it at an improved rate after scaling. It should be noted scaling of this type requires a coordinate transformation and the function has to be known in matrix notation.

The effect of scaling the function can be created in variable metric algorithms by initial scaling of the approximate inverse hessian only or by scaling the update formula during each iteration [2,4,31,32,33,34,38]. For general nonlinear functions, scaling during each iteration appears superior to methods which do not employ

scaling [4,33,38]. In numerical experiments Spedicato [38] scaled the initial approximate inverse hessian by letting it be a diagonal matrix whose elements were those of the true inverse hessian at a minimum. For general nonlinear functions it was competitive with methods that scaled the update at each iteration. But it was not as efficient in minimizing a Hilbert quadratic with a large number of variables as when the initial matrix used in estimating the inverse hessian was the identity matrix. Indeed, it has been proven by Bard [2] improper scaling may worsen the problem and cause a variable metric algorithm to become unstable.

1.3 Algorithm Selection

The selection of the algorithm used in this study is based upon which of the algorithms surveyed best satisfies the requirements given in this section. The problem will be to minimize the total potential energy function of an assemblage of linear beam-column elements. The function may be expressed by the following quadratic form:

$$f(x) = \frac{1}{2} \{x\}^T [A] \{x\} - \{b\}^T \{x\} \quad (1.2)$$

where

$\{x\}$ = variables

$[A]$ = hessian matrix

$\{b\}$ = vector of constants

Equation 1.2 will be minimized several times where the hessian matrix remains constant while the vector of constants is changed (in structural analysis this corresponds to applying different load

vectors to the same structure).

The variable metric algorithms solve the following one dimensional minimization problem during each iteration:

$$\{x^{k+1}\} = \{x^k\} - \alpha_k [\tilde{A}_k]^{-1} \{g^k\} \quad (1.3)$$

where

$$\begin{aligned} \alpha_k &= \text{scalar step length that minimizes } f(x) \\ &\quad \text{along the direction of search} \\ [\tilde{A}_k]^{-1} &= \text{estimate of inverse hessian at } \{x^k\} \\ &\quad \text{(updated during each iteration)} \\ \{g^k\} &= \text{gradient vector evaluated at } \{x^k\} \end{aligned}$$

Because of the form of Eq. 1.2 the step length and gradient vector can be computed explicitly. Knowing the step length explicitly allows for an "exact" line search (dependent upon the precision of the math used). Explicit gradient evaluation also improves the numerical qualities of the algorithms [23].

Because it is desired to minimize Eq. 1.2 with several different values of the vector of constants while the hessian remains the same, the update of the inverse hessian in Eq. 1.3 becomes of special interest. If the inverse hessian is accurately approximated during the first minimization of Eq. 1.2 then it may be used as the initial estimate of the inverse hessian during the next minimization of Eq. 1.2. When Eq. 1.3 is applied it will now be reduced to Newton's method where the step length will be unity and the minimum will be located in a single iteration, a full Newton step. Therefore, the only algorithms that

will be considered are those that guarantee in n iterations the approximate inverse hessian will be the true inverse hessian; quadratic convergence is a necessary but not sufficient requirement for this.

The choice of algorithms was the Davidon-Fletcher-Powell variable metric algorithm which is supported by the literature surveyed as a good selection. It satisfies quadratic convergence and the approximate inverse hessian is the inverse hessian after n iterations. The method is also easily implemented into a computer program. Another possible choice could have been the Broyden-Fletcher-Goldfarb-Shanno, BFGS, algorithm. It appears to be preferred over the DFP algorithm in the minimization of some nonlinear functions. No indication is given, however, that the BFGS algorithm is superior to the DFP algorithm in minimizing quadratic functions, which fully satisfies the requirements of this section.

The algorithms that relax the line search were immediately rejected since they do not guarantee quadratic convergence and a relaxed line search is of no value in this study since the step length can be computed exactly. The self-scaling variable metric algorithms relinquish the property that the approximate inverse hessian will be the inverse hessian in n iterations if scaling is applied during each iteration. This eliminates SSVM algorithms even if quadratic convergence is satisfied.

Although the conjugate gradient algorithms do not compute the inverse hessian as a result of minimizing a function, they have two properties which make them attractive:

- a) easily implemented into a computer code requiring modest storage
- b) in the process of minimizing a positive definite quadratic function A-conjugate directions are generated

Property (a) is important from a programming standpoint but more important because of savings in cost in terms of computer time. Conjugate gradient algorithms only require matrix operations involving $(n \times 1)$ column vectors while variable metric algorithms require matrix operations involving $(n \times 1)$ column vectors as well as manipulation of a full $(n \times n)$ matrix. Although the $(n \times n)$ matrix is symmetric and this may be taken advantage of in storage, the variable metric algorithms still require much more computational effort than the conjugate gradient algorithms.

Property (b) is of importance because of the following relation:

$$[A]^{-1} = \sum_{i=1}^n \frac{\{d^i\}\{d^i\}^T}{\{d^i\}^T[A]\{d^i\}} \quad (1.4)$$

where

$\{d^i\}$ = search direction at i^{th} iteration

If the search directions are A-conjugate and n iterations are used in minimizing the function, Eq. 1.4 can be used to compute the inverse hessian as a by-product of the information required by the conjugate gradient algorithm (although Eq. 1.4 requires the storage of an $(n \times n)$ symmetric matrix, considerably less computational effort is required

to compute the inverse hessian by this method than by an update formula required by a variable metric algorithm). The result of Eq. 1.4 can now be used in Eq. 1.3 as the approximate inverse hessian. For a new vector of constants the minimum should be located in one iteration as previously stated.

The only requirement for a conjugate gradient algorithm is that A-conjugate search directions are generated; this implies quadratic convergence [19]. The methods which employ relaxed line search will not be used because quadratic convergence is not guaranteed. The algorithms of Fletcher-Reeves, Polak-Ribière and Daniel perform identically when applied to minimizing a quadratic function. They all are guaranteed quadratic convergence. The Fletcher-Reeves algorithm has the simplest method of generating conjugate directions. Because of its simplicity and quadratic convergence the FR algorithm was chosen. Although scaling has not been used in the algorithms selected and will not be used in the first minimization of Eq. 1.2 it is inferred in the second and subsequent minimization of Eq. 1.2. The use of the inverse hessian obtained during the first minimization as the approximate inverse hessian for the next minimization is actually the best scaled choice possible, the inverse hessian of the function being minimized.

Chapter 2

PROBLEM FORMULATION

This chapter contains the energy principles used in this study and a brief outline of the direct stiffness method of structural analysis.

2.1 Energy Method

a. Total Potential Energy

The following assumptions are used in this study: a) the system is conservative; b) the system behaves linearly; c) the body weight of the system is neglected; d) external forces consist of only joint loads; e) all members have prismatic cross sections; f) deformations caused by external forces occur infinitesimally slowly; g) all processes are adiabatic.

The total potential of a structural system is formulated in terms of the generalized coordinates of that structure and may be expressed by the following relation:

$$U = \Pi + \Omega \quad (2.1)$$

where

U = total potential

Π = total potential energy of internal forces

Ω = total potential energy of external forces

The total potential energy of the external forces is the negative of the work performed by these forces. The forces applied to structures in this study are concentrated forces and moments. The

values of the forces are constant and therefore independent of displacements or rotations. These external forces will undergo displacements expressed in units of length and rotations expressed in the nondimensional units of radians respectively. The external forces are applied in the direction of the generalized coordinates of the structure and are represented by the following load vector:

$$\{Q\}^T = \{Q_1 \quad Q_2 \quad Q_3 \quad \dots \quad Q_n\} \quad (2.2)$$

The displacements and rotations corresponding to the load vector are represented by the following vector:

$$\{q\}^T = \{q_1 \quad q_2 \quad q_3 \quad \dots \quad q_n\} \quad (2.3)$$

The total potential of the external forces, which is referred to as load potential, may be expressed as the negative of the scalar product of the preceding two vectors (where Q is constant).

$$\Omega = - \{Q\}^T \{q\} \quad (2.4)$$

The strain energy is a result of the internal forces developed in a structure. These internal forces are a result of the stresses caused by the deformation of the structure. The strain energy of a structure in a given configuration is equal to the work done in the absence of external forces to lead the structure slowly and adiabatically from the zero configuration to the given configuration [24]. The strain energy is the total potential of the internal forces. Neglecting the effects of shear, the strain energy for a linear beam-

column element is composed of two parts, the strain energy due to axial deformation and the strain energy due to bending. The strain energy of such an element may be computed by the following equation:

$$\Pi = \iiint_V \Pi^* dV \quad (2.5)$$

where

$$\Pi^* = \int_0^\epsilon \sigma d\epsilon \quad (2.6)$$

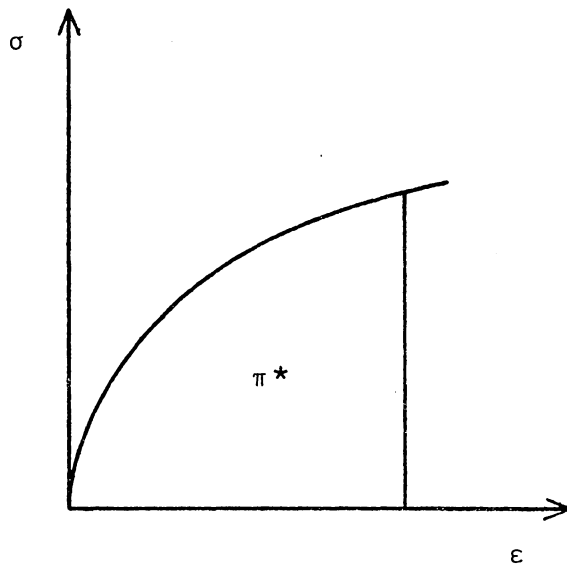
Equation 2.6 is the expression for strain energy density, the value of the strain energy at a point. The strain energy density can be illustrated graphically. Figure 2.1a represents the strain energy density for a general material and Fig. 2.1b represents the strain energy density for a material that obeys Hooke's law. From Fig. 2.1b and Hooke's law Eq. 2.6 can be rewritten as:

$$\Pi^* = \frac{\sigma^2}{2E} \quad (2.7)$$

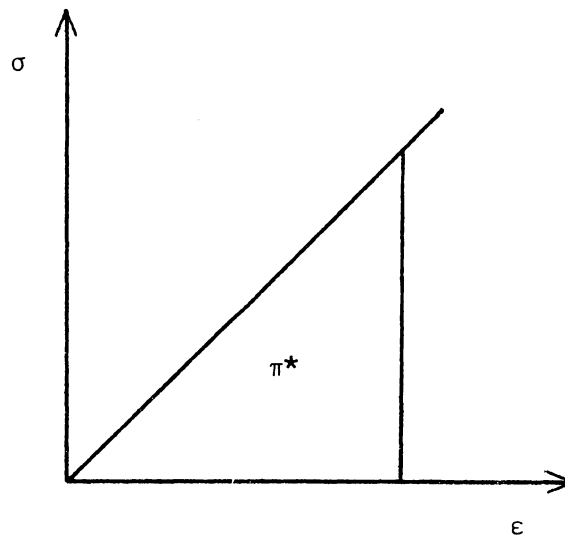
The strain energy density of a linear beam-column element is computed by substituting the relation for normal stress due to bending and axial displacement into Eq. 2.7. This value of the strain energy density is then substituted into Eq. 2.5. After simplification the strain energy in the linear beam-column element can be expressed as:

$$\Pi = \Pi_b + \Pi_a \quad (2.8)$$

where



(a)



(b)

FIGURE 2.1 STRAIN ENERGY DENSITY

$$\Pi_b = \frac{EI}{2} \int_0^L \left(\frac{\partial^2 y}{\partial x^2} \right)^2 dx \quad (2.9)$$

$$\Pi_a = \frac{AE}{2L} \Delta x^2 \quad (2.10)$$

Δx = change in axial length

b. Principle of Minimum Potential Energy

The basis for the energy method used in this study is the principle of minimum potential energy. This principle may be stated as:

Of all the displacements which satisfy the boundary conditions of a structural system, those corresponding to stable equilibrium configurations make the total potential energy a relative minimum [30].

This principle can be illustrated by Figs. 2.2a and 2.2b. Figure 2.2a is a conservative system which represents different locations of a rigid ball of weight W on a fixed contour. Figure 2.2b is a plot of the total potential of the ball for locations corresponding to those in Fig. 2.2a. The total potential of the ball at any point may be expressed as:

$$U = Wy \quad (2.11)$$

In Fig. 2.2a, points A, B, C and D represent equilibrium points. The stability of these points is determined by their behavior when they are subject to any possible small disturbance caused by an external force. If the ball at point A is slightly disturbed it will move to a new point and remain there. Since there is no change in total potential, this represents neutral equilibrium. If the ball at point B is

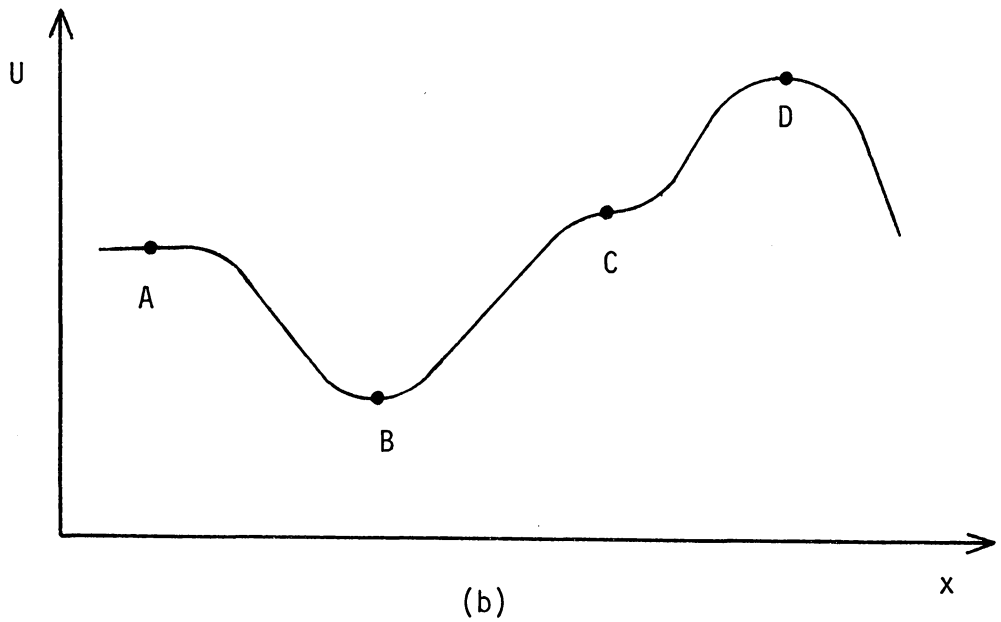
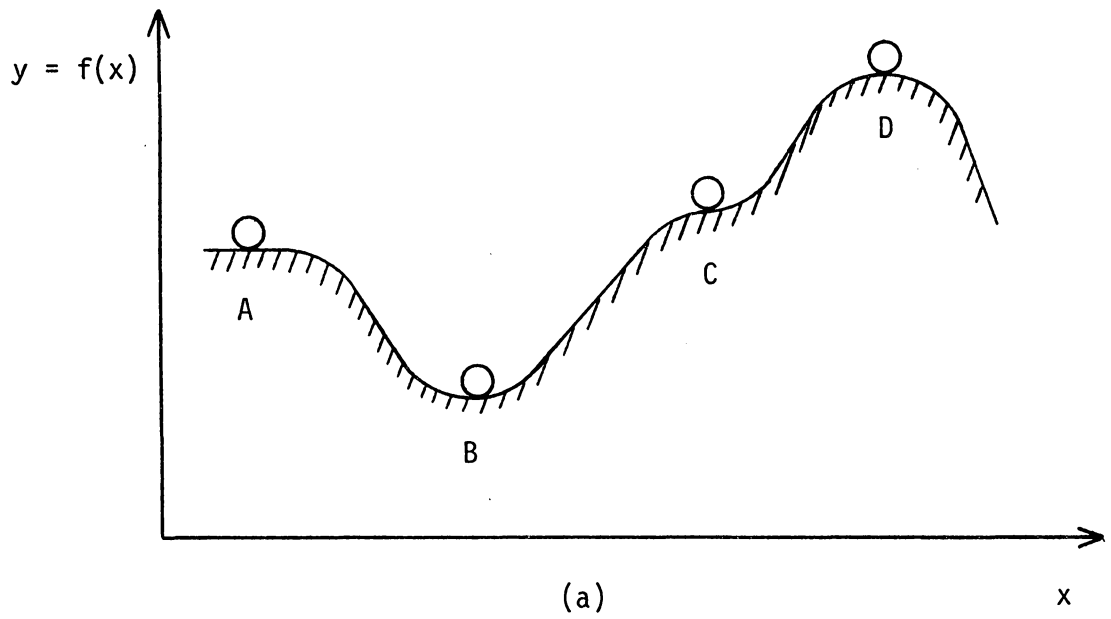


FIGURE 2.2 EQUILIBRIUM POINTS

slightly disturbed, it will oscillate about its original point, any disturbance causes an initial increase in total potential. This represents stable equilibrium. If the ball at point C is slightly disturbed, there is either an increase in total potential initially or a continuous decrease in total potential. This is unstable equilibrium. For any displacement of the ball at point D, there is an initial decrease in the total potential, which is also unstable equilibrium. From these conditions of equilibrium the only stable equilibrium point is that for which all possible small disturbances cause an increase in total potential. This requires the value of the total potential to be a relative minimum as stated in the principle of minimum potential energy.

c. Total Potential of a Structural System and its Gradient Vector

The total potential of a continuous structure is computed by modeling it as an assemblage of finite elements. The total potential of the structure may then be computed as the sum of the strain energy of each element added to the sum of the load potentials at all nodes.

A general finite element is represented by Fig. 2.3. The load potential is computed in terms of the global coordinates and the strain energy is computed in terms of the local coordinates. The load potential of an entire structure determined by Eq. 2.4 may be rewritten as:

$$\Omega = - \sum_{i=1}^{NDF} Q_i q_i \quad (2.12)$$

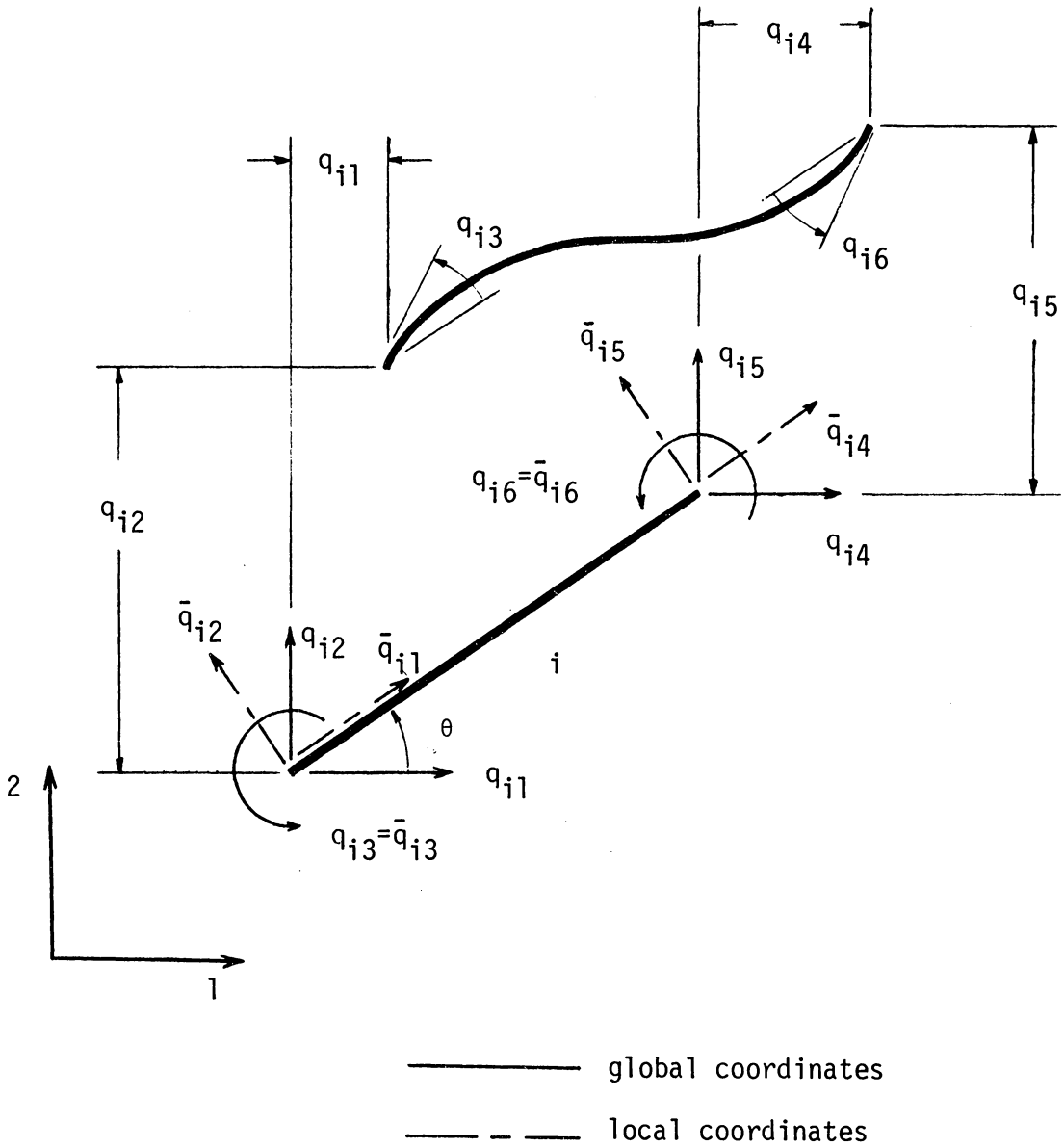


FIGURE 2.3 FINITE ELEMENT

where

NDF = number of degrees of freedom

The strain energy is computed in two parts, the strain energy due to bending and the strain energy due to axial displacement.

