ARTIFICIAL NEURAL NETWORKS APPLICATION TO ALLOCATION OF RESOURCES IN FARM PLANNING

THESIS

Submitted to the Punjab Agricultural University
in partial fulfilment of the requirements
for the degree of

MASTER OF TECHNOLOGY
IN
ELECTRICAL ENGINEERING
(Minor Subject : Mathematics)

by

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1997

CERTIFICATE -I

This is to certify that the thesis entitled, **ARTIFICIAL NEURAL NETWORKS APPLICATION TO ALLOCATION OF RESOURCES IN FARM PLANNING** and submitted for the degree of M. Tech. in Electrical Engineering of Punjab Agricultural University, is a bonafide research work carried out by Manpreet Singh Bajwa under my supervision and that no part of this thesis has been submitted for any other degree.

The assistance received during course of investigation have been fully acknowledged.

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CERTIFICATE -II

This is to certify that this thesis entitled, **ARTIFICIAL NEURAL NETWORKS APPLICATION TO ALLOCATION OF RESOURCES IN FARM PLANNING** submitted by Manpreet Singh Bajwa to Punjab Agricultural University, Ludhiana in partial fulfilment of the requirements for the degree of M. Tech. in Electrical Engineering has been approved by the student's advisory committee after an oral examination on the same in collaboration with an external examiner.

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ACKNOWLEDGEMENT

I feel immense pleasure in expressing my sincere gratitude and indebtedness to my major advisor Prof. Jagmohan Singh, Professor, Deptt. of Computer Sciences and Electrical Engineering, for his able guidance, invaluable suggestions and constructive criticism which lead to the completion of this work.

I am also thankful to him, for providing computer facilities during the course of present investigation. I also greatly acknowledge his constant encouragement and ample assistance.

I extend my thanks to Dr. Dinesh Grover, Professor, Deptt. of Computer Science, & Electrical Engineering, Prof. M.S. Seekree, Professor, Deptt. of Computer Science & Electrical Engineering and Dr. Tejwant Singh ~~Gill~~, Professor and Head, Deptt. of Mathematics and Statistics as members of my advisory committee for their valuable suggestions and comments.

I am also thankful to Dr. J.S. Sohal, Head, Deptt.

of Computer Science & Electrical Engineering, for his useful suggestions and help during this work.

I am also thankful to the Er. M.S. Bhatti, Er. Salamdin, and Er. Derminder Singh for their coopertion.

I am also thankful to the staff members of Computer Centre of COAE, PAU, Ludhiana, for extending cooperation during this investigation.

I am thankful to my friends, Surinder, Ashok, Satyan, Rudra, Ravinder, Satwinder, Parveen, Gurpadam, Ramandeep, Ravijeet, Gurpreet, Gurinder, Sunraj and Nilesh for their moral support and untiring help and cooperation.

Manpreet Singh

MANPREET SINGH BAJWA

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CHAPTER 1

INTRODUCTION

1.1 Introduction

Over the last few years the artificial neural networks have invoked wide intrest of the scientific community. Artificial neural networks as the name suggests, are inspired by the human nervous system.Modern computers and algorithmic computations are very good for well defined tasks.Biological brain, on the other hand, easily solve speech and vision problems under a wide range of conditions and also have ability to refine their responses. These features, which have not been incorporated satisfactorily in digital computers, prompted the scientists to study biological nervous system to design computational systems with brain like capabilities.

Neural networks consist of large number of highly interconnected elements termed as "neurons", which function to some extent like biological neurons. Modern analog and digital integrated circuit technology is offering potential for implementing massively parallel networks of simple processing elements. Neurocomputing will enable us to take the advantage of these advances in VLSI by producing computational models necessary to program and coordinate the behaviour of thousands of processing elements. Artificial neural networks will influence every aspect of technology in the days to come.

Agriculture, the backbone of our economy, cannot be kept isolated from these developments.Especially in the new economic environment which demands best quality at competetive prices. Therefore, to be successful, the farmer must be efficient and thus optimize the utilization of the available resources and refine his decision taking process. Any attempt to bring the latest technology in this field will be highly welcome.Again,artificial neural networks are very suitable for dynamic systems which involve a high degree of uncertainty, analogous to the environment in which our farming community operates.All these factors make Artificial neural networks attractive for their application to the farm planning.

1.2 Review Of Literature

1.2.1 Development of Neural Networks:

Warren Mcculloch and Walter Pitts designed what are generally regarded as the first neural networks(Mcculloch & Pitts,1943).These researchers recognised that combining many simple neurons into neural systems was the source of increased computational power.The neurons can be arranged into a net to produce any output that can be represented as a combination of logic functions. Mcculloch and Pitts neurons are used most widely as logic circuits(Anderson & Rosenfield, 1988).

Donald Hebb, a psychologist at Mcgill university, designed the first learning law for artificial neural networks (Hebb, 1949). His premise was that if two neurons were active simultaneously, then the strength of connection between them should be increased. Refinements were subsequently made to this rather general statement to allow computer simulations(Rochester et al., 1956). Together with several other researchers (Block, 1962; Minsky & Papert, 1988), Frank Rosenblatt introduced and developed a large class of artificial neural networks called perceptron. The perceptron learning rule used an iterative weight adjustment that is more powerful than Hebb rule. In 1960 Bernard widrow developed learning rule for a single layer network, called Adaline, which is a precursor of back propagation rule for multilayer nets(Widrow & Hoff, 1960). The 1970s were quite years for neural networks development.However, the work was being carried mostly related to associative memory neural nets(Kohonen,1972; Anderson, 1968, 1972). Among the areas of applications of these nets are medical diagnosis and learning multiplication tables. Also works of Stephen Grossberg and Carpenter led to the development of theory of self organising neural networks called adaptive resonance theory (Carpenter & Grossberg, 1976, 1985, 1987, 1990). The 1980s saw the renewed enthusiasm in