In computing the strain energy the local coordinates are defined as components of the global coordinates in accordance with Fig. 2.3

$$\bar{q}_{i1} = q_{i2}s_i + q_{i1}c_i \quad (2.13a)$$

$$\bar{q}_{i2} = q_{i2}c_i - q_{i1}s_i \quad (2.13b)$$

$$\bar{q}_{i3} = q_{i3} \quad (2.13c)$$

$$\bar{q}_{i4} = q_{i5}s_i + q_{i4}c_i \quad (2.13d)$$

$$\bar{q}_{i5} = q_{i5}c_i - q_{i4}s_i \quad (2.13e)$$

$$\bar{q}_{i6} = q_{i6} \quad (2.13f)$$

where

q_{ij} = global coordinate of element i in j direction

\bar{q}_{ij} = local coordinate of element i in j direction

c_i = $\cos\theta$ of element i

s_i = $\sin\theta$ of element i

The strain energy due to bending is based on the transverse deflection, $y(x)$, at any point along the longitudinal axis of the

element. The function $y(x)$ can be obtained by solving the differential equation of a beam in bending and applying the local coordinates which contribute to bending as the boundary conditions. This expression for $y(x)$ is used in Eq. 2.9 where the local coordinates are replaced by components of the global coordinates yielding the following expression for strain energy due to bending in element i :

$$\Pi_{bi} = \frac{E_i I_i}{2L_i} \left\{ \phi_i^2 + 2\phi_i \xi_i + \frac{4}{3} \xi_i^2 \right\} \quad (2.14)$$

where

$$\phi_i = \frac{6}{L_i} \left\{ q_{i1}s_i - q_{i2}c_i - \frac{2}{3} q_{i3}L_i - q_{i4}s_i + q_{i5}c_i - \frac{L_i}{3} q_{i6} \right\} \quad (2.15)$$

$$\xi_i = \frac{6}{L_i} \left\{ -q_{i1}s_i + q_{i2}c_i + \frac{1}{2} q_{i3} + q_{i4}s_i - q_{i5}c_i + \frac{L_i}{2} q_{i6} \right\} \quad (2.16)$$

The strain energy due to axial deformation is computed by using Eq. 2.10. Again, the local coordinates are replaced by components of the global coordinates to obtain for element i :

$$\Pi_{ai} = \frac{A_i E_i}{2L_i} \beta_i^2 \quad (2.17)$$

where

$$\beta_i^2 = -q_{i1}c_i - q_{i2}s_i + q_{i4}c_i + q_{i5}s_i \quad (2.18)$$

The strain energy of any element, i , can now be expressed as the sum of Eqs. 2.14 and 2.17:

$$\Pi_i = \frac{E_i I_i}{2L_i} \left\{ \phi_i^2 + 2\phi_i \xi_i + \frac{4}{3} \xi_i^2 \right\} + \frac{A_i E_i}{2L_i} \beta_i^2 \quad (2.19)$$

The total potential of a system of linear beam column elements is represented by:

$$U = \sum_{i=1}^{NEL} \left[\frac{E_i I_i}{2L_i} \{ \phi_i^2 + 2\phi_i \xi_i + \frac{4}{3} \xi_i^2 \} + \frac{A_i E_i}{2L_i} \beta_i^2 \right] - \sum_{j=1}^{NDF} Q_j q_j \quad (2.20)$$

where

NEL = Number of elements

The gradient vector (see section 3.1 for definition and structural interpretations) required by the minimization algorithms consists of the following contributions from the strain energy in each element:

$$\frac{\partial \Pi_i}{\partial q_{i1}} = - \frac{A_i E_i}{L_i} \beta_i c_i - \frac{2E_i I_i}{L_i^2} \xi_i s_i \quad (2.21)$$

$$\frac{\partial \Pi_i}{\partial q_{i2}} = - \frac{A_i E_i}{L_i} \beta_i s_i + \frac{2E_i I_i}{L_i^2} \xi_i c_i \quad (2.22)$$

$$\frac{\partial \Pi_i}{\partial q_{i3}} = - \frac{E_i I_i}{L_i} \phi_i \quad (2.23)$$

$$\frac{\partial \Pi_i}{\partial q_{i4}} = - \frac{\partial \Pi_i}{\partial q_{i1}} \quad (2.24)$$

$$\frac{\partial \Pi_i}{\partial q_{i5}} = - \frac{\partial \Pi_i}{\partial q_{i2}} \quad (2.25)$$

$$\frac{\partial \Pi_i}{\partial q_{i6}} = \frac{E_i I_i}{L_i} \{ \phi_i + 2\xi_i \} \quad (2.26)$$

The contribution to each component, j , of the gradient vector from the load potential is:

$$\frac{\partial \Omega}{\partial q_j} = - Q_j \quad (2.27)$$

Each component of the gradient vector may now be computed by using:

$$\frac{\partial U}{\partial q_j} = \sum_{i=1}^{NEL} \frac{\partial \Pi_i}{\partial q_j} - Q_j \quad (2.28)$$

where

q_{in} , $n = 1, 2, \dots, 6$ used in Eqs. 2.21 through 2.26
have been replaced by the corresponding nodal
degree of freedom q_j

2.2 Stiffness Method

The purpose of structural analysis is to determine the state of deformation or stress of a structure, based on known force-displacement characteristics of the component parts, and satisfying all the conditions of compatibility and equilibrium [22]. The analysis technique described in this section is matrix structural analysis via stiffness method [20]. The stiffness method is well known and highly suited to computer programming and analysis of large structures. Because of its notoriety only a brief outline of the stiffness method used in this study is presented. This method is used in comparison with the energy method used in this study.

This section is developed around the flow chart of the stiffness method shown in Fig. 2.4 [20]. The element model is represented in

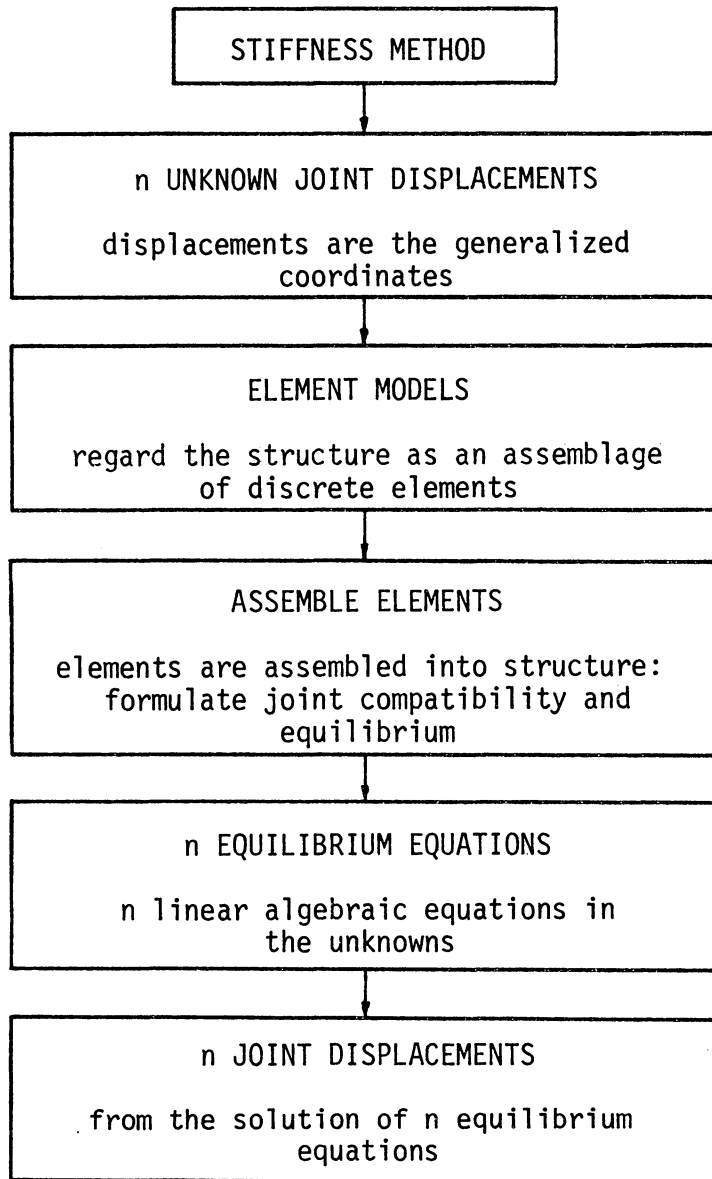


FIGURE 2.4 STIFFNESS METHOD

local coordinates by the force-displacement relation:

$$\{f\} = [k]\{u\} \quad (2.29)$$

where

$\{f\}$ = force vector

$[k]$ = element stiffness matrix

$\{u\}$ = unknown displacements

The elements of $[k]$, k_{ij} , are coefficients of the displacements defined as the force at i induced by a unit displacement at j while all other displacements are constrained. Any general element may be represented by the same finite element in Fig. 2.3 with the exception that all \bar{q}_{ij} are replaced by u_{ij} .

Before assembling the element models to form the system model each element stiffness matrix must be transformed from the local form to the global form. This is done by the following transformation

$$[K] = [R][k][R]^T \quad (2.30)$$

where

$$[R] = \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} \quad (2.31)$$

$$\lambda = \begin{bmatrix} c & -s & 0 \\ s & c & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (2.32)$$

$$c = \cos\theta$$

$$s = \sin\theta$$

The system stiffness matrix is assembled from the global element models so that compatibility at the nodes is guaranteed. The assemblage is done by the degrees of freedom of the system so that constraints are omitted in the process, thereby generating the constrained stiffness matrix directly. Since the stiffness matrix is symmetric and usually banded, only the elements contained in the upper semiband width are computed.

Equilibrium at the joints requires that the joint forces must be balanced by the corresponding element forces. This allows the equilibrium equations to be expressed as:

$$\{Q\} = [K]\{q\} \quad (2.33)$$

where

$[K]$ = stiffness matrix

$\{Q\}$ = applied joint loads

$\{q\}$ = deformation vector in global coordinates

Equation 2.33 is a system of linear equations whose solution is the unknown joint displacements.

Chapter 3

SOLUTION PROCESS

This chapter identifies the structural interpretations of some of the mathematical relations used in the Davidon-Fletcher-Powell variable metric and Fletcher-Reeves conjugate gradient algorithms. The DFP algorithm is developed taking advantage of known characteristics of the total potential. These characteristics are also applied to the FR algorithm. The method of solving the set of equilibrium equations generated by the stiffness method is also included.

3.1 Structural Interpretations of Mathematical Relations Used by the Minimization Algorithms

There are several important relations used in the minimization algorithms that have significant interpretations when applied to structural analysis. The relations used in the minimization algorithms and their counterparts in structural analysis are linked together by the hessian matrix and gradient vector of the function being minimized, the total potential. The total potential defined by Eq. 2.20 is a quadratic function and may be represented in matrix notation as:

$$U = \frac{1}{2} \{q\}^T [K] \{q\} - \{Q\}^T \{q\} \quad (3.1)$$

where

$$\Pi = \frac{1}{2} \{q\}^T [K] \{q\} \quad (3.2)$$

$$\Omega = - \{Q\}^T \{q\} \quad (3.3)$$

$[K]$ = stiffness matrix

$\{Q\}$ = load vector

The hessian is a square matrix of second partial derivatives of a function, $f(x)$, evaluated at x and may be represented as:

$$\nabla^2 f(x) = \begin{bmatrix} \frac{\partial^2 f(x)}{\partial x_1^2} & \frac{\partial^2 f(x)}{\partial x_1 \partial x_2} & \dots & \frac{\partial^2 f(x)}{\partial x_1 \partial x_n} \\ \frac{\partial^2 f(x)}{\partial x_2 \partial x_1} & \dots & \dots & \dots \\ \vdots & \dots & \dots & \dots \\ \frac{\partial^2 f(x)}{\partial x_n \partial x_1} & \dots & \dots & \frac{\partial^2 f(x)}{\partial x_n^2} \end{bmatrix} \quad (3.4)$$

The hessian of a quadratic function results in a matrix of constant coefficients. The hessian of the strain energy of a structure composed of linear beam-column elements is the stiffness matrix of that structure. In the case of Eq. 3.1 where the load vector is not a function of the displacement, the hessian of the total potential is the same as the hessian of the strain energy:

$$\nabla^2 U = [K] \quad (3.5)$$

$$\nabla^2 \Pi = [K] \quad (3.6)$$

In mathematical terms the hessian can be used to identify the type of surface defined by a function. Equation 3.1 defines a strictly convex surface; this is a surface that has only one minimum value and no

inflection points. This is determined by the fact that the stiffness (or hessian) matrix for a linear beam-column element is positive definite, which is also a stability requirement in structural analysis. This type of surface is represented in Fig. 3.1 for a two degree of freedom system. The energy surface is an elliptical hollow; the contours are ellipses and represent constant energy values.

The importance of the hessian to the DFP algorithm is that an approximation of its inverse is used in generating the search direction to be used during each iteration in minimizing a function. These directions are generated as follows:

$$\{d^k\} = - [\tilde{K}_k]^{-1} \{g^k\} \quad (3.7)$$

$$\{d^k\} = k^{\text{th}} \text{ search direction}$$

$$\{g^k\} = \text{gradient vector evaluated at } \{q^k\}$$

$$[\tilde{K}_k]^{-1} = \text{approximate inverse hessian at the } k^{\text{th}} \text{ iteration}$$

The inverse of the hessian provides a measure of the curvature of the function in the vicinity where it is evaluated [19]. The approximate inverse hessian used in Eq. 3.7 allows the use of an approximation of the curvature of the function being minimized to be used in generating the search directions. The approximate inverse hessian is in turn updated during each iteration, therefore accumulating information about the curvature of the function during each iteration.

The significance of the inverse hessian of Eq. 3.1 is that it is the flexibility matrix of the structure represented by Eq. 3.1. The elements of the flexibility matrix are referred to as flexibility

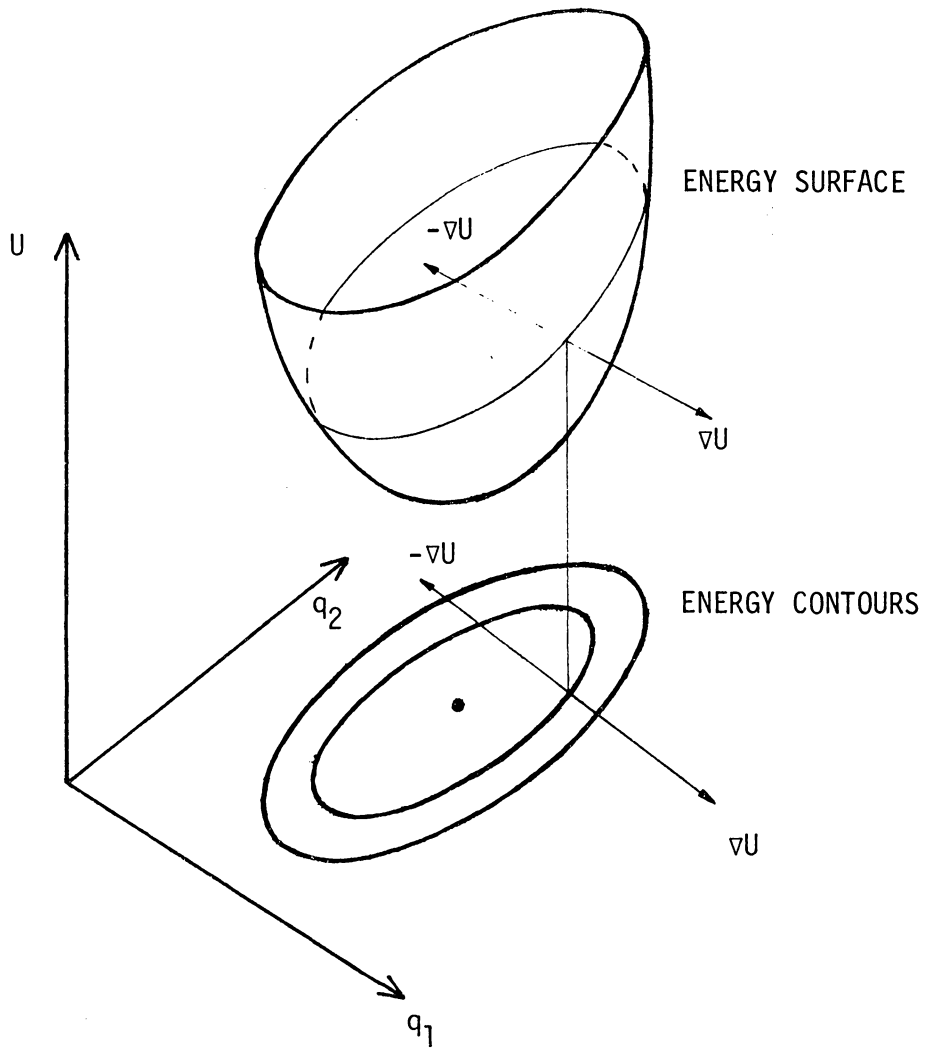


FIGURE 3.1 ENERGY SURFACE

influence coefficients. The coefficients are identified as f_{ij} which is the displacement in the direction of i due to a unit force in the direction of j [22]. Once the flexibility matrix is known the deformation vector may be solved for directly by simple matrix multiplication:

$$\{q\} = [K]^{-1}\{Q\} \quad (3.8)$$

where

$$[K]^{-1} = \text{flexibility matrix (or inverse hessian)}$$

If the flexibility matrix can be obtained as a by-product of the DFP algorithms solution process it must be considered as a valuable piece of information when several load vectors are considered for the same structure. This is indicated by Eq. 3.8.

The gradient is the column vector of first partial derivatives of a function, $f(x)$, evaluated at x and may be represented as:

$$\nabla f(x) = \left\{ \frac{\partial f(x)}{\partial x_1} \quad \frac{\partial f(x)}{\partial x_2} \quad \dots \quad \frac{\partial f(x)}{\partial x_n} \right\}^T \quad (3.9)$$

The negative of the gradient points in the direction of greatest decrease, locally, in a function's value, the steepest descent, and is illustrated in Fig. 3.1. The gradient vector is used in the FR conjugate gradient algorithm exclusively in constructing the search directions. The directions are generated by the following equation where the first search direction is the steepest descent (DFP also uses the gradient, refer Eq. 3.7):

$$\{d^{k+1}\} = \{d^k\} - \frac{\{g^{k+1}\}^T \{g^{k+1}\}}{\{g^k\}^T \{g^k\}} \{g^{k+1}\} \quad (3.10)$$

The search directions defined by Eqs. 3.7 and 3.10 are illustrated in Fig. 3.2 for a two degree of freedom system defined by Eq. 3.1. The initial search direction, $\{d^0\}$, is the steepest descent. The next search direction, $\{d^1\}$, is taken such that it is A-conjugate (refer to Eq. 1.1). The minimum is located in two iterations; quadratic convergence for the two degree of freedom system is therefore satisfied. In this case, because the initial search direction was the steepest descent, the DFP and FR algorithms generated identical search directions. Figure 3.2 also illustrates the expected superiority of the DFP and FR algorithms, which use A-conjugate directions, over the method of using the steepest descent during each iteration. When the second search direction was the steepest descent, $-\{g^1\}$, it can be seen that it did not point to the global minimum as did the A-conjugate search direction computed by the DFP and FR algorithms.

The gradient of Eq. 3.1 may be expressed as follows:

$$\nabla U = [K]\{q\} - \{Q\} \quad (3.11)$$

When the initial estimate of the deformation vector is zero and the steepest descent is used for the first search direction, the gradient vector is the negative of the load vector and the initial search direction is defined by the load vector:

$$\{g^0\} = -\{Q\} \quad (3.12)$$

$$\{d^0\} = \{Q\} \quad (3.13)$$

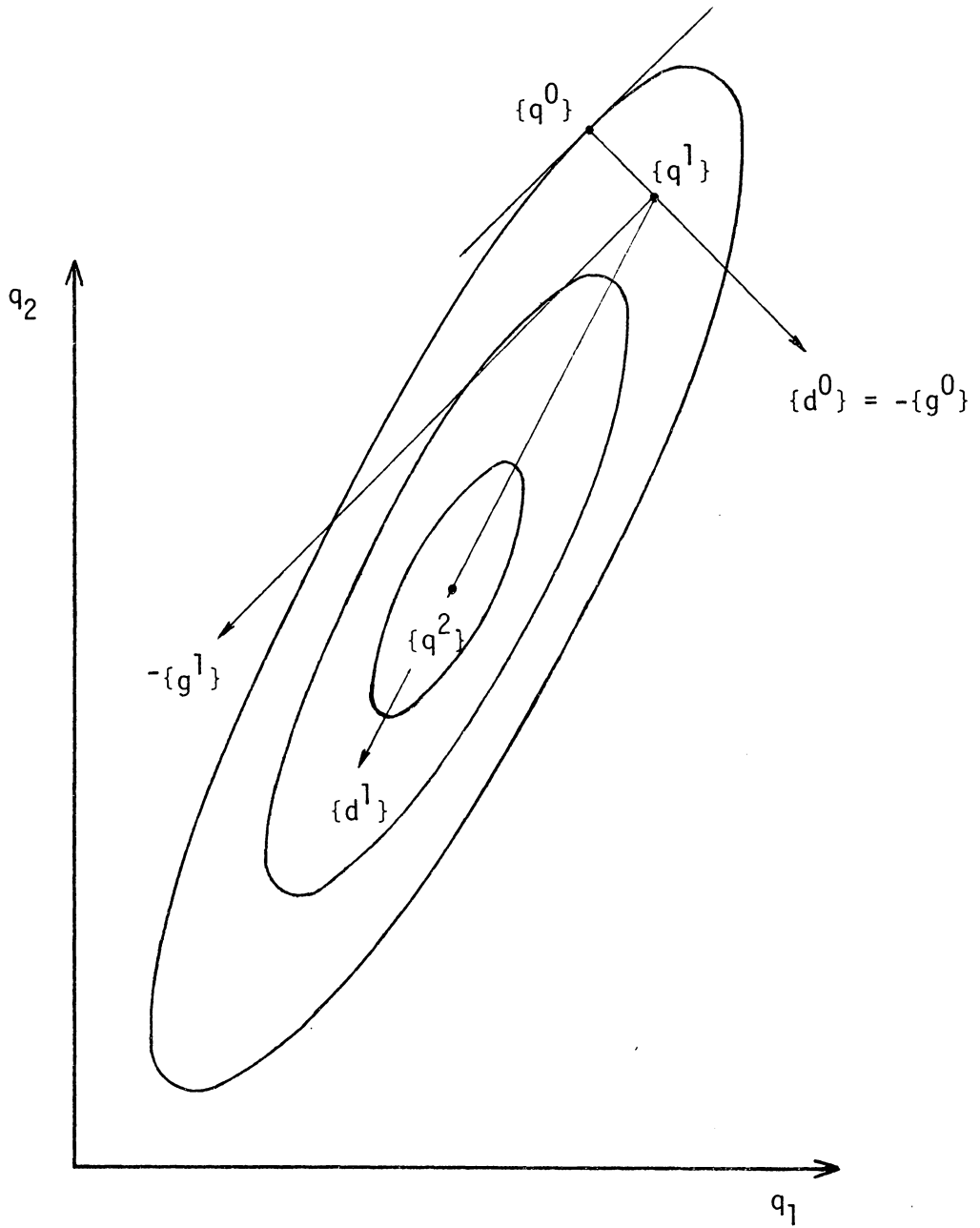


FIGURE 3.2 SEARCH DIRECTIONS

This applies to both the DFP and FR algorithms.

In structural analysis an equilibrium point can be defined as a point where the gradient vector is zero. A zero gradient vector may also be used as a termination criterion for the minimization algorithms. But because a zero gradient value may define an unstable equilibrium point additional convergence criteria should be considered for a general function. However in this study the function being minimized is strictly convex; therefore a zero gradient value guarantees a stable equilibrium point. When this convergence criterion is applied to Eq. 3.11 the equilibrium equations of the structure being considered are obtained:

$$[K]\{q\} = \{Q\} \quad (3.14)$$

This is the identical system of equations solved by the stiffness method which were arrived at by a completely different process (section 2.2).

By applying some of the previous conditions mentioned in this section it can be shown that in special cases where several load vectors are applied to the same structure Eq. 1.3 (which describes the linear minimization problem solved by the DFP algorithm during each iteration) reduces to Eq. 3.8 (a direct solution for the deformation vector by simple matrix multiplication). If the inverse hessian is accurately computed during the minimization of the total potential for the first load vector Eq. 1.3 reduces to Newton's method:

$$\{q^{k+1}\} = \{q^k\} - [K]^{-1}\{g^k\} \quad (3.15)$$

When Eq. 3.12 and the conditions that lead to it are applied to Eq. 3.15 Eq. 3.8 is arrived at:

$$\{q\} = [K]^{-1}\{Q\} \quad (3.16)$$

where

$$\{q\} = \{q^{k+1}\} \quad (3.17)$$

reducing an iterative technique, Eq. 1.3, to a simple matrix multiplication.

3.2 Variable Metric Algorithm

The Davidon-Fletcher-Powell variable metric algorithm is developed in this section. Several simplifications to the general DFP algorithm are made possible because the total potential is a quadratic function and its form is known in matrix notation (Eq. 3.1). A flow chart of the basic algorithm used in this study is illustrated in Fig. 3.3. The algorithm is iterative and requires initial starting conditions. An initial estimate of the deformation vector, $\{q\}$, and the inverse hessian are required for the algorithm to begin the minimization process. The material and geometric properties of the structure to be analyzed and the load vector, $\{Q\}$, are required to define the total potential. Theoretically the load vector and initial estimate of the deformation vector do not influence convergence in linear problems [16]. Since a good estimate of the deformation vector would be difficult to obtain and any estimate is theoretically acceptable as equally good, the

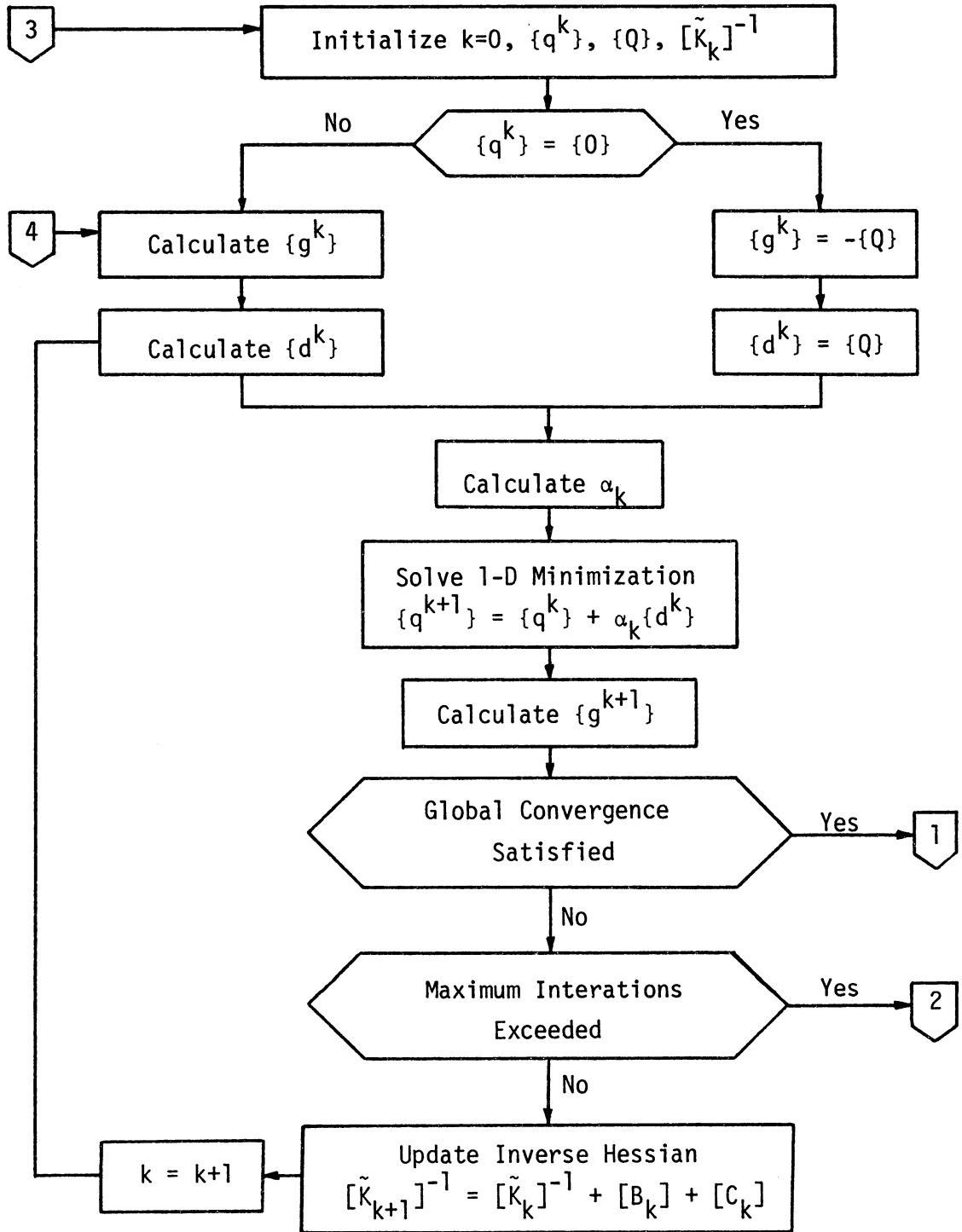


FIGURE 3.3 DFP ALGORITHM

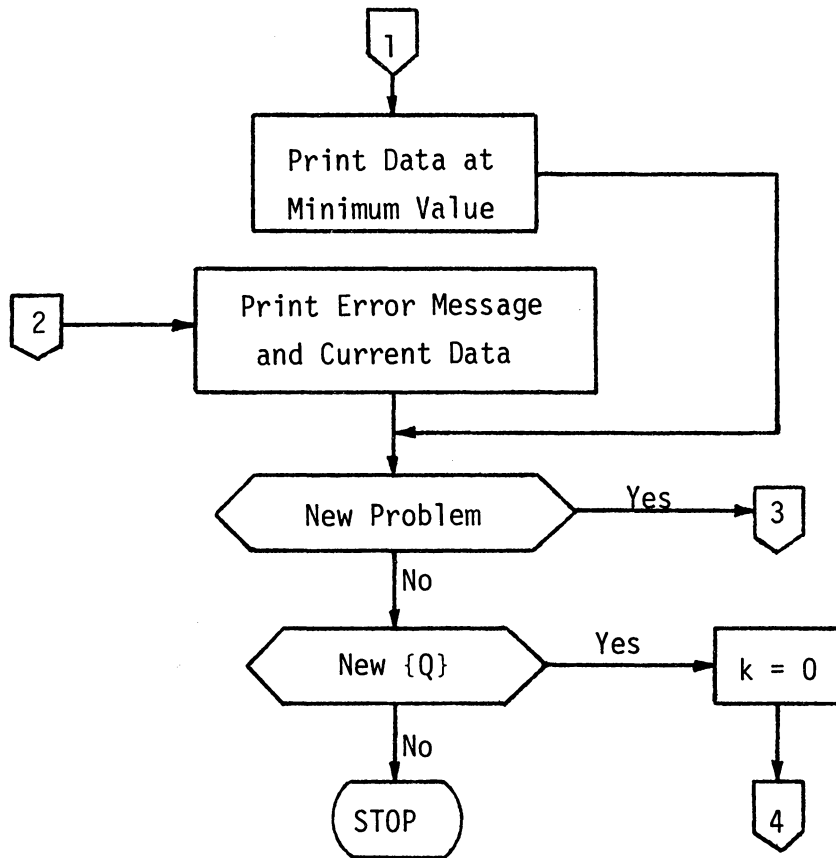


FIGURE 3.3 (continued)

initial estimate will be the zero vector. The estimate of the initial inverse hessian is of extreme importance. It is essential that this estimate be a symmetric positive definite matrix. The requirement that it be positive definite insures the stability of the algorithm by guaranteeing that the initial search direction will decrease the function value. If the initial estimate is positive definite, all updates will be positive definite. Each update is symmetric and made by the following relation:

$$[\tilde{K}_{k+1}]^{-1} = [\tilde{K}_k]^{-1} + [B_k] + [C_k] \quad (3.18)$$

where

$$[B_k] = \frac{\Delta q^k (\Delta q^k)^T}{(\Delta q^k)^T \Delta q^k} \quad (3.19)$$

$$[C_k] = - \frac{[\tilde{K}_k]^{-1} \Delta g^k ([\tilde{K}_k]^{-1} \Delta g_k)^T}{(\Delta g^k)^T [\tilde{K}_k]^{-1} \Delta g_k} \quad (3.20)$$

$$\Delta q^k = \{q^{k+1}\} - \{q^k\} \quad (3.21)$$

$$\Delta g^k = \{g^{k+1}\} - \{g^k\} \quad (3.22)$$

Equation 3.19 is intended to ensure $[\tilde{K}]^{-1}$ approaches $[K]^{-1}$ and Eq. 3.20 is intended to cancel out the initial estimate of the inverse hessian in the limit. For a quadratic function Eq. 3.19 will produce the true inverse hessian if n iterations are used (n is the number of unknowns), assuming no roundoff errors. In section 1.2c it was indicated that

the best initial estimate of the inverse hessian, $[\tilde{K}]^{-1}$, would be the true inverse hessian or some properly scaled matrix. But when no information is available to rationally make an estimate of $[\tilde{K}]^{-1}$ the identity matrix should be used. The identity matrix is symmetric and positive definite and will produce an initial search direction of the steepest descent. An improper estimate of $[\tilde{K}]^{-1}$ could destroy the convergence rate of the algorithm by possibly causing a search in a direction away from the minimum.

Once the initial values have been determined the gradient and search direction vectors discussed in the previous section are required. It is now necessary to solve the one dimensional minimization problem:

$$\{q^{k+1}\} = \{q^k\} + \alpha_k \{d^k\} \quad (3.23)$$

The scalar α_k for a quadratic function is arrived at by the minimization of $f(\{q^k\} + \alpha_k \{d^k\})$ with respect to α_k :

$$\alpha_k = - \frac{\{g^k\}^T \{d^k\}}{\{d^k\}^T [K] \{d^k\}} \quad (3.24)$$

Although the hessian is required in Eq. 3.24, it does not need to be explicitly known due to the form of the strain energy. The strain energy is computed by Eq. 2.19 which does not require the stiffness matrix but is equivalent to the matrix form of Eq. 3.2. By multiplying Eq. 2.19 by a factor of two and using values from the direction vector instead of the deformation vector the scalar value in the denominator of Eq. 3.24 is computed without using matrix operations. The use of

Eq. 3.24 greatly simplifies the operation of the DFP algorithm. The line search which has been repeatedly mentioned in the literature as a major expenditure of time and source of error has now been replaced by a single "exact" step.

After the one dimensional minimization problem has been solved it is necessary to check the solution to see if it sufficiently locates the minimum of the total potential. Although quadratic convergence is guaranteed theoretically, it may not be realized due to roundoff error. It is also possible the minimum of a quadratic function may be reached in less than n iterations. Quadratic convergence can only be used as an estimate of the maximum number of iterations probably required to locate the minimum. The value of the gradient vector will be used as a convergence criterion. When it is equal to zero it defines the minimum of the total potential and therefore satisfies the equilibrium equations of the structure being analyzed. Due to roundoff errors it is unlikely a zero gradient vector will ever be found. Therefore a sufficiently small value, ϵ_1 , is chosen such that if the absolute value of all elements of the gradient vector is less than ϵ_1 the gradient vector will be considered close enough to zero to define the minimum. This will be known as property one and represented by:

$$|g_i^k| < \epsilon_1 \quad i = 1, \dots, n \quad (3.25)$$

Since property one is an approximation and dependent upon the selection of ϵ_1 another convergence criterion, property two, must also be satisfied.

Property two requires the distance to the next minimum be less than some predetermined value, ϵ_2 . This is represented by the following equation:

$$|\alpha_{k+1}| \left(\{d^k\}^T \{d^k\} \right)^{\frac{1}{2}} < \epsilon_2 \quad (3.26)$$

The left hand side of Eq. 3.26 is the distance to the next minimum that would be located during the one dimensional minimization if the process were continued. The new search direction used in this convergence test is generated prior to updating the inverse hessian, therefore the distance to the next minimum is approximated. Because this value approximates the distance to the next minimum, it represents a maximum change that can be expected to occur in any member of the present deformation vector. This allows the left hand side of Eq. 3.26 to be interpreted as a measure of the movement of the calculated minimum when a new search direction is generated.

3.3 Conjugate Gradient Algorithm

The Fletcher-Reeves conjugate gradient algorithm is discussed in this section. The simplifications used in developing the DFP algorithm in section 3.2 are applicable to the FR algorithm. A flow chart of the basic FR algorithm used in this study is illustrated in Fig. 3.4. The FR algorithm is iterative and has the identical requirements for the initial starting conditions as the DFP algorithm with the exception that the inverse hessian is not required. Other than the difference in the methods of generating search directions, Eqs. 3.7 and 3.10, the FR algorithm requires the same steps as the DFP algorithm in mini-

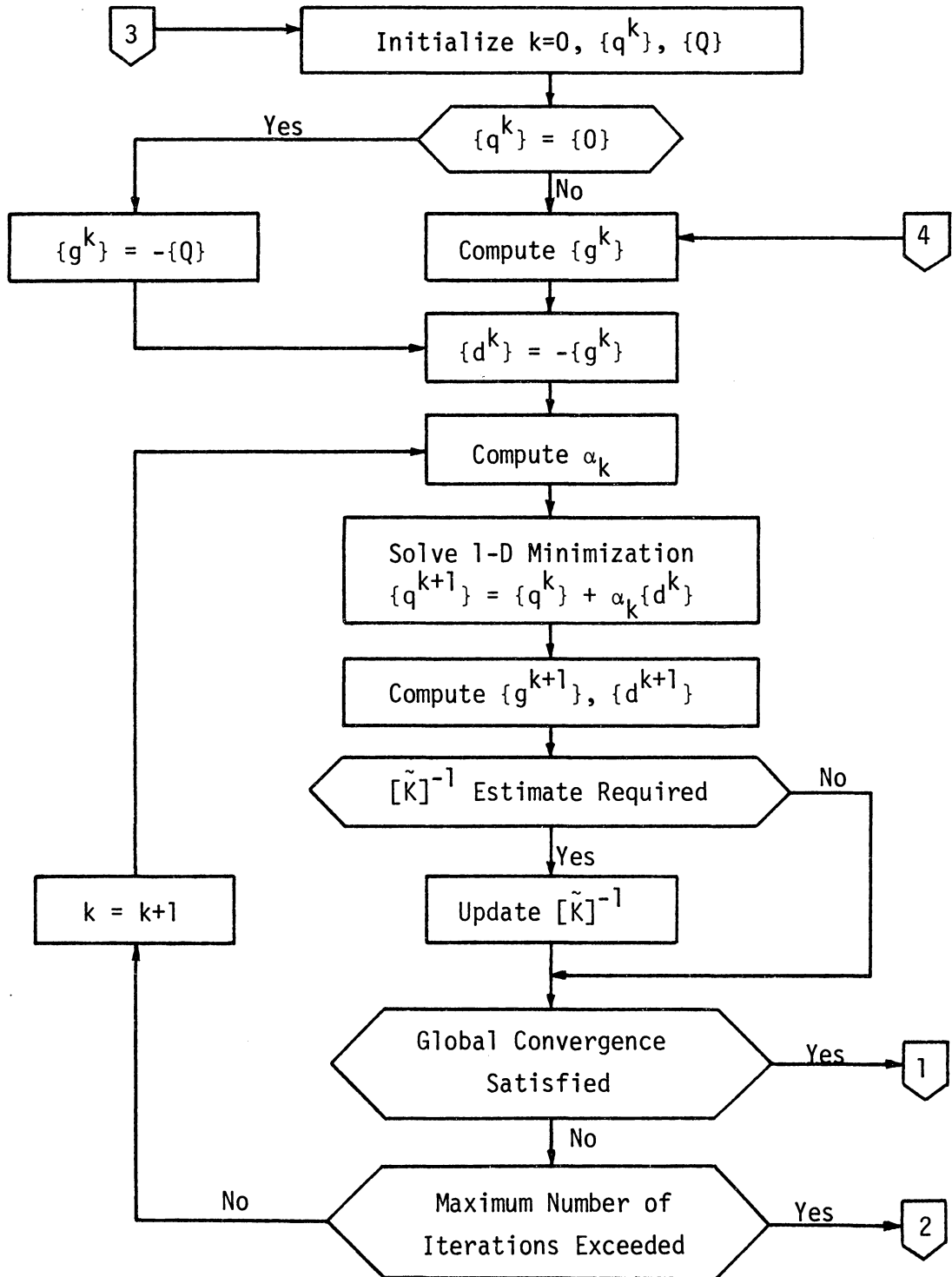


FIGURE 3.4 FR ALGORITHM

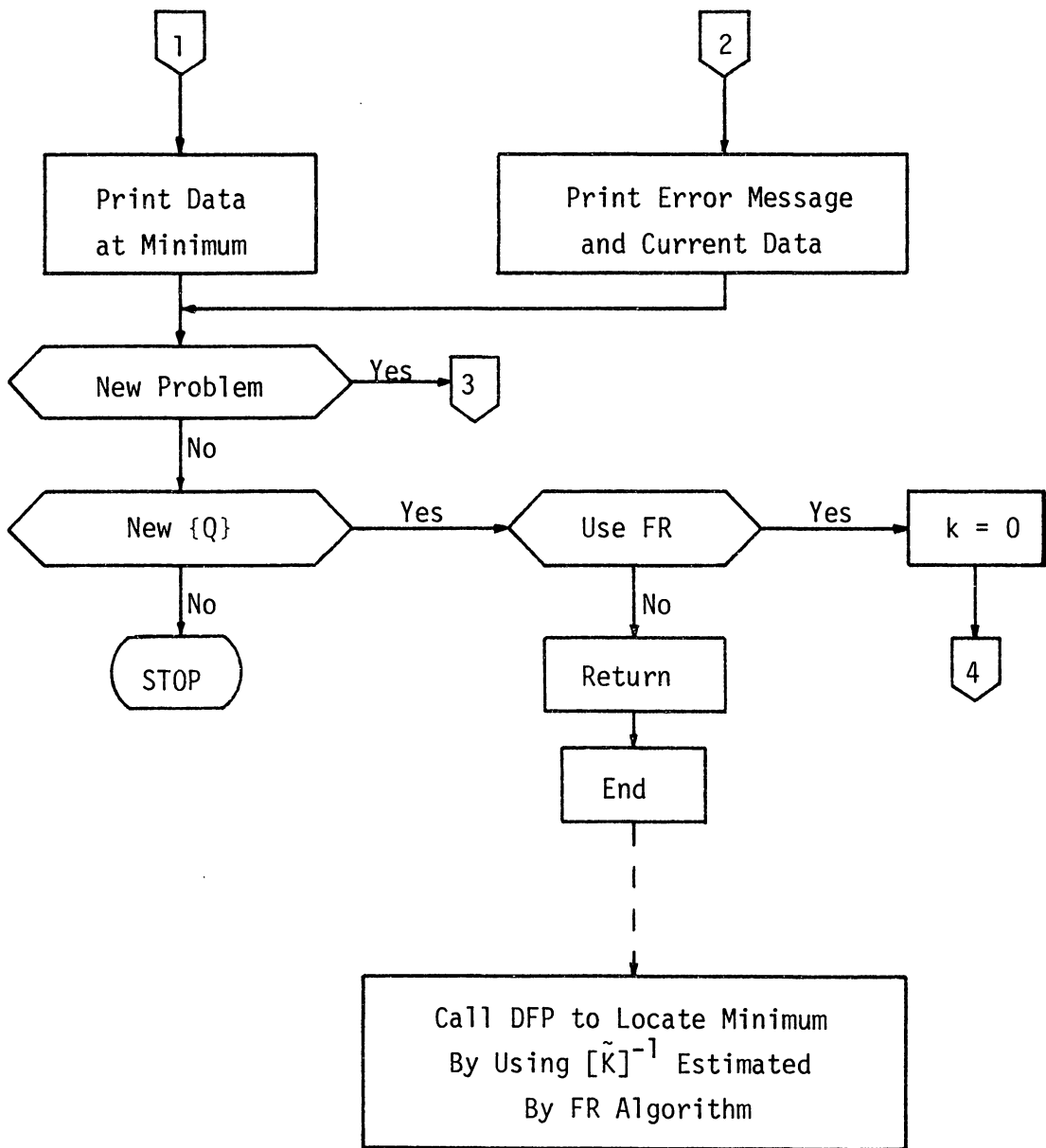


FIGURE 3.4 (continued)

mizing the total potential. The one dimensional minimization problem is solved identically by both methods and the same convergence criteria must be satisfied by both methods.

The significance of this algorithm is its modest storage and ability to estimate the inverse hessian. During the minimization of the total potential, an option is available to use Eq. 3.19 to construct the inverse hessian of the total potential. Although this increases the storage requirements of the FR algorithm, the estimate of the inverse hessian is not required in any operations. The economy of only using column vectors in the minimization process is still retained by the FR algorithm. The use of Eq. 3.19 allows information generated by the FR algorithm to be retained and used to improve the convergence rate of the DFP algorithm when new load vectors are considered for the same structure.

3.4 Gaussian Elimination

This section describes the method of solution, Gaussian elimination, of the equilibrium equations generated by the stiffness method. Symmetry and bandedness of the stiffness matrix (matrix of coefficients) is used to reduce storage requirements in computer application. The Gaussian elimination algorithm used in this study is taken from Desai and Able [9].

Gaussian elimination is a direct method of solving a system of linear equations. Unlike the iterative algorithms discussed in sections 3.2 and 3.3 no convergence criteria must be satisfied. The number of operations required to solve a system of equations

and therefore satisfy equilibrium is fixed and determined by the matrix of coefficients (in some cases the accuracy of the elimination may need to be improved by iteration on the residuals [9], but is not necessary in this study). The equilibrium equations to be solved are:

$$[K]\{q\} = \{Q\} \quad (3.27)$$

Gaussian elimination transforms the coefficient matrix, $[K]$, into a unit upper triangular matrix by forward reduction. During this process the load vector, $\{Q\}$, is also modified. This allows for the solution of the deformation vector directly by back-substitution. When several load vectors are to be considered for the same structure and therefore same $[K]$ it is desirable to separate the reduction of the stiffness matrix and load vector. Forward reduction of the stiffness matrix is only required once, while forward reduction of the load vector and back-substitution are done as many times as there are load vectors [7].

The algorithm used in this study separates the reduction of the stiffness matrix and the load vector. The following symmetric decomposition of the stiffness matrix is used [12]:

$$[K] = [L][D][L]^T \quad (3.28)$$

where

$[L]$ = unit lower triangular matrix

$[D]$ = diagonal matrix

Only the product $[D][L]^T$ in Eq. 3.28 must be stored. Due to the symmetry and banded form of the stiffness matrix storage requirements

are reduced from an $(n \times n)$ matrix to that of an $(n \times \text{IBAND})$ matrix, where IBAND is the semiband width of the stiffness matrix. The product $[D][L]^T$ is required for the reduction of the load vector. The matrix $[L]^T$ corresponds to the reduced stiffness matrix and the matrix $[D]$ contains terms used in the reduction of the stiffness matrix that are required to reduce the load vector. The product $[D][L]^T$ is stored by overwriting terms of the stiffness matrix. Once the load vector has been reduced, the deformation vector can be solved for directly by back substitution using $[L]^T$. By inferring the diagonal elements are unity $[D][L]^T$ becomes $[L]^T$. This process is continued for as many load vectors as desired.

Chapter 4

RESULTS

This chapter contains the results obtained from the analysis of several plane frames by both the stiffness method and energy method. Both the Fletcher-Reeves conjugate gradient algorithm and the Davidon-Fletcher-Powell variable metric algorithm are used to minimize the total potential. Also included is the analysis of a frame subject to multiple load conditions.

4.1 Example Problems

The frames listed in this section were chosen to demonstrate the effect of the number of degrees of freedom, d.o.f., as well as the configuration of a frame on the two methods of analysis. Figures 4.1 through 4.7 illustrate the frames used in this study. They range from 6 to 63 d.o.f. The members in all frames generally decrease in stiffness as the height of the frame is increased. For example, the members in the bottom row of frame 18A, Fig. 4.2, will not be as stiff as the respective members in the bottom row of frame 18B, Fig. 4.3, while the respective members in the top row of both frames will have the same stiffness. Frames 18A and 18B have the same d.o.f. and frames 36A and 36B have the same d.o.f. Frames 60A and 63B differ in d.o.f. by three. These pairs of frames have been selected to demonstrate, in some methods of analysis, that configuration and member properties are more significant than d.o.f. in determining solution time. The frames which have the same number of bays in both the



FIGURE 4.1 FRAME 6A

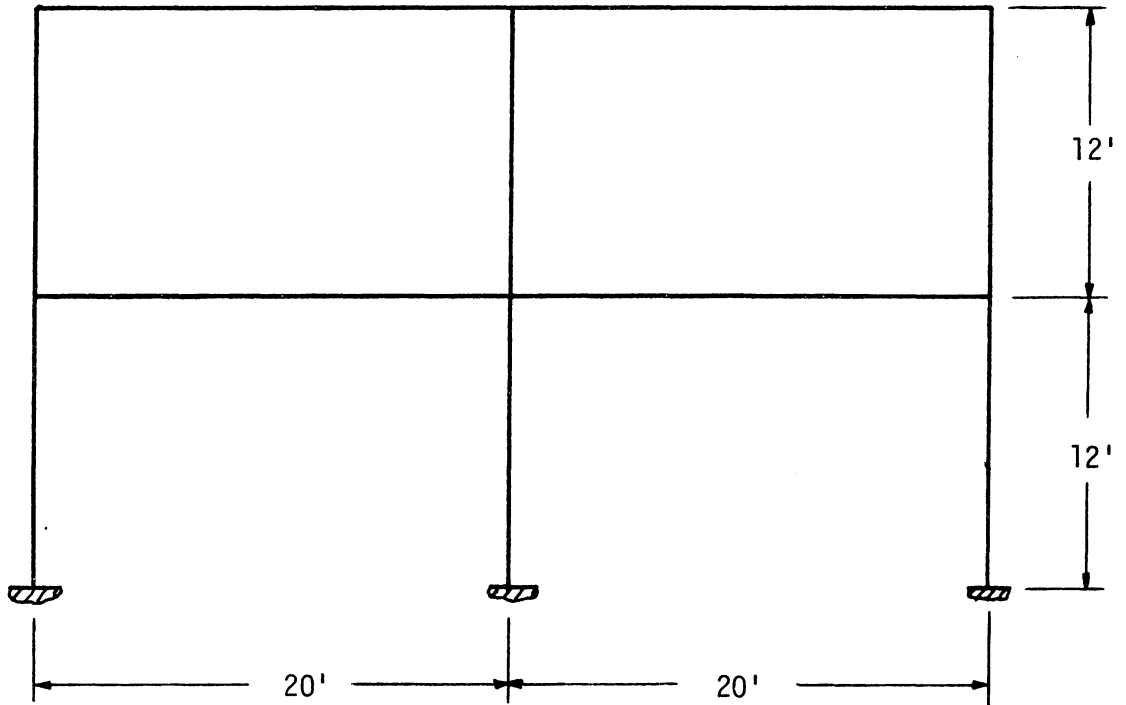


FIGURE 4.2 FRAME 18A

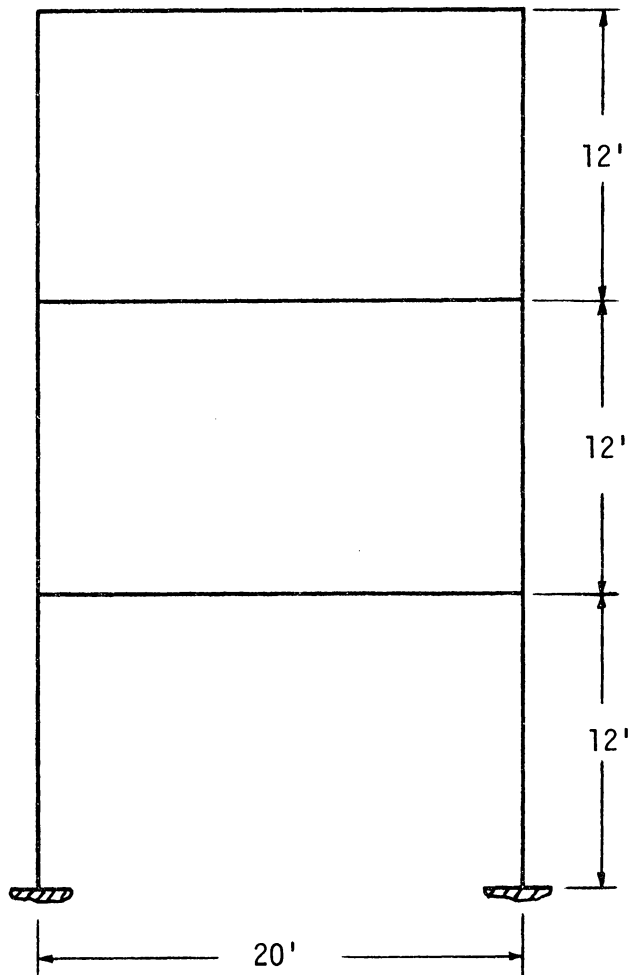


FIGURE 4.3 FRAME 18B

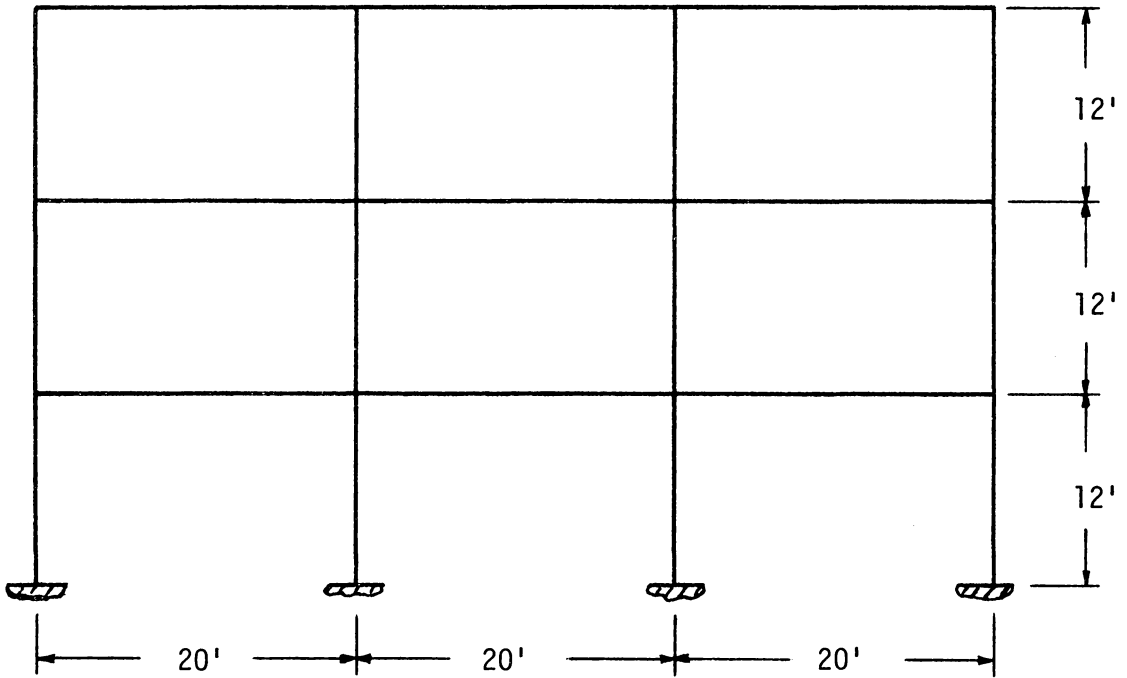


FIGURE 4.4 FRAME 36A

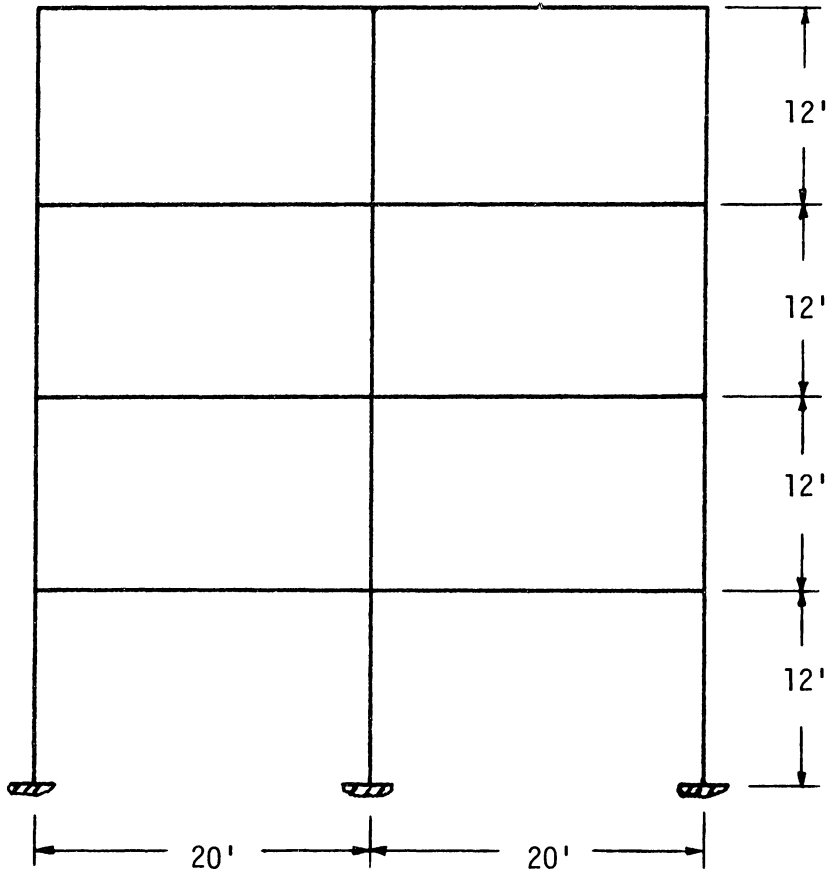


FIGURE 4.5 FRAME 36B

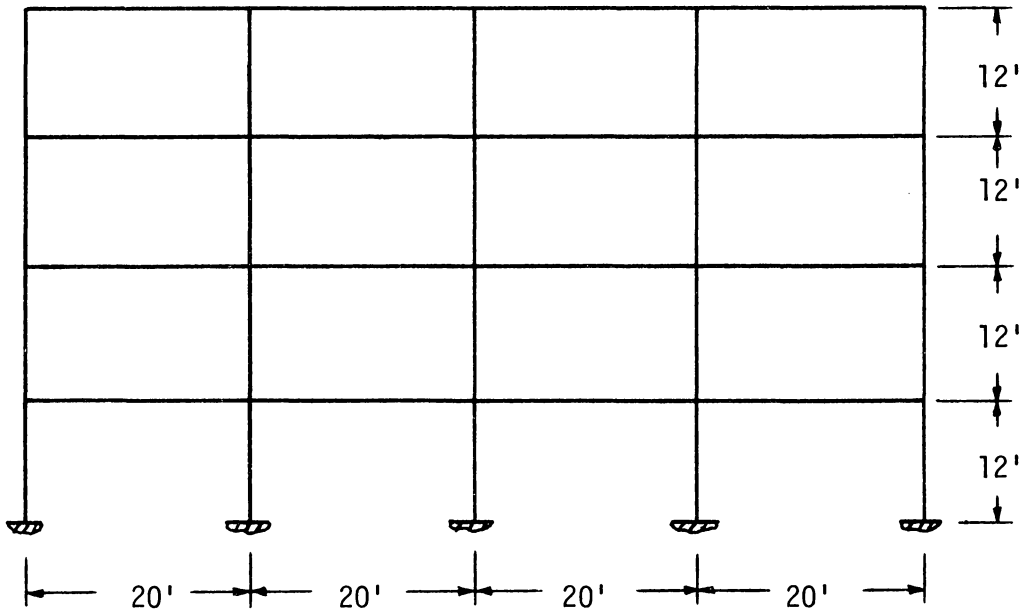


FIGURE 4.6 FRAME 60A

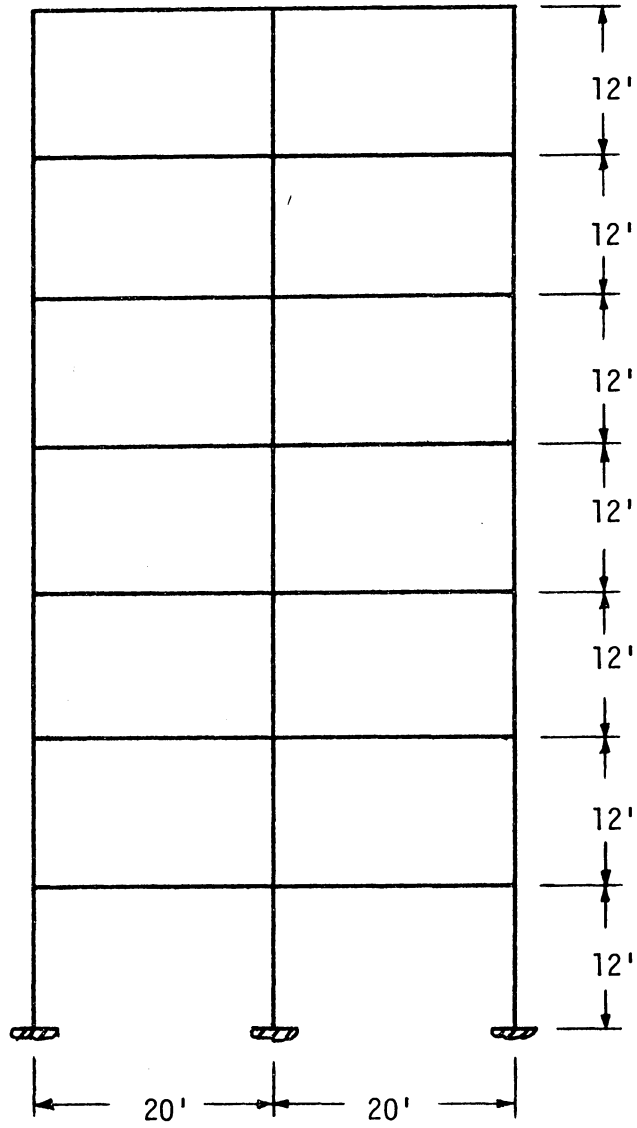


FIGURE 4.7 FRAME 63B

horizontal and vertical directions will be known as class A frames. Those with more bays in the vertical than horizontal direction will be known as class B frames. Frame 6A will be considered the first member in both classes, since both classes are constructed from this basic frame.

Except where noted, all data has been generated by the following type of load. Horizontal joint forces are applied on one side and uniformly decrease in value with story height. Vertical joint loads, all having the same value, are applied along the top row of joints. All other joint forces are zero.

All mathematical operations were done in double precision arithmetic. Numerical results from both methods were identical up to the eight significant digits examined. Execution times reported include all computations required for analysis.

4.2 Results From a Single Load Condition

a. Results From the Energy Method

The frames in Figs. 4.1 through 4.7 have all been analyzed for a single load condition. The energy method, ENERGY, was used and the total potential was minimized by both the Fletcher-Reeves conjugate gradient algorithm, FR, and the Davidon-Fletcher-Powell variable metric algorithm, DFP. The results in terms of execution time for both methods are illustrated in Fig. 4.8.

For a small d.o.f. (10 or less d.o.f.) both the FR and DFP algorithms perform almost identically. As the d.o.f. increases, the amount of execution time increases exponentially, with DFP

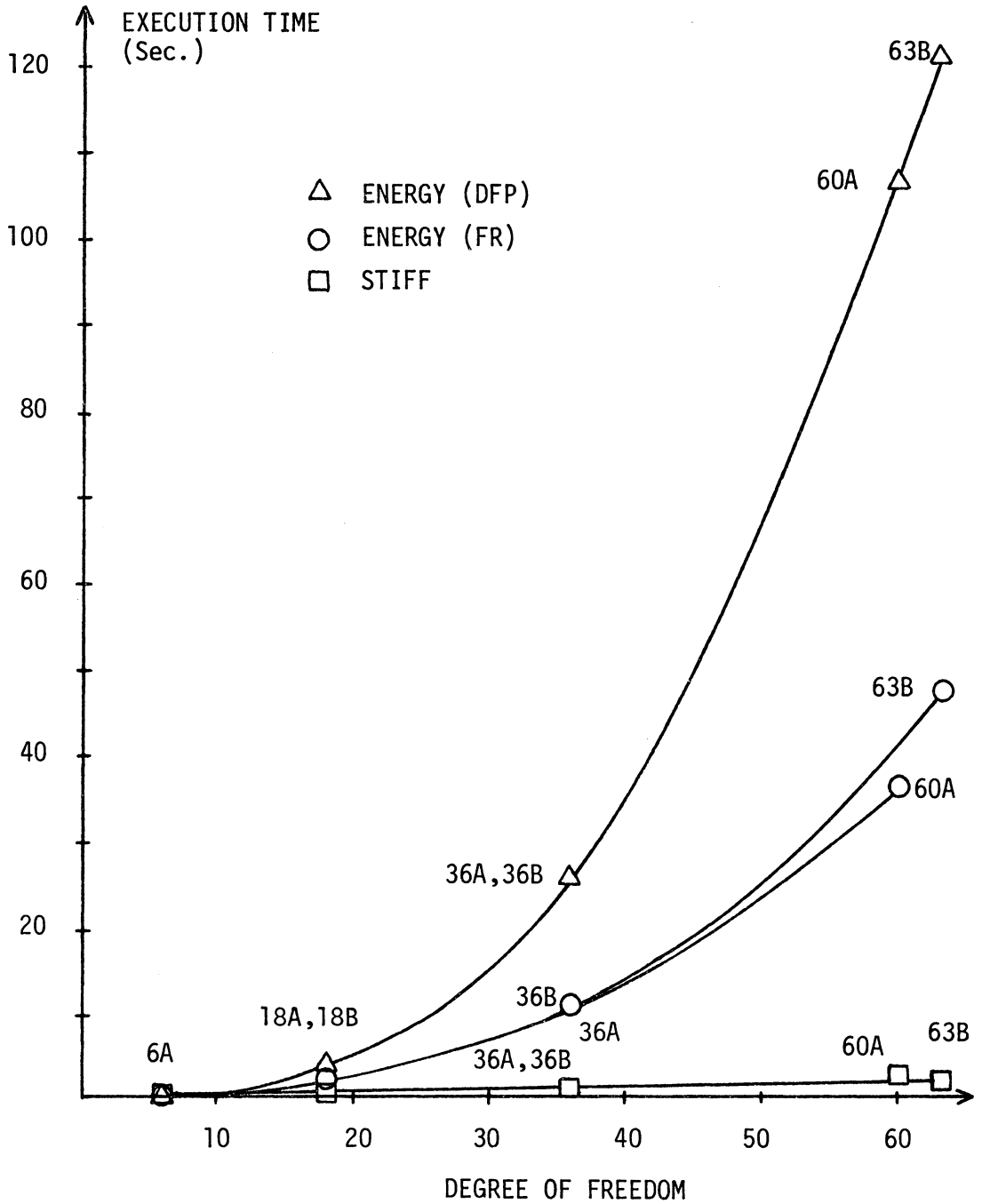


FIGURE 4.8 EXECUTION TIME vs. D.O.F. FOR ENERGY AND STIFF

increasing much more rapidly than FR. The increase when DFP was used produced a smooth curve connecting all points generated by both class A and class B frames. The increase in execution time when FR was used also increased exponentially, but along two different paths, one defined by class A frames and one by class B frames. The reason for the two different paths, shown in Fig. 4.8, is a result of the number of iterations required to minimize the total potential of each frame by FR. Figure 4.9 illustrates that when FR is used to minimize the total potential, the number of iterations required to locate the minimum is always much greater than the quadratic convergence rate required by theory. It also shows more iterations are required to minimize class B frames than class A frames (the number of iterations has a direct effect on execution time). This is influenced by the scale of the total potential function. Due to the wider range in stiffness of the members of class B than of class A the elements of the stiffness matrix, for example along the diagonal, for the same d.o.f. frame will have a larger difference in values for class B frames. This will produce a higher condition number for the stiffness matrix of class B frames than class A frames. This results in class A frames being "scaled better naturally" than class B frames for the same d.o.f. (refer sec. 1.2c). Figure 4.9 indicates that the scale of the total potential has a more dominant effect on the computational effort required to minimize the total potential by FR than the d.o.f. This makes predictions of the behavior of FR for minimizing the total potential uncertain, with Figs. 4.8 and 4.9 being only a rough guide.

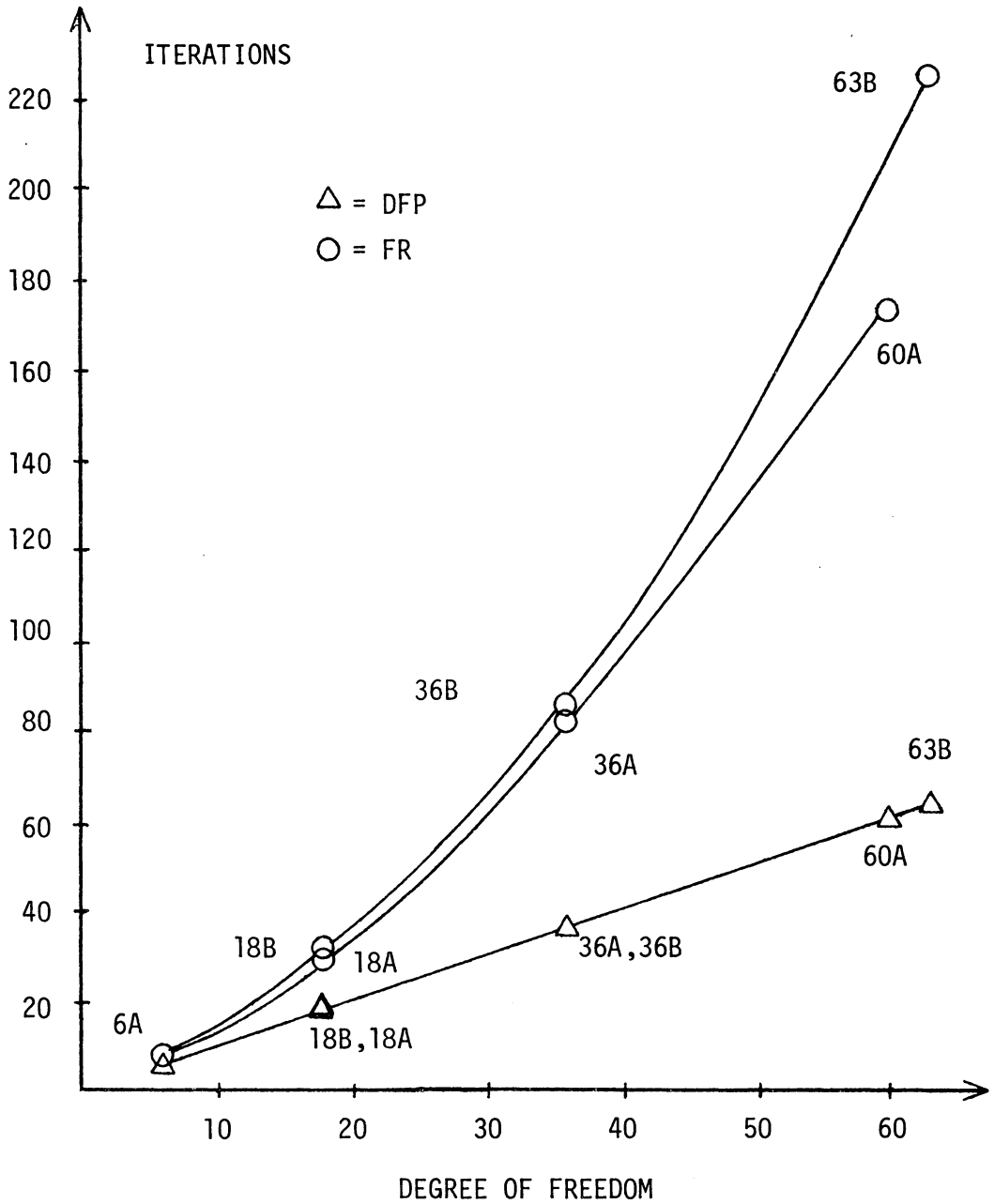


FIGURE 4.9 ITERATIONS PER D.O.F. REQUIRED BY FR AND DFP

The DFP algorithm appears insensitive to the scale problems experienced by FR, based on number of maximum iterations required by theory to minimize the total potential. Figure 4.9 illustrates this by the linear relation between iterations and d.o.f. All problems took $NDF+1$ iterations except frame 18A, which required only NDF iterations. Theory states NDF is the maximum number of iterations required to minimize a quadratic function of NDF variables, and NDF updates produce the true inverse hessian. In this study, $NDF+1$ iterations correspond to NDF updates of the inverse hessian. The exponential increase in execution time, Fig. 4.8, with increase in d.o.f. is expected. Figure 4.10 shows the relation between the main user of storage, the approximate inverse hessian, $[\tilde{K}]^{-1}$, and the d.o.f. The increase in execution time can be expected to increase more rapidly than the increase in $[\tilde{K}]^{-1}$ storage. An increase in d.o.f. exponentially increases $[\tilde{K}]^{-1}$ storage requirements and also increases the expected number of times $[\tilde{K}]^{-1}$ must be manipulated. Results from both Figs. 4.9 and 4.10 indicate the behavior of the DFP algorithm, with increase in d.o.f., reliable for the type of problems in this study.

b. Results From the Stiffness Method

The frames, with the same load conditions, used in section 4.2a have also been analyzed by the stiffness method, STIFF. Since STIFF uses a direct solution technique, there is a fixed number of operations required to analyze each structure. The number of operations is directly related to the number of elements of the

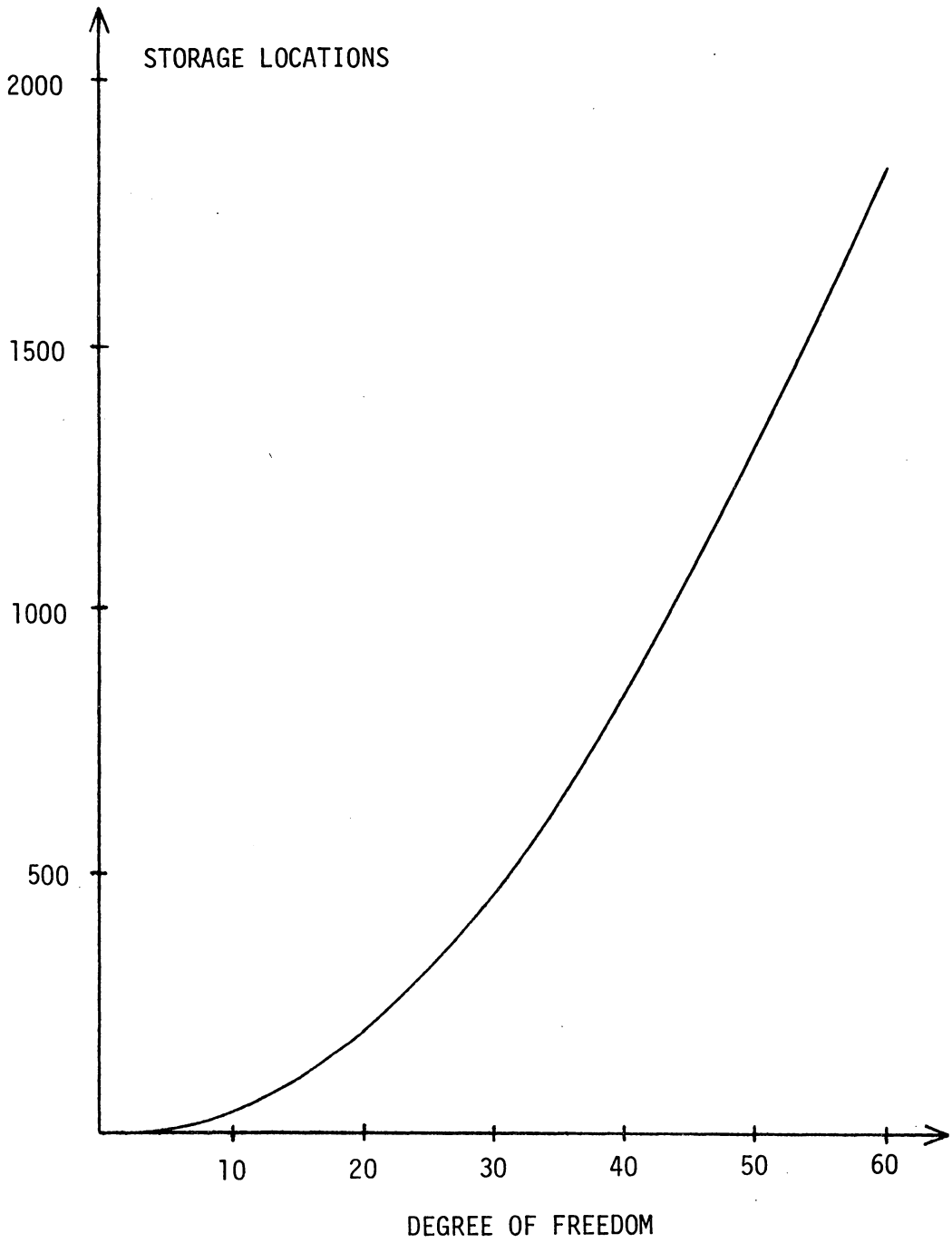


FIGURE 4.10 INCREASE IN COMPUTER STORAGE FOR $[\tilde{K}]^{-1}$ BASED ON D.O.F.

stiffness matrix that must be stored. This value is affected by configuration as well as d.o.f. It is determined by the numbering scheme used to identify the joints of the structure. The numbering scheme determines the semiband width and, therefore, required number of storage locations. The joints of all frames in this study have been optimally numbered. The difference in storage for the same d.o.f., but different configuration, is shown in Table 4.1. Table 4.1 also shows the excessive storage requirements of the inverse hessian used by ENERGY compared to STIFF requirements.

Figure 4.11 shows that the relation between execution time and storage requirement is closely linear. The execution time for class B frames with the same or nearly the same d.o.f. as class A frames shows they were analyzed more quickly as a result of smaller storage demands. A direct comparison between STIFF and ENERGY for each frame analyzed is shown in Fig. 4.8.

4.3 Results of Multiple Load Conditions

This section compares the rate of increase in execution time required by STIFF and ENERGY when several load conditions are applied to the same structure. The additional load vectors are increments of the original load vector except where noted differently. Only the DFP algorithm is used in minimizing the total potential. The FR algorithm retains no information that would improve the solution process when several load conditions are given. The property of using FR to estimate the inverse hessian (sec. 3.3) is lost due to the excessive

TABLE 4.1
MAJOR COMPUTER STORAGE REQUIREMENTS OF
ENERGY (DFP) AND STIFF

FRAME	D.O.F.	$[K]^{-1}$ STORAGE	$[K]$ STORAGE
6A	6	21	36
18A	18	171	216
18B	18	171	162
36A	36	666	540
36B	36	666	432
60A	60	1830	1080
63B	63	2016	756

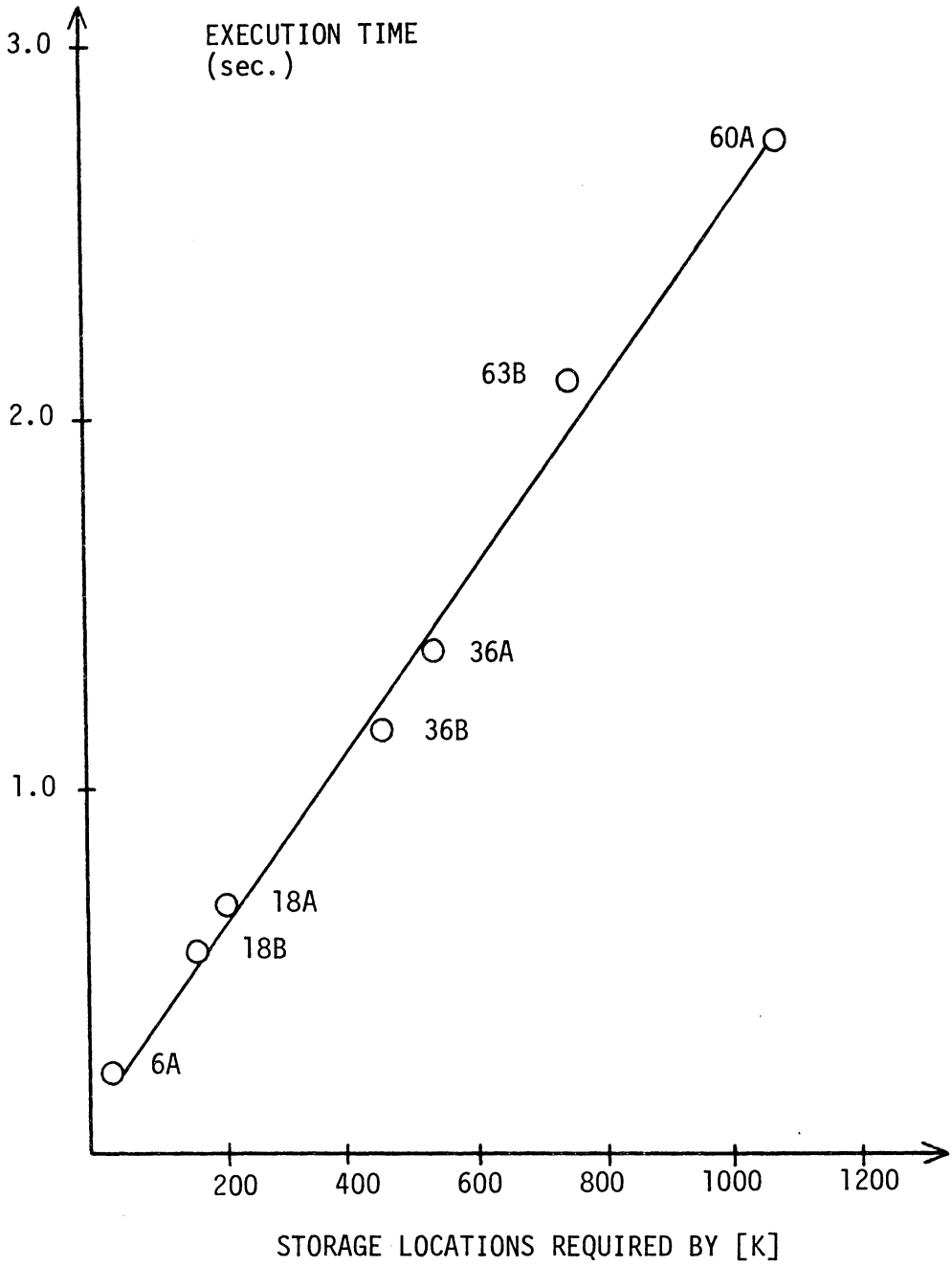


FIGURE 4.11 EFFECT OF PROBLEM SIZE ON STIFF EXECUTION TIME

number of iterations required to minimize the total potential (refer Fig. 4.9). Frame 18B was chosen for the comparison. From the previous solution, ENERGY (DFP) retains the estimate of the inverse hessian and uses the previously found minimum as the initial starting point, while STIFF retains the decomposed stiffness matrix computed during the first solution process and uses it when additional load vectors are applied.

The results, in terms of execution time versus the number of load increments, of applying load increments to frame 18B by both ENERGY (DFP) and STIFF are shown in Fig. 4.12. The increase in execution time when additional load vectors are applied using STIFF is linear. Figure 4.12 shows that requiring computation and decomposition of the stiffness matrix only once significantly reduces the time required for analysis using additional load vectors. The rate of increase in execution time, Fig. 4.12, using ENERGY (DFP) is greatly reduced after the solution using the initial load vector and even further reduced after the first load increment. After the first load increment there is a linear increase in execution time. The reason the increase in execution time for ENERGY (DFP) is not continuously linear after the initial load vector is demonstrated by Fig. 4.13a. Figure 4.13a shows the number of iterations required to minimize the total potential for each load vector. The initial load vector took 18 iterations and required 17 updates of the inverse hessian. The first load increment took 3 iterations, requiring two updates of the inverse hessian. After the first load increment,

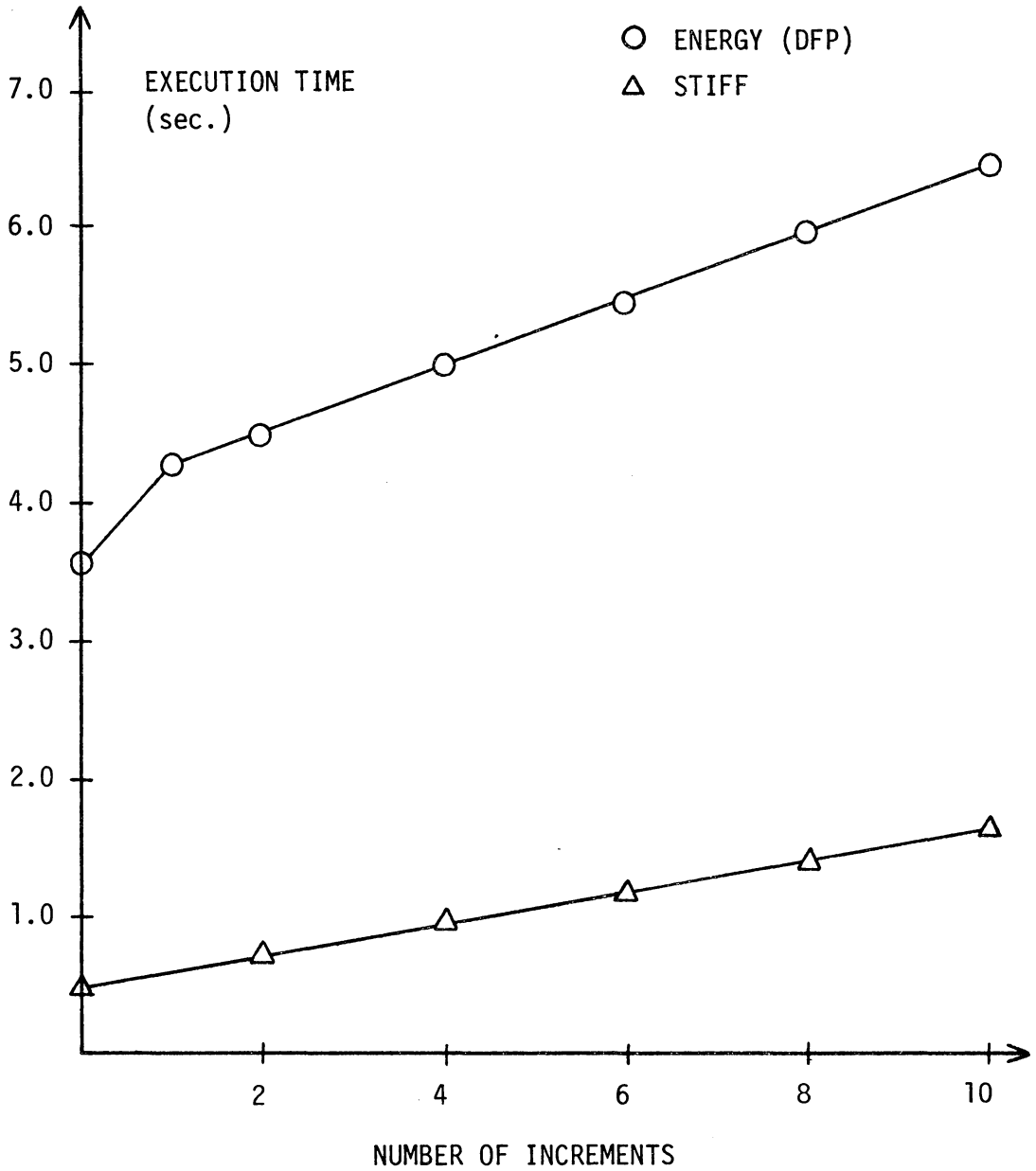


FIGURE 4.12 EFFECT OF LOAD INCREMENTS ON ENERGY (DFP) AND STIFF

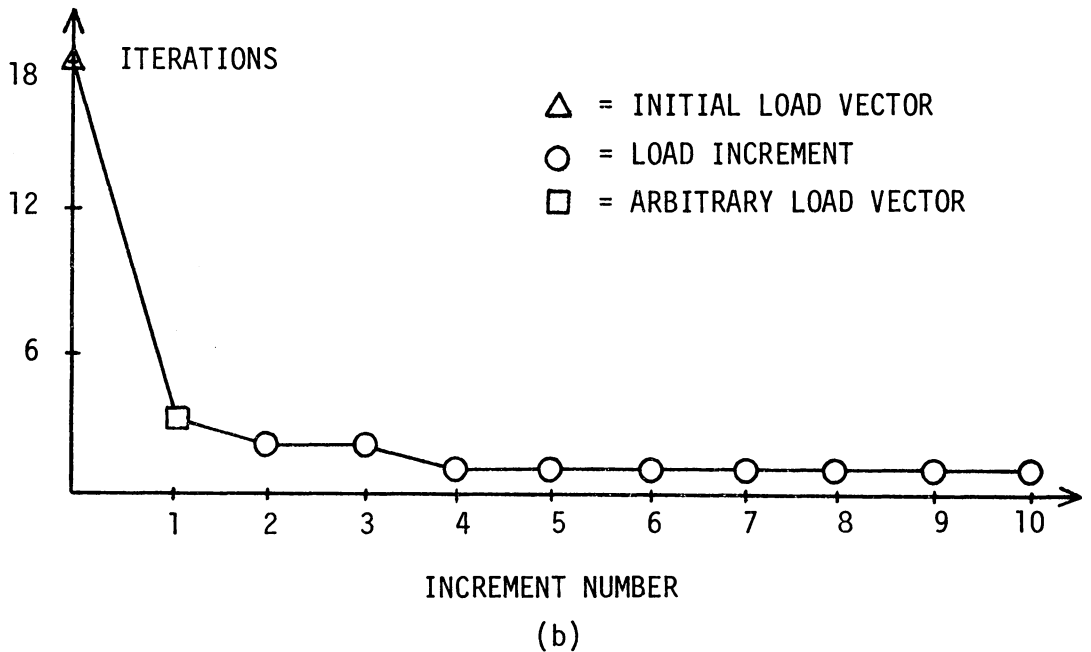
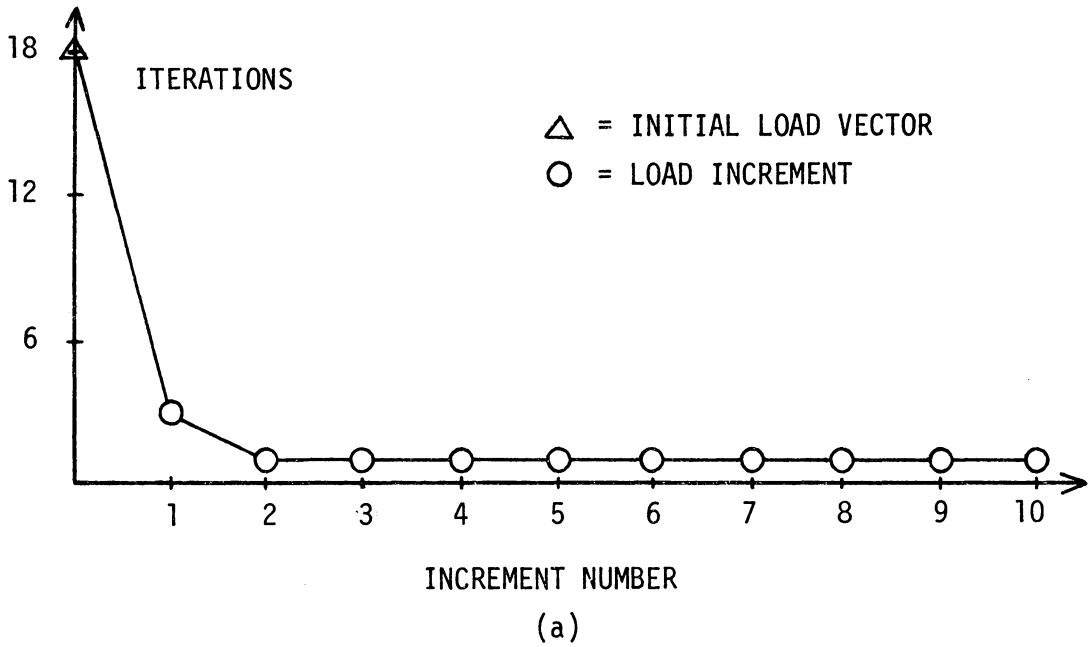
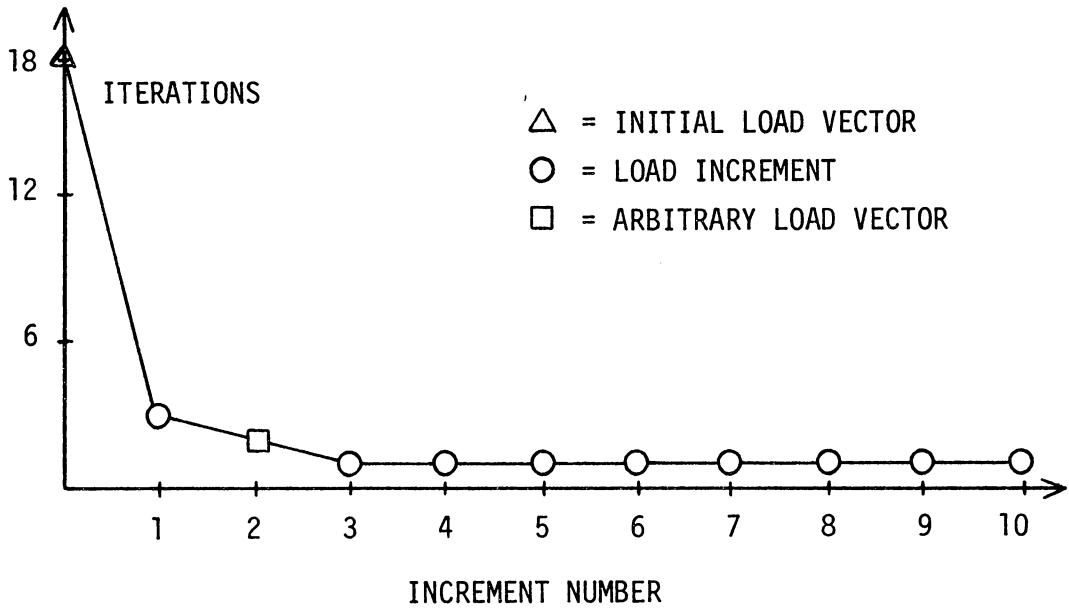
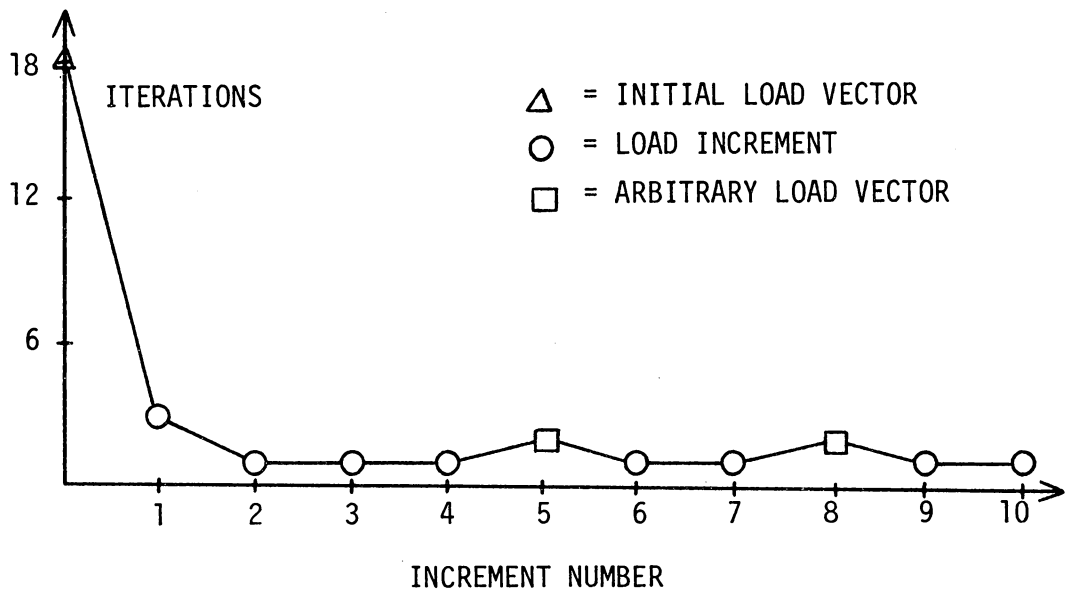


FIGURE 4.13 EFFECT OF ADDITIONAL LOAD VECTORS ON NUMBER OF ITERATIONS REQUIRED BY ENERGY (DFP)



(c)



(d)

FIGURE 4.13 (continued)

only 1 iteration was required to minimize the total potential and, therefore, no updates of the inverse hessian were required. This suggests the inverse hessian was not sufficiently well defined until after the first load increment. The number of iterations during each minimization gives an indication of the required execution time during that solution process. Figure 4.14 is a plot of the cumulative number of iterations during each load increment. The form of this graph indicates the trend in increase of execution time based on iterations required (refer Fig. 4.12 for DFP).

Since there is no guarantee the inverse hessian is sufficiently well defined, a convergence test must be made after each one dimensional minimization problem is solved. Because of this a direct solution by Eq. 3.16 can not be used. Using Eq. 3.16 would give the same results after increment number one as minimizing the function by the DFP algorithm, but there is no way of knowing this a priori. Therefore, after increment number one, using DFP results in many unnecessary operations (convergence tests) which could be avoided if the inverse hessian were known to be satisfactorily defined. Figures 4.13b through 4.13d show the effect on the number of iterations and the requirement that the inverse hessian may have to be updated at any time when an arbitrary load vector replaces an incremental load vector. This further indicates the need of having a convergence test after each iteration. The execution time for STIFF would be unaffected by the load type for the problems illustrated in Figs. 4.13b through 4.13d and would be the same as in Fig. 4.12.

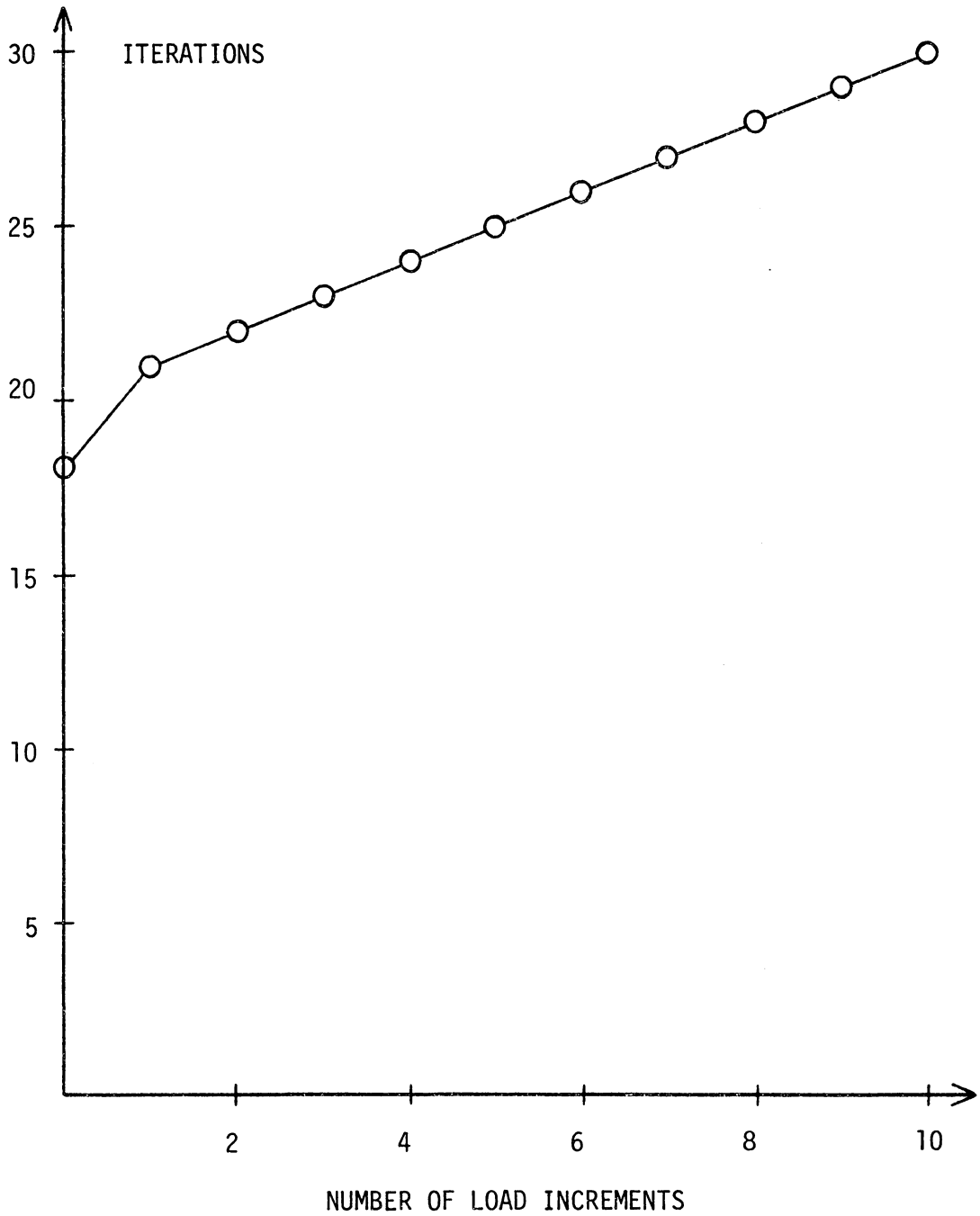


FIGURE 4.14 CUMULATIVE NUMBER OF ITERATIONS REQUIRED BY ENERGY (DFP) WHEN LOAD INCREMENTS ARE APPLIED

This is due to the direct method of solution of the equilibrium equations.

Chapter 5

SUMMARY

This chapter contains the conclusions arrived at based on the results of this study. Also included are recommendations for future study.

5.1 Conclusions

The performance of the stiffness method, STIFF, was superior to the energy method, ENERGY, in all comparisons based on execution time. This superiority is increasingly evident with only a small increase in problem size (6 d.o.f. compared to 18 d.o.f.). For larger problems (60 d.o.f.) the difference is so great further comparison based on execution time is meaningless. The accuracy of both methods was equivalent and, therefore, had no influence on the comparison.

The use of the FR and DFP algorithms to minimize the total potential indicates FR superior when only one load condition is considered. Although the convergence rate of DFP is superior to FR in all cases, the modest storage requirements of FR allows more iterations at a lower cost. The excessive number of iterations required by FR disallows the possibility of using it to estimate the inverse hessian.

When several load conditions were considered for the same structure ENERGY, using DFP, did compare more closely with STIFF after the initial solution process. Since DFP retains information from one solution process that will reduce the computational effort when additional load

vectors are applied, while FR does not, it is used when several load conditions are considered. However, the rate of increase in execution time by ENERGY (DFP) was uncertain and always greater than that of STIFF. From the indicated behavior of both methods it is expected this relation between ENERGY (DFP) and STIFF will continue for most problems.

The large storage requirements and iterative nature of ENERGY (DFP) creates the large gap between it and STIFF. An increase in d.o.f. means an increase in the size of the inverse hessian and the probable number of times it must be manipulated. Advantage is taken of the banded nature of the stiffness matrix by STIFF that keeps the storage requirements of the stiffness matrix from increasing as rapidly as the requirements of the inverse hessian. A convergence test is required during each iteration by ENERGY (DFP). This takes additional computational effort that is not required by STIFF since it uses a direct method of solution. The improvement in ENERGY (DFP) illustrated in Fig. 4.12 (Chapt. 4) still is not as efficient as STIFF, even when no updates of the inverse hessian are made. There still is the need to compute the gradient vector and the equivalent of a function evaluation in addition to a new search direction by ENERGY (DFP). This is required by the convergence criteria used.

The excessive storage demands and requirement of convergence tests at each iteration, even when a good initial estimate of the inverse hessian is available, makes ENERGY (DFP) inferior to STIFF for linear structural analysis.

5.2 Recommendations

The results of this study clearly show the superiority of the stiffness method over the method of minimizing the total potential energy for linear structural analysis. A future extension of this study should answer the question of how well the methods compare for nonlinear structural analysis. The material and results contained in this study give a reference point for such a study by giving insight into the performance of each method based on the linear problem. The performance of both methods should be much closer for nonlinear analysis. The superiority of the stiffness method in linear analysis does not necessarily indicate it superior for nonlinear analysis. When geometric and/or material nonlinearities are introduced, the force-displacement relation is no longer linear. Therefore the use of the stiffness method for nonlinear analysis becomes an iterative process. The stiffness matrix becomes a function of the generalized coordinates. If it is required for each iteration, that iteration uses approximately the same computational effort as solving a completely new problem.

The use of the energy method for nonlinear analysis is a natural extension of the linear analysis problem. Although linear analysis was done in this study, the total potential was a nonlinear function. Because it was quadratic, the variable metric algorithm used exhibited good convergence rates. (The use of a conjugate gradient algorithm is not recommended for nonlinear analysis due to the poor convergence rate for the linear case and the inability to retain information to reduce solution time when load increments are applied.) In some cases,

by using load increments in nonlinear analysis, the performance of the minimization algorithm may be expected to be similar to that reported in this study (if the initial load vector is small enough the total potential will be closely quadratic in form) when good gradient evaluations and line searches are available. Much of the material in this study, although heavily oriented toward quadratic functions, is also applicable to nonlinear analysis.

The literature survey included in this report indicates there are several variable metric algorithms that are preferred over the Davidon-Fletcher-Powell variable metric algorithm, used in this study, for minimization of general nonlinear functions. The use of the references cited in this survey is recommended as a guide to possibly selecting an algorithm superior to DFP. These references also indicate how the minimization code used in this study can be modified to handle general nonlinear functions.

APPENDIX I

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APPENDIX II

USER'S GUIDE FOR ENERGY

ENERGY is a computer code used for linear structural analysis. The analysis is performed by minimizing the total potential of the structure. The minimization is done by the Fletcher-Reeves conjugate gradient algorithm or the Davidon-Fletcher-Powell variable metric algorithm. The code is written in WATFIV computer language. A list of the subroutines used in ENERGY and a description of each is given below.

SUBROUTINE	DESCRIPTION
MAIN	Reads data to determine array dimensions and specify minimization algorithm to use.
DIMN	Dimensions all arrays and calls all subroutines required for solution process.
INPUT	Reads data required to compute total potential and initializes starting values used by the minimization algorithms.
CONGRD	Minimizes the total potential by the FR algorithm and has option to estimate the inverse hessian.
DFP	Minimizes the total potential by the DFP algorithm.
COMPUT	Computes the gradient vector and helps in computing the step length during each iteration.
WLOAD	Prints solution data and reads additional load vectors when applied.

The required data and input formats are given below.

CARD 1

KODE, COMENT

(I5,9A8)

CARD 2

N3,NM (2I5)

CARD 3

(ICON(I),I=1,NJ3) (80I1)

CARD 4

EP1,EP2 (2D20.10)

CARD 5

LI,ICG,IDFP (3I5)

CARD 6

((XCORD(I,J),J=1,2),I=1,NJ) (4D20.10)

CARD 7

A(I),E(I),FMI(I) I=1,NM (3D20.10)

CARD 8

((INC(I,J),J=1,2),I=1,NM) (16I5)

CARD 9

(P(I),I=1,NDF) (4D20.10)

CARD 10

see below

When all data has been read leave CARD 10 blank to terminate code.

When additional load vectors are applied replace CARD 10 by CARD 9.

When a new problem begins go to CARD 1 and continue sequence.

The names used above have the following meanings

KODE indicates solution process

KODE = 1 FR used ICG times to estimate the inverse
hessian, final solution done by DFP

APPENDIX III

USER'S GUIDE FOR STIFF

STIFF is a computer code used for linear structural analysis. The analysis is performed by the direct stiffness method. The equilibrium equations generated are solved by Gaussian elimination. The code is written in WATFIV computer language. A list of the subroutines used in STIFF and a description of each is given below.

SUBROUTINE	DESCRIPTION
MAIN	Reads data to determine array dimensions and data for additional problems or load vectors.
DIMN	Dimensions all arrays and calls all subroutines required for solution process.
INPUT	Reads data on structure required to begin solution process and prints these values.
MPROP	Computes member properties required to generate the stiffness matrix and prints these values.
SSTIFF	Assembles the constrained stiffness matrix in banded form by degree of freedom.
SOLVE	Solves the equilibrium equations by Gaussian elimination and prints solution.

The required data and input formats are given below.

CARD 1

KODE, COMENT (I5,9A8)

CARD 2

NJ,NM (2,I5)

CARD 3

((INC(I,J),J=1,2),I=1,NM) (16,I5)

CARD 4

(ICON(I),I=1,NJB) 80I1

CARD 5

((XCORD(I,J),I=1,2),I=1,NJ) 4D20.10

CARD 6

A(I),E(I),FMI(I) I=1,NM 3D20.10

CARD 7

(P(I),I=1,NDF) 4D20.10

CARD 8

KODE,B I5,9A8

If KODE = 0 terminate code

IF KODE = 2 a new problem follows, return to CARD 1 and continued
solution

If KODE = 5 go to CARD 7 and continue sequence

The names used above have the following meaning

COMENT any comment the user may want to identify the problem

NJ number of joints

NM number of members

INC(I,J) member incidence matrix

ICON(I,J) constraint matrix 0 = unconstrained

1 = constrained

NJ3 NJ x 3

XCORD(I,J) joint coordinate matrix

A(I) area of element I

E(I)	Young's modulus for element I
FMI(I)	moment of inertia for element I
P(I)	load vector
NDF	number of degrees of freedom

APPENDIX IV

C	READ DATA TO DETERMINE SOLUTION ALGORITHM TO BE USED AND	MAIN	1
C	ARRAY DIMENSIONS AND CALLS DIMN TO DIMENSION ARRAYS AND BEGIN	MAIN	2
C	ANALYSIS	MAIN	3
C		MAIN	4
	IMPLICIT REAL*8 (A-H,O-Z)	MAIN	5
	COMMON /ONE/ F1,EP1,EP2,AK,SK	MAIN	6
	COMMON /TWO/ ICON(100),K,KODE,L1,NDF,NEL,NHMOD,NJ,NJ3,NLI,NM,NM2,IMAIN	MAIN	7
	ICG,IDFP	MAIN	8
	DIMENSION RD(5000), ID(500), COMENT(9)	MAIN	9
10	READ (5,50) KODE,COMENT	MAIN	10
	IF (KODE.EQ.0) WRITE (6,70)	MAIN	11
	IF (KODE.EQ.0) STOP	MAIN	12
	READ (5,30) NJ,NM	MAIN	13
	NM2=2*NM	MAIN	14
	NJ3=NJ*3	MAIN	15
	READ (5,40) (ICON(I),I=1,NJ3)	MAIN	16
	J=1	MAIN	17
	DO 20 I=1,NJ3	MAIN	18
	IF (ICON(I).NE.0) GO TO 20	MAIN	19
	J=J+1	MAIN	20
	ICON(I)=J	MAIN	21
20	CONTINUE	MAIN	22
	NDF=J-1	MAIN	23
	NEL=NDF*(NDF+1)/2	MAIN	24
	WRITE (6,60) (COMENT(I),I=1,9)	MAIN	25
C		MAIN	26
C	VARIABLE ARRAY DIMENSIONS	MAIN	27
	N1=1	MAIN	28
	N2=1+NEL	MAIN	29
	N3=N2+NJ3	MAIN	30
	N4=N3+NJ3	MAIN	31
	N5=N4+NDF	MAIN	32

	N6=N5+NDF	MAIN	33
	N7=N6+NDF	MAIN	34
	N8=N7+NDF	MAIN	35
	N9=N8+NDF	MAIN	36
	N10=N9+NDF	MAIN	37
	N11=N10+NJ*2	MAIN	38
	N12=N11+NJ3	MAIN	39
	N13=N12+NM	MAIN	40
	N14=N13+NM	MAIN	41
	N15=N14+NM	MAIN	42
	N16=N15+NM	MAIN	43
	N17=N16+NM	MAIN	44
	N18=1	MAIN	45
	CALL DIMN (RD(N1),RD(N2),RD(N3),RD(N4),RD(N5),RD(N6),RD(N7),RD(N8)	MAIN	46
	1,RD(N9),RD(N10),RD(N11),RD(N12),RD(N13),RD(N14),RD(N15),RD(N16),RD	MAIN	47
	2(N17),ID(N18))	MAIN	48
	GO TO 10	MAIN	49
C		MAIN	50
30	FORMAT (16I5)	MAIN	51
40	FORMAT (8GI1)	MAIN	52
50	FORMAT (15,9A8)	MAIN	53
60	FORMAT (1H1,12,9A8//)	MAIN	54
70	FORMAT (1H1)	MAIN	55
	END	MAIN	56

	SUBROUTINE DIMN (H,B,GD,G,GI,DG,D,P,X,XCORD,V,XL,A,FMI,SIN,COS,E, IDIMN	1
	INC)	DIMN 2
C	DIMN DIMENSIONS ARRAYS AND CALLS SUBROUTINES FOR	DIMN 3
C	SOLUTION PROCESS	DIMN 4
C		DIMN 5
	IMPLICIT REAL*8(A-H,O-Z)	DIMN 6
	COMMON /ONE/ F1,EP1,EP2,AK,SK	DIMN 7
	COMMON /TWO/ ICON(100),K,KODE,L1,NDF,NEL,NHMOD,NJ,NJ3,NLI,NM,NM2, IDIMN	8
	ICG,IDFP	DIMN 9
	DIMENSION H(NEL), B(NJ3), GD(NJ3), G(NDF), GI(NDF), DG(NDF), D(NDF)	DIMN 10
	1), P(NDF), X(NDF), XCORD(NJ,2), V(NJ3), XL(NM), A(NM), FMI(NM),	SIDIMN 11
	2N(NM), COS(NM), E(NM), INC(NM,2)	DIMN 12
	CALL INPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INC)	DIMN 13
	IF (KODE.EQ.3) GO TO 30	DIMN 14
10	CALL CONGRD (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INC)	DIMN 15
	IF (KODE.EQ.1) GO TO 30	DIMN 16
	CALL WLOAD (G,D,P,X)	DIMN 17
	IF (NLI.GT.LI) GO TO 40	DIMN 18
	K=2	DIMN 19
	CALL COMPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INC)	DIMN 20
	DO 20 I=1,NDF	DIMN 21
20	D(I)=-GD(I)	DIMN 22
	GO TO 10	DIMN 23
30	CALL DFP (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INC)	DIMN 24
	CALL WLOAD (G,D,P,X)	DIMN 25
	IF (NLI.GT.LI) GO TO 40	DIMN 26
	K=2	DIMN 27
	CALL COMPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INC)	DIMN 28
	GO TO 30	DIMN 29
40	RETURN	DIMN 30
	END	DIMN 31

	SUBROUTINE INPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INPT	1
	1 INC)	INPT 2
C	INPUT READS INITIAL DATA AND COMPUTES ALL CONSTANTS REQUIRED	INPT 3
C	BY THE SOLUTION PROCESS AND INITIALIZES DATA REQUIRED BY THE	INPT 4
C	SOLUTION PROCESS	INPT 5
C		INPT 6
	IMPLICIT REAL*8(A-H,O-Z)	INPT 7
	COMMON /ONE/ F1,EP1,EP2,AK,SK	INPT 8
	COMMON /TWO/ ICON(100),K,KODE,LI,NDF,NEL,NHMOD,NJ,NJ3,NLI,NM,NM2,IINPT	9
	ICG,IDFP	INPT 10
	DIMENSION H(NEL), B(NJ3), GD(NJ3), G(NDF), GI(NDF), DG(NDF), D(NDF	INPT 11
	1), P(NDF), X(NDF), V(NJ3), XL(NM), A(NM), FMI(NM), SIN(NM), COS(NM	INPT 12
	2), E(NM), XCORD(NJ,2), INC(NM,2)	INPT 13
	READ (5,110) EP1,EP2	INPT 14
	READ (5,120) LI,ICG,IDFP	INPT 15
	READ (5,110) ((XCORD(I,J),J=1,2),I=1,NJ)	INPT 16
	DO 10 I=1,NM	INPT 17
10	READ (5,130) A(I),E(I),FMI(I)	INPT 18
	READ (5,120) ((INC(I,J),J=1,2),I=1,NM)	INPT 19
	READ (5,110) (P(I),I=1,NDF)	INPT 20
C		INPT 21
C	INITIALIZE STARTING POINT DATA	INPT 22
	DO 20 I=1,NDF	INPT 23
	X(I)=0.00	INPT 24
	D(I)=P(I)	INPT 25
20	GD(I)=-P(I)	INPT 26
	IF (KODE.EQ.2) GO TO 50	INPT 27
	DO 30 I=1,NEL	INPT 28
30	H(I)=0.00	INPT 29
	IF (KODE.EQ.1) GO TO 50	INPT 30
	DO 40 I=1,NDF	INPT 31
	G(I)=GD(I)	INPT 32

	J=NDF*(I-1)+I-I*(I-1)/2	INPT	33
40	H(J)=1.D0	INPT	34
50	CONTINUE	INPT	35
	NLI=0	INPT	36
C		INPT	37
C	COMPUTE MEMBER LENGTHS,SINES AND COSINES	INPT	38
	DO 60 I=1,NM	INPT	39
	J1=INC(I,1)	INPT	40
	J2=INC(I,2)	INPT	41
	XJ1=XCORD(J1,1)	INPT	42
	XJ2=XCORD(J1,2)	INPT	43
	XK1=XCORD(J2,1)	INPT	44
	XK2=XCORD(J2,2)	INPT	45
	DX1=XK1-XJ1	INPT	46
	DX2=XK2-XJ2	INPT	47
	XL(I)=DSQRT(DX1*DX1+DX2*DX2)	INPT	48
	COS(I)=DX1/XL(I)	INPT	49
	SIN(I)=DX2/XL(I)	INPT	50
60	CONTINUE	INPT	51
	WRITE (6,140) EP1,EP2	INPT	52
	WRITE (6,150) LI,NM,NM2,NJ,NJ3,NDF,NEL,ICG,IDFP,KODE	INPT	53
	WRITE (6,180)	INPT	54
	DO 70 I=1,NM	INPT	55
70	WRITE (6,190) A(I),E(I),FMI(I),XL(I),INC(I,1),INC(I,2)	INPT	56
	WRITE (6,200)	INPT	57
	DO 80 I=1,NM	INPT	58
80	WRITE (6,220) SIN(I),COS(I)	INPT	59
	WRITE (6,210)	INPT	60
	DO 90 I=1,NJ	INPT	61
90	WRITE (6,220) XCORD(I,1),XCORD(I,2)	INPT	62
	WRITE (6,160)	INPT	63
	DO 100 I=1,NDF	INPT	64

100	WRITE (6,170) I,P(1)	INPT	65
	RETURN	INPT	66
C		INPT	67
110	FORMAT (4D20.10)	INPT	68
120	FORMAT (16I5)	INPT	69
130	FORMAT (3D20.10)	INPT	70
140	FORMAT (T18,3HEP1,T38,3HEP2/2D20.10)	INPT	71
150	FORMAT (/T4,2HLI,T9,2HNM,T13,3HNM2,T19,2HNJ,T23,3HNJ3,T28,3HNDF,T31,3HNEL,T38,3HICG,T42,4HIDFP,T47,4HKODE/10I5)	INPT	72
160	FORMAT (/T2,19HDIRECTION OF D.O.F.,T37,4HP(1))	INPT	73
170	FORMAT (I20,T21,D20.10)	INPT	74
180	FORMAT (/T17,4HA(I),T37,4HE(I),T55,6HFMI(I),T76,5HXL(I),T83,8HINC(I,1),T93,8HINC(I,2))	INPT	75
190	FORMAT (D20.10,T21,D20.10,T41,D20.10,T61,D20.10,T81,I10,T91,I10,T101,I10)	INPT	76
200	FORMAT (/T15,6HSIN(I),T35,6HCOS(I))	INPT	77
210	FORMAT (/T11,10HXCORD(I,1),T31,10HXCORD(I,2))	INPT	78
220	FORMAT (2D20.10)	INPT	79
	END	INPT	80
		INPT	81
		INPT	82
		INPT	83

	SUBROUTINE CONGRD (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,FRCG	1
	1,INC)	FRCG 2
C	CONGRD USES THE FLETCHER-REEVES CONJUGATE GRADIENT ALGORITHM	FRCG 3
C	TO MINIMIZE THE TOTAL POTENTIAL	FRCG 4
C		FRCG 5
	IMPLICIT REAL*8 (A-H,O-Z)	FRCG 6
	COMMON /ONE/ F1,EP1,EP2,AK,SK	FRCG 7
	COMMON /TWO/ ICON(100),K,KODE,LI,NDF,NEL,NHMOD,NJ,NJ3,NLI,NM,NM2,IFRCG	8
	1CG,IDFP	FRCG 9
	DIMENSION H(NEL), B(NJ3), GD(NJ3), G(NDF), GI(NDF), DG(NDF), D(NDF)	FRCG 10
	1), P(NDF), X(NDF), V(NJ3), XL(NM), A(NM), FMI(NM), SIN(NM), COS(NM)	FRCG 11
	2), E(NM), XCORD(NJ,2), INC(NM,2)	FRCG 12
	IZ=0	FRCG 13
	NHMOD=0	FRCG 14
	IF (KODE.NE.2.OR.NLI.EQ.0) GO TO 10	FRCG 15
C		FRCG 16
C	COMPUTE STEPLENGTH FOR 1-D MINIMIZATION	FRCG 17
10	GS=0.DO	FRCG 18
	GK=0.DO	FRCG 19
	DO 20 I=1,NDF	FRCG 20
	GK=GK+GD(I)*GD(I)	FRCG 21
20	GS=GS+GD(I)*D(I)	FRCG 22
	K=1	FRCG 23
	CALL COMPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INC)	FRCG 24
	AK=GS/F1	FRCG 25
C		FRCG 26
C	VALUE OF MINIMUM ALONG SEARCH DIRECTION	FRCG 27
	DO 30 I=1,NDF	FRCG 28
30	X(I)=X(I)-AK*D(I)	FRCG 29
	NHMOD=NHMOD+1	FRCG 30
C		FRCG 31
C	COMPUTE GRADIENT AND DIRECTION VECTORS	FRCG 32

	K=2	FRCG	33
	GK1=0.DO	FRCG	34
	CALL COMPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCOR,INC)	FRCG	35
	DO 40 I=1,NDF	FRCG	36
40	GK1=GK1+GD(I)*GD(I)	FRCG	37
	BK1=GK1/GK	FRCG	38
	DO 50 I=1,NDF	FRCG	39
50	D(I)=BK1*D(I)-GD(I)	FRCG	40
	IF (KODE.NE.1) GO TO 70	FRCG	41
C		FRCG	42
C	ESTIMATE INVERSE HESSIAN	FRCG	43
	M=0	FRCG	44
	DO 60 I=1,NDF	FRCG	45
	DO 60 J=I,NDF	FRCG	46
	M=M+1	FRCG	47
60	H(M)=H(M)+D(I)*D(J)/F1	FRCG	48
	IF (NHMOD.EQ.ICG) GO TO 130	FRCG	49
	GO TO 10	FRCG	50
70	CONTINUE	FRCG	51
C		FRCG	52
C	CONVERGENCE TEST	FRCG	53
	SK=0.DO	FRCG	54
	I=0	FRCG	55
80	I=I+1	FRCG	56
	IF (DABS(GD(I)).GT.EP1) GO TO 110	FRCG	57
	IF (I.LT.NDF) GO TO 80	FRCG	58
90	CONTINUE	FRCG	59
	DO 100 I=1,NDF	FRCG	60
100	SK=SK+D(I)*D(I)	FRCG	61
	IF (DABS(AK)*DSQRT(SK).LT.EP2) GO TO 120	FRCG	62
110	CONTINUE	FRCG	63
C		FRCG	64

```
      K=3
      IF (NHMOD.EQ.ICG) GO TO 120
      GO TO 10
120   CONTINUE
      IF (KODE.EQ.1) GO TO 130
      IF (NHMOD.NE.ICG) GO TO 130
      IZ=IZ+1
      IF (IZ.EQ.2) GO TO 130
      IF (SK.EQ.0.D0) GO TO 90
130   CONTINUE
      DO 140 I=1,NDF
140   G(I)=GD(I)
      RETURN
      END
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FRCG 65
FRCG 66
FRCG 67
FRCG 68
FRCG 69
FRCG 70
FRCG 71
FRCG 72
FRCG 73
FRCG 74
FRCG 75
FRCG 76
FRCG 77
FRCG 78
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	SUBROUTINE DFP (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INDFPM	1
	1C)	DFPM 2
C	DFP USES THE DAVIDON-FLETCHER-POWELL VARIABLE METRIC ALGORITHM	DFPM 3
C	TO MINIMIZE THE TOTAL POTENTIAL	DFPM 4
C		DFPM 5
	IMPLICIT REAL*8 (A-H,O-Z)	DFPM 6
	COMMON /ONE/ F1,EP1,EP2,AK,SK	DFPM 7
	COMMON /TWO/ ICON(100),K,KODE,LI,NDF,NEL,NHMOD,NJ,NJ3,NLI,NM,NM2,10DFPM	8
	ICG,IDFP	DFPM 9
	DIMENSION H(NEL), B(NJ3), GD(NJ3), G(NDF), GI(NDF), DG(NDF), D(NDFDFPM	10
	1), P(NDF), X(NDF), V(NJ3), XL(NM), A(NM), FMI(NM), SIN(NM), COS(NMDFPM	11
	2), E(NM), XCORD(NJ,2), INC(NM,2)	DFPM 12
	NHMOD=0	DFPM 13
	IJ=0	DFPM 14
	KKK=0	DFPM 15
	IF (KODE.EQ.3.AND.NLI.EQ.0) GO TO 70	DFPM 16
10	CONTINUE	DFPM 17
	DO 20 I=1,NDF	DFPM 18
20	G(I)=GD(I)	DFPM 19
30	CONTINUE	DFPM 20
C		DFPM 21
C	COMPUTATION OF SEARCH DIRECTION	DFPM 22
	M=0	DFPM 23
	DO 60 I=1,NDF	DFPM 24
	D(I)=0.DO	DFPM 25
	DO 40 J=I,NDF	DFPM 26
	M=M+1	DFPM 27
40	D(I)=D(I)-H(M)*GD(J)	DFPM 28
	IF (I.EQ.1) GO TO 60	DFPM 29
	J1=I-1	DFPM 30
	DO 50 J=1,J1	DFPM 31
	L=NDF*(J-1)+I-J*(J-1)/2	DFPM 32

50	D(I)=D(I)-H(L)*GD(J)	DFPM	33
60	CONTINUE	DFPM	34
70	CONTINUE	DFPM	35
C		DFPM	36
C	COMPUTATION OF MAGNITUDE OF STEPLENGTH ALONG SEARCH DIRECTION	DFPM	37
	K=1	DFPM	38
	CALL COMPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INC)	DFPM	39
	GS=C.DG	DFPM	40
	DO 80 I=1,NDF	DFPM	41
80	GS=GS+GD(I)*D(I)	DFPM	42
	AK=GS/F1	DFPM	43
	IF (KKK.EQ.1) GO TO 120	DFPM	44
C		DFPM	45
C	VALUE OF MINIMUM ALONG SEARCH DIRECTION	DFPM	46
	DO 90 I=1,NDF	DFPM	47
90	X(I)=X(I)-AK*D(I)	DFPM	48
	NHMOD=NHMOD+1	DFPM	49
C		DFPM	50
C	TEST IF GRADIENT VALUES ARE WITHIN PRESCRIBED LIMIT	DFPM	51
	K=2	DFPM	52
	CALL COMPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORD,INC)	DFPM	53
	I=0	DFPM	54
100	I=I+1	DFPM	55
	IF (DABS(GD(I)).GT.EP1) GO TO 150	DFPM	56
	IF (I.NE.NDF) GO TO 100	DFPM	57
	DO 110 I=1,NDF	DFPM	58
110	GI(I)=D(I)	DFPM	59
	F2=F1	DFPM	60
	KKK=1	DFPM	61
	GO TO 30	DFPM	62
120	CONTINUE	DFPM	63
C		DFPM	64

C	TEST TO DETERMINE IF DISTANCE TO NEXT MINIMUM IS WITHIN	DFPM	65
C	PRESCRIBED LIMITS	DFPM	66
	SK=0.DO	DFPM	67
	DO 130 I=1,NDF	DFPM	68
130	SK=SK+D(I)*D(I)	DFPM	69
	IF (DABS(AK)*DSQRT(SK).LT.EP2) GO TO 220	DFPM	70
	DO 140 I=1,NDF	DFPM	71
140	D(I)=GI(I)	DFPM	72
	F1=F2	DFPM	73
	KKK=0	DFPM	74
150	CONTINUE	DFPM	75
	K=4	DFPM	76
	IF (IDFP.LT.NHMOD) GO TO 220	DFPM	77
C		DFPM	78
C	MODIFICATION OF THE INVERSE HESSIAN (FLEXIBILITY MATRIX)	DFPM	79
	DO 160 I=1,NDF	DFPM	80
160	DG(I)=GD(I)-G(I)	DFPM	81
	BI=0.DO	DFPM	82
	M=0	DFPM	83
	DO 200 I=1,NDF	DFPM	84
	B(I)=0.DO	DFPM	85
	DO 170 J=I,NDF	DFPM	86
	M=M+1	DFPM	87
170	B(I)=B(I)+H(M)*DG(J)	DFPM	88
	IF (I.EQ.1) GO TO 190	DFPM	89
	J1=I-1	DFPM	90
	DO 180 J=1,J1	DFPM	91
	L=NDF*(J-1)+I-J*(J-1)/2	DFPM	92
180	B(I)=B(I)+H(L)*DG(J)	DFPM	93
190	BI=BI+B(I)*DG(I)	DFPM	94
200	CONTINUE	DFPM	95
	M=0	DFPM	96

	DO 210 I=1,NDF	DFPM 97
	DO 210 J=I,NDF	DFPM 98
	M=M+1	DFPM 99
210	H(M)=H(M)+D(I)*D(J)/F1-B(I)*B(J)/BI	DFPM 100
	GO TO 10	DFPM 101
220	CONTINUE	DFPM 102
	DO 230 I=1,NDF	DFPM 103
230	G(I)=GD(I)	DFPM 104
	RETURN	DFPM 105
	END	DFPM 106

	SUBROUTINE COMPUT (H,B,GD,G,GI,DG,D,P,X,V,XL,A,FMI,SIN,COS,E,XCORDCOMP	1
	1,INC)	COMP 2
C	COMPUT COMPUTES THE GRADIENT VECTOR AND HELPS IN COMPUTING	COMP 3
C	THE STEPLENGTH FOR 1-D MINIMIZATION	COMP 4
C		COMP 5
	IMPLICIT REAL*8(A-H,O-Z)	COMP 6
	COMMON /ONE/ F1,EP1,EP2,AK,SK	COMP 7
	COMMON /TWO/ ICON(100),K,KODE,LI,NDF,NEL,NHMOD,NJ,NJ3,NLI,NM,NM2,ICOMP	8
	ICG,IDFP	COMP 9
	DIMENSION H(NEL), B(NJ3), GD(NJ3), G(NDF), GI(NDF), DG(NDF), D(NDFCOMP	10
	1), P(NDF), X(NDF), V(NJ3), XL(NM), A(NM), FMI(NM), SIN(NM), COS(NMCOMP	11
	2), E(NM), XCORD(NJ,2), INC(NM,2)	COMP 12
	J=0	COMP 13
	IF (K.NE.1) GO TO 20	COMP 14
	F1=0.00	COMP 15
	DO 10 I=1,NJ3	COMP 16
	V(I)=0.00	COMP 17
	IF (ICON(I).EQ.1) GO TO 10	COMP 18
	J=J+1	COMP 19
	V(I)=D(J)	COMP 20
10	CONTINUE	COMP 21
	GO TO 40	COMP 22
20	CONTINUE	COMP 23
	DO 30 I=1,NJ3	COMP 24
	V(I)=0.00	COMP 25
	GD(I)=0.00	COMP 26
	IF (ICON(I).EQ.1) GO TO 30	COMP 27
	J=J+1	COMP 28
	V(I)=X(J)	COMP 29
30	CONTINUE	COMP 30
40	CONTINUE	COMP 31
	DO 60 I=1,NM	COMP 32

	J3=3*INC(I,1)	COMP	33
	J2=J3-1	COMP	34
	J1=J2-1	COMP	35
	J6=3*INC(I,2)	COMP	36
	J5=J6-1	COMP	37
	J4=J5-1	COMP	38
	C=COS(I)	COMP	39
	S=SIN(I)	COMP	40
	IF (K.NE.1) GO TO 50	COMP	41
	FVAL=A(I)*E(I)/(2.D0*XL(I))*(V(J5)*S+V(J4)*C-V(J2)*S-V(J1)*C)**2+2	COMP	42
	1.D0*E(I)*FMI(I)/XL(I)*(V(J3)*V(J3)+V(J3)*V(J6)+V(J6)*V(J6)-3.D0/XL	COMP	43
	2(I)*(V(J5)*C-V(J4)*S-V(J2)*C+V(J1)*S)*(V(J3)+V(J6))+3.D0/(XL(I)*XL	COMP	44
	3(I))*(V(J5)*C-V(J4)*S-V(J2)*C+V(J1)*S)**2)	COMP	45
	F1=F1+2.D0*FVAL	COMP	46
	GO TO 60	COMP	47
50	CONTINUE	COMP	48
	A1=6.D0*E(I)*FMI(I)/(XL(I)*XL(I))*S*(-V(J3)-V(J6)+2.D0/XL(I)*(V(J5)	COMP	49
	1)*C-V(J4)*S-V(J2)*C+V(J1)*S)-A(I)*E(I)*C/XL(I)*(V(J5)*S+V(J4)*C-V	COMP	50
	2(J2)*S-V(J1)*C)	COMP	51
	A2=6.D0*E(I)*FMI(I)/(XL(I)*XL(I))*C*(V(J3)+V(J6)-2.D0/XL(I)*(V(J5)	COMP	52
	1)*C-V(J4)*S-V(J2)*C+V(J1)*S)-A(I)*E(I)*S/XL(I)*(V(J5)*S+V(J4)*C-V	COMP	53
	2(J2)*S-V(J1)*C)	COMP	54
	A3=2.D0*E(I)*FMI(I)/XL(I)*(2.D0*V(J3)+V(J6)-3.D0/XL(I)*(V(J5)*C-V	COMP	55
	1(J4)*S-V(J2)*C+V(J1)*S))	COMP	56
	A4=2.D0*E(I)*FMI(I)/XL(I)*(2.D0*V(J6)+V(J3)-3.D0/XL(I)*(V(J5)*C-V	COMP	57
	1(J4)*S-V(J2)*C+V(J1)*S))	COMP	58
	GD(J1)=GD(J1)+A1	COMP	59
	GD(J2)=GD(J2)+A2	COMP	60
	GD(J3)=GD(J3)+A3	COMP	61
	GD(J4)=GD(J4)-A1	COMP	62
	GD(J5)=GD(J5)-A2	COMP	63
	GD(J6)=GD(J6)+A4	COMP	64

```
60  CONTINUE
    IF (K.EQ.1) GO TO 80
    DO 70 I=1,NJ3
    IF (ICON(I).EQ.1) GO TO 70
    ICI=ICON(I)-1
    GD(ICI)=GD(I)-P(ICI)
70  CONTINUE
80  CONTINUE
    RETURN
    END
```

```
COMP 65
COMP 66
COMP 67
COMP 68
COMP 69
COMP 70
COMP 71
COMP 72
COMP 73
COMP 74
```

	SUBROUTINE WLOAD (G,D,P,X)	LOAD	1
C	WLOAD PRINTS SOLUTION AND GRADIENT VECTOR AND READS VALUES OF	LOAD	2
C	ADDITIONAL LOAD VECTORS WHEN APPLIED	LOAD	3
C		LOAD	4
	IMPLICIT REAL*8 (A-H,O-Z)	LOAD	5
	COMMON /ONE/ F1,EP1,EP2,AK,SK	LOAD	6
	COMMON /TWO/ ICON(100),K,KODE,LI,NDF,NEL,NHMOD,NJ,NJ3,NLI,NM,NM2,ILOAD	LOAD	7
	ICG,IDFP	LOAD	8
	DIMENSION G(NDF), D(NDF), P(NDF), X(NDF)	LOAD	9
	NLI=NLI+1	LOAD	10
	SK1=DABS(AK)*DSQRT(SK)	LOAD	11
	IF (KODE.EQ.1) GO TO 40	LOAD	12
	IF (KODE.EQ.2) GO TO 30	LOAD	13
	IF (K.NE.4) GO TO 20	LOAD	14
10	WRITE (6,100)	LOAD	15
	GO TO 60	LOAD	16
20	WRITE (6,150) NHMOD,NLI	LOAD	17
	GO TO 60	LOAD	18
30	IF (K.EQ.3) GO TO 10	LOAD	19
	WRITE (6,130) NHMOD,NLI	LOAD	20
	GO TO 60	LOAD	21
40	IF (NLI.NE.1) GO TO 50	LOAD	22
	WRITE (6,140)	LOAD	23
50	IF (K.NE.4) GO TO 20	LOAD	24
	GO TO 10	LOAD	25
60	WRITE (6,110)	LOAD	26
	DO 70 I=1,NDF	LOAD	27
70	WRITE (6,160) I,X(I),P(I),G(I)	LOAD	28
	IF (K.GT.2) GO TO 80	LOAD	29
	WRITE (6,120) SK1	LOAD	30
80	CONTINUE	LOAD	31
	IF (NLI.GT.LI) GO TO 90	LOAD	32

	READ (5,170) (P(I),I=1,NDF)	LOAD	33
90	RETURN	LOAD	34
C		LOAD	35
C		LOAD	36
100	FORMAT (T2,79H***CONVERGENCE CRITERIA NOT SATISFIED WITHIN PRESCRIBED	LOAD	37
	NUMBER OF ITERATIONS***/T2,81HVALUES OF MINIMUM ALONG SEARCH DIRECTION	LOAD	38
	PRIOR TO TERMINATION OF SOLUTION PROCESS)	LOAD	39
110	FORMAT (/T2,9HDIRECTION,T20,19HDISPLACEMENT VECTOR,T45,11HLOAD VECTOR,	LOAD	40
	TOR,T70,15HGRADIENT VECTOR/T2,9HOF D.O.F.,T20,10HAT MINIMUM,T45,10HLOAD	LOAD	41
	2HAT MINIMUM,T70,10HAT MINIMUM)	LOAD	42
120	FORMAT (/T2,54HDISTANCE TO NEXT MINIMUM IF SOLUTION PROCESS CONTINUED,	LOAD	43
	T56,D20.10///)	LOAD	44
130	FORMAT (T2,41HMINIMUM LOCATED BY CONJUGATE GRADIENTS IN,T43,I3,T47HLOAD	LOAD	45
	1,26HITERATIONS FOR LOAD VECTOR,T73,I3)	LOAD	46
140	FORMAT (T2,78HINITIAL H INVERSE USED BY DFP VARIABLE METRIC ESTIMATED	LOAD	47
	BY CONJUGATE GRADIENTS)	LOAD	48
150	FORMAT (T2,41HMINIMUM LOCATED BY DFP VARIABLE METRIC IN,T43,I3,T47HLOAD	LOAD	49
	1,26HITERATIONS FOR LOAD VECTOR,T73,I3)	LOAD	50
160	FORMAT (T6,I5,T11,3D25.10)	LOAD	51
170	FORMAT (4D20.10)	LOAD	52
	END	LOAD	53

APPENDIX V

C	READ DATA TO DETERMINE ARRAY DIMENSIONS AND CALL DIMN TO	MAIN	1
C	DIMENSION ARRAYS AND BEGIN ANALYSIS	MAIN	2
C		MAIN	3
	IMPLICIT REAL*8 (A-H,O-Z)	MAIN	4
	COMMON INC(75,2),ICON(99),NM,NJ,NEQ,IBAND,KODE,NDF,LINC	MAIN	5
	DIMENSION S(5000), II(500)	MAIN	6
	DIMENSION B(9)	MAIN	7
10	READ (5,60) KODE,B	MAIN	8
	IF (KODE.EQ.0) GO TO 50	MAIN	9
	WRITE (6,70) (B(J),J=1,9)	MAIN	10
	IF (KODE.EQ.5) GO TO 40	MAIN	11
	LINC=0	MAIN	12
	READ (5,80) NJ,NM	MAIN	13
	READ (5,80) ((INC(I,J),J=1,2),I=1,NM)	MAIN	14
	NEQ=3*NJ	MAIN	15
	READ (5,90) (ICON(I),I=1,NEQ)	MAIN	16
	NDF=0	MAIN	17
	DO 20 I=1,NEQ	MAIN	18
	IF (ICON(I).EQ.1) GO TO 20	MAIN	19
	NDF=NDF+1	MAIN	20
	ICON(I)=NDF+1	MAIN	21
20	CONTINUE	MAIN	22
C		MAIN	23
C	COMPUTE MAXIMUM SEMI-BAND WIDTH	MAIN	24
	MAXDIF=0	MAIN	25
	DO 30 I=1,NM	MAIN	26
	MDIF=INC(I,2)-INC(I,1)	MAIN	27
30	IF (MDIF.GT.MAXDIF) MAXDIF=MDIF	MAIN	28
	IBAND=3*(MAXDIF+1)	MAIN	29
C		MAIN	30
C	VARIABLE ARRAY DIMENSIONS	MAIN	31
	N1=1	MAIN	32

	N2=1+NEQ	MAIN	33
	N3=N2+NJ*2	MAIN	34
	N4=N3+NM	MAIN	35
	N5=N4+NM	MAIN	36
	N6=N5+NM	MAIN	37
	N7=N6+NM	MAIN	38
	N8=N7+NM	MAIN	39
	N9=N8+NM	MAIN	40
	N10=N9+NM	MAIN	41
	N11=N10+NM	MAIN	42
	N12=N11+IBAND*NDF	MAIN	43
	N13=N12+NM*6	MAIN	44
	N14=1	MAIN	45
C		MAIN	46
40	CALL DIMN (S(N1),S(N2),S(N3),S(N4),S(N5),S(N6),S(N7),S(N8),S(N9),S(N10),S(N11),S(N12),S(N13),II(N14))	MAIN	47
	GO TO 10	MAIN	48
50	WRITE (6,100)	MAIN	49
	STOP	MAIN	50
C		MAIN	51
60	FORMAT (I5,9A8)	MAIN	52
70	FORMAT (1H1,T5,9A8//)	MAIN	53
80	FORMAT (16I5)	MAIN	54
90	FORMAT (80I1)	MAIN	55
100	FORMAT (1H1)	MAIN	56
	END	MAIN	57
		MAIN	58

	SUBROUTINE DIMN (P,X,FMI,E,A,XL,COS,SIN,ALPHA,BETA,AK,FTIL,PIJ,MCODE)	DIMN	1
	1DE)	DIMN	2
C	DIMN DIMENSIONS ARRAYS AND CALLS SUBROUTINES	DIMN	3
C	FOR SOLUTION PROCESS	DIMN	4
C		DIMN	5
	IMPLICIT REAL*8(A-H,O-Z)	DIMN	6
	COMMON INC(75,2),ICON(99),NM,NJ,NEQ,IBAND,KODE,NDF,LINC	DIMN	7
	DIMENSION P(NEQ), X(NJ,2), FMI(NM), E(NM), A(NM), XL(NM), COS(NM),	DIMN	8
	1 SIN(NM), ALPHA(NM), BETA(NM), AK(NEQ,IBAND), FTIL(NM,6), PIJ(NDF)	DIMN	9
	2, MCODE(NM,6)	DIMN	10
	CALL INPUT (X,A,FMI,E,P,PIJ)	DIMN	11
	IF (KODE.EQ.5) GO TO 10	DIMN	12
	CALL MPROP (X,COS,SIN,E,FMI,A,XL,ALPHA,BETA)	DIMN	13
	CALL SSTIFF (COS,SIN,ALPHA,BETA,XL,AK,MCODE)	DIMN	14
10	CALL SOLVE (AK,P,PIJ)	DIMN	15
	RETURN	DIMN	16
	END	DIMN	17

	SUBROUTINE INPUT (X,A,FMI,E,P,PIJ)	INPT	1
C	INPUT READS IN KNOWN DATA ON STRUCTURE AND LOADING	INPT	2
C	NJ= NUMBER OF JOINTS, NM= NUMBER OF MEMBERS	INPT	3
C	A= AREA, E= YOUNG'S MODULUS, FMI= MOMENT OF INERTIA	INPT	4
C	P= (3*NJ) VECTOR SPECIFYING APPLIED JOINT FORCES	INPT	5
C	X= (NJ,2) MATRIX OF JOINT COORDINATES	INPT	6
C	INC(NM,2)= JOINT NUMBER AT A AND B ENDS RESPECTIVELY	INPT	7
C	ICON(3*NJ)=MATRIX SPECIFYING JOINT STATUS	INPT	8
C	1= CONSTRAINED, 0= UNCONSTRAINED	INPT	9
C		INPT	10
	IMPLICIT REAL*8 (A-H,O-Z)	INPT	11
	COMMON INC(75,2),ICON(99),NM,NJ,NEQ,IBAND,KODE,NDF,LINC	INPT	12
	DIMENSION X(NJ,2), A(NM), FMI(NM), E(NM), P(NEQ), PIJ(NDF)	INPT	13
	LINC=LINC+1	INPT	14
	IF (KODE.EQ.5) GO TO 20	INPT	15
	READ (5,90) ((X(I,J),J=1,2),I=1,NJ)	INPT	16
	DO 10 I=1,NM	INPT	17
10	READ (5,90) A(I),E(I),FMI(I)	INPT	18
20	READ (5,90) (PIJ(I),I=1,NDF)	INPT	19
	J=0	INPT	20
	DO 30 I=1,NEQ	INPT	21
	P(I)=0.D0	INPT	22
	IF (ICON(I).EQ.1) GO TO 30	INPT	23
	J=J+1	INPT	24
	P(I)=PIJ(J)	INPT	25
30	CONTINUE	INPT	26
	IF (KODE.NE.5) GO TO 40	INPT	27
	WRITE (6,170) LINC	INPT	28
	WRITE (6,180) (P(I),I=1,NEQ)	INPT	29
	GO TO 80	INPT	30
40	WRITE (6,100) NJ,NM,NDF,NEQ	INPT	31
	WRITE (6,110)	INPT	32

	DO 50 I=1,NJ	INPT 33
50	WRITE (6,120) I,X(I,1),X(I,2)	INPT 34
	WRITE (6,130)	INPT 35
	DO 60 I=1,NM	INPT 36
60	WRITE (6,140) I,INC(I,1),INC(I,2)	INPT 37
	WRITE (6,150)	INPT 38
	DO 70 I=1,NJ	INPT 39
	DO 70 M=1,3	INPT 40
	J=3*(I-1)+M	INPT 41
70	WRITE (6,160) I,M,ICON(J),I,M,P(J)	INPT 42
80	RETURN	INPT 43
C		INPT 44
90	FORMAT (4D20.10)	INPT 45
100	FORMAT (T2,4HNJ =,T8,I3,T14,4HNM =,T20,I3,T26,5HNDF =,T33,I3,T39,5INPT	46
	1HNEQ =,T46,I3)	INPT 47
110	FORMAT (//T25,23HJOINT COORDINATE MATRIX/T32,8H(INCHES)//T18,12HX INPT	48
	1COORDINATE,T43,12HY COORDINATE/)	INPT 49
120	FORMAT (T2,5HJOINT,T9,I2,T12,D23.16,T37,D23.16)	INPT 50
130	FORMAT (//T12,23HMEMBER INCIDENCE MATRIX/T15,17H(NON DIMENSIONAL)/INPT	51
	1/T14,5HA END,T28,5HB END/)	INPT 52
140	FORMAT (T2,6HMEMBER,T9,I2,T16,I2,T30,I2)	INPT 53
150	FORMAT (///T26,17HJOINT CONSTRAINTS,T75,20HAPPLIED JOINT FORCES/T2INPT	54
	16,17H(NON DIMENSIONAL),T78,14H(INCHES, KIPS)/)	INPT 55
160	FORMAT (T2,5HJOINT,T9,I2,T13,I2,T15,9HDIRECTION,T34,I2,T50,5HJOINTINPT	56
	1,T57,I2,T61,I1,T63,9HDIRECTION,T74,D23.16)	INPT 57
170	FORMAT (//T2,20HDATA FOR LOAD VECTOR,T22,I3/)	INPT 58
180	FORMAT (D20.10)	INPT 59
	END	INPT 60

	SUBROUTINE MPROP (X,COS,SIN,E,FMI,A,XL,ALPHA,BETA)	MPRP	1
C	MPROP COMPUTES THE MEMBER PROPERTIES, COSINE, SINE, ALPHA, BETA,	MPRP	2
C	AND LENGTH, WHERE ALPHA=EI/L**3, BETA=(L/R)**2, XI(I)=LENGTH	MPRP	3
C		MPRP	4
	IMPLICIT REAL * 8 (A-H,O-Z)	MPRP	5
	COMMON INC(75,2),ICON(99),NM,NJ,NEQ,IBAND,KODE,NDF,LINC	MPRP	6
	DIMENSION X(NJ,2), COS(NM), SIN(NM), E(NM), FMI(NM), A(NM), XL(NM)	MPRP	7
	1, ALPHA(NM), BETA(NM)	MPRP	8
	DO 10 I=1,NM	MPRP	9
	J=INC(I,1)	MPRP	10
	K=INC(I,2)	MPRP	11
	XJ1=X(J,1)	MPRP	12
	XJ2=X(J,2)	MPRP	13
	XK1=X(K,1)	MPRP	14
	XK2=X(K,2)	MPRP	15
	DX1=XK1-XJ1	MPRP	16
	DX2=XK2-XJ2	MPRP	17
	XLEN=DSQRT(DX1**2+DX2**2)	MPRP	18
	XL(I)=XLEN	MPRP	19
	COS(I)=DX1/XLEN	MPRP	20
	SIN(I)=DX2/XLEN	MPRP	21
	ALPHA(I)=E(I)*FMI(I)/XL(I)**3	MPRP	22
10	BETA(I)=(XL(I)/DSQRT(FMI(I)/A(I)))**2	MPRP	23
	WRITE (6,40)	MPRP	24
	DO 20 I=1,NM	MPRP	25
20	WRITE (6,50) I,A(I),E(I),FMI(I),XL(I)	MPRP	26
	WRITE (6,60)	MPRP	27
	DO 30 I=1,NM	MPRP	28
30	WRITE (6,70) I,COS(I),SIN(I),ALPHA(I),BETA(I)	MPRP	29
	RETURN	MPRP	30
C		MPRP	31
40	FORMAT (///T53,17HMEMBER PROPERTIES/T54,14H(INCHES, KIPS)//T21,4HMPRP	MPRP	32

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1 AREA, T38, 21 HMODULUS OF ELASTICITY, T65, 17 H MOMENT OF INERTIA, T92, 14 H MPRP 33
2 MEMBER LENGTHS //) MPRP 34
50  FORMAT (T2, 6 H MEMBER, T9, I2, T12, D23.16, T37, D23.16, T62, D23.16, T87, D23 MPRP 35
1.16) MPRP 36
60  FORMAT (///T20, 7 H COSINES, T46, 5 H SINES, T68, 12 H ALPHA VALUES, T93, 11 H BEMPRP 37
1 TA VALUES /) MPRP 38
70  FORMAT (T2, 6 H MEMBER, T9, I2, T12, D23.16, T37, D23.16, T62, D23.16, T87, D23 MPRP 39
1.16) MPRP 40
END MPRP 41

```

	SUBROUTINE SSTIFF (COS,SIN,ALPHA,BETA,XL,AK,MCODE)	STIF	1
C	STIFF COMPUTES THE ELEMENTS OF THE CONSTRAINED STIFFNESS MATRIX	STIF	2
C	CONTAINED IN THE SEMIBAND WIDTH	STIF	3
C		STIF	4
	IMPLICIT REAL*8 (A-H,O-Z)	STIF	5
	COMMON INC(75,2),ICON(99),NM,NJ,NEQ,IBAND,KODE,NDF,LINC	STIF	6
	DIMENSION COS(NM), SIN(NM), ALPHA(NM), BETA(NM), XL(NM), AK(NDF,IBSTIF	7	
	1AND), MCODE(NM,6)	STIF	8
	DIMENSION INDEX(6,6), AA(7)	STIF	9
	DATA INDEX/1,2,3,-1,-2,3,2,4,5,-2,-4,5,3,5,6,-3,-5,7,-1,-2,-3,1,2,	STIF	10
	1-3,-2,-4,-5,2,4,-5,3,5,7,-3,-5,6/	STIF	11
	DO 10 I=1,NM	STIF	12
	DO 10 J=1,6	STIF	13
10	MCODE(I,J)=0	STIF	14
	DO 20 I=1,NM	STIF	15
	J1=3*INC(I,1)-2	STIF	16
	J2=3*INC(I,1)-1	STIF	17
	J3=3*INC(I,1)	STIF	18
	J4=3*INC(I,2)-2	STIF	19
	J5=3*INC(I,2)-1	STIF	20
	J6=3*INC(I,2)	STIF	21
	IF (ICON(J1).NE.1) MCODE(I,1)=ICON(J1)-1	STIF	22
	IF (ICON(J2).NE.1) MCODE(I,2)=ICON(J2)-1	STIF	23
	IF (ICON(J3).NE.1) MCODE(I,3)=ICON(J3)-1	STIF	24
	IF (ICON(J4).NE.1) MCODE(I,4)=ICON(J4)-1	STIF	25
	IF (ICON(J5).NE.1) MCODE(I,5)=ICON(J5)-1	STIF	26
	IF (ICON(J6).NE.1) MCODE(I,6)=ICON(J6)-1	STIF	27
20	CONTINUE	STIF	28
	DO 30 I=1,NDF	STIF	29
	DO 30 J=1,IBAND	STIF	30
30	AK(I,J)=0.DO	STIF	31
	DO 70 M=1,NM	STIF	32

ALPHAI=ALPHA(M)	STIF 33
BETAI=BETA(M)	STIF 34
S=SIN(M)	STIF 35
C=COS(M)	STIF 36
XLEN=XL(M)	STIF 37
AA(1)=ALPHAI*(BETAI*C*C+12.DO*S*S)	STIF 38
AA(2)=ALPHAI*C*S*(BETAI-12.DO)	STIF 39
AA(3)=-6.DO*S*XLEN*ALPHAI	STIF 40
AA(4)=ALPHAI*(BETAI*S*S+12.DO*C*C)	STIF 41
AA(5)=ALPHAI*6.DO*XLEN*C	STIF 42
AA(6)=ALPHAI*4.DO*XLEN*XLEN	STIF 43
AA(7)=AA(6)*0.5DO	STIF 44
DO 60 JM=1,6	STIF 45
J=MCODE(M,JM)	STIF 46
IF (J.EQ.0) GO TO 60	STIF 47
DO 50 KM=JM,6	STIF 48
K=MCODE(M,KM)	STIF 49
IF (K.EQ.0) GO TO 50	STIF 50
KB=K-J+1	STIF 51
L=INDEX(JM,KM)	STIF 52
IF (L.LT.0) GO TO 40	STIF 53
AK(J,KB)=AK(J,KB)+AA(L)	STIF 54
GO TO 50	STIF 55
40 L=-L	STIF 56
AK(J,KB)=AK(J,KB)-AA(L)	STIF 57
50 CONTINUE	STIF 58
60 CONTINUE	STIF 59
70 CONTINUE	STIF 60
RETURN	STIF 61
END	STIF 62

	SUBROUTINE SOLVE (AK,P,PIJ)	SOLV	1
C	SOLVE USES GAUSSIAN ELIMINATION TO SOLVE THE EQUILIBRIUM	SOLV	2
C	EQUATIONS AND PRINTS OUTPUT	SOLV	3
C		SOLV	4
	IMPLICIT REAL*8 (A-H,O-Z)	SOLV	5
	COMMON INC(75,2),ICON(99),NM,NJ,NEQ,IBAND,KODE,NDF,LINC	SOLV	6
	DIMENSION AK(NDF,IBAND), P(NEQ), PIJ(NDF)	SOLV	7
	IF (KODE.EQ.5) GO TO 30	SOLV	8
C		SOLV	9
C	TRIANGULARZATION OF CONSTRAINED SYSTEM STIFFNESS MATRIX	SOLV	10
	NRS=NDF-1	SOLV	11
	NR=NDF	SOLV	12
	DO 20 N=1,NRS	SOLV	13
	M=N-1	SOLV	14
	MR=NR-M	SOLV	15
	IF (IBAND.LT.MR) MR=IBAND	SOLV	16
	PIVOT=AK(N,1)	SOLV	17
	DO 20 L=2,MR	SOLV	18
	CP=AK(N,L)/PIVOT	SOLV	19
	I=M+L	SOLV	20
	J=0	SOLV	21
	DO 10 K=L,MR	SOLV	22
	J=J+1	SOLV	23
10	AK(I,J)=AK(I,J)-CP*AK(N,K)	SOLV	24
20	AK(N,L)=CP	SOLV	25
C		SOLV	26
C	REDUCTION OF THE LOAD VECTOR	SOLV	27
30	DO 40 N=1,NRS	SOLV	28
	M=N-1	SOLV	29
	MR=NR-M	SOLV	30
	IF (IBAND.LT.MR) MR=IBAND	SOLV	31
	CP=PIJ(N)	SOLV	32

	PIJ(N)=CP/AK(N,1)	SOLV	33
	DO 40 L=2,MR	SOLV	34
	I=M+L	SOLV	35
40	PIJ(I)=PIJ(I)-AK(N,L)*CP	SOLV	36
	PIJ(NR)=PIJ(NR)/AK(NR,1)	SOLV	37
C		SOLV	38
C	SOLUTION OF REDUCED SYSTEM OF EQUATIONS BY BACK SUBSTITUTION	SOLV	39
	DO 50 I=1,NRS	SOLV	40
	N=NR-I	SOLV	41
	M=N-1	SOLV	42
	MR=NR-M	SOLV	43
	IF (IBAND.LT.MR) MR=IBAND	SOLV	44
	DO 50 K=2,MR	SOLV	45
	L=M+K	SOLV	46
50	PIJ(N)=PIJ(N)-AK(N,K)*PIJ(L)	SOLV	47
C		SOLV	48
	KK=0	SOLV	49
	DO 60 J=1,NEQ	SOLV	50
	P(J)=0.DO	SOLV	51
	IF (ICON(J).EQ.1) GO TO 60	SOLV	52
	KK=KK+1	SOLV	53
	P(J)=PIJ(KK)	SOLV	54
60	CONTINUE	SOLV	55
	WRITE (6,80)	SOLV	56
	DO 70 I=1,NJ	SOLV	57
	DO 70 M=1,3	SOLV	58
	J=3*(I-1)+M	SOLV	59
	WRITE (6,90) I,M,P(J)	SOLV	60
70	CONTINUE	SOLV	61
	RETURN	SOLV	62
C		SOLV	63
80	FORMAT (//T26,27HGLOBAL JOINT DISPLACEMENTS /T31,16H(INCHES,RADIANS	SOLV	64

```
1S)//)
90  FORMAT (T2,5HJOINT,T9,I2,T13,I1,T15,9HDIRECTION,T27,D20.10)
    END
```

```
SOLV 65
SOLV 66
SOLV 67
```

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COMPARISON OF ENERGY MINIMIZATION WITH DIRECT STIFFNESS FOR LINEAR STRUCTURAL ANALYSIS

by

David Thomas Griffith

(ABSTRACT)

This study compares energy minimization with direct stiffness for linear structural analysis. The energy minimization approach locates the generalized displacement vector by minimizing the total potential energy of the structure being analyzed. From the survey of variable metric and conjugate gradient algorithms included in this study, the Davidon-Fletcher-Powell variable metric algorithm and the Fletcher-Reeves conjugate gradient algorithm were chosen to minimize the total potential energy. A description of both algorithms is presented.

The direct stiffness method assembles the equilibrium equations of the structure being analyzed. These equations are solved by Gaussian elimination to determine the generalized displacement vector.

Computer codes have been written for the energy minimization and direct stiffness methods. The comparison was based on computational effort, in terms of computer time, required for analysis. The results of this study show energy minimization is not competitive with direct stiffness for linear structural analysis. As the problem size increases by degree of freedom the direct stiffness method rapidly increases in superiority over the energy minimization method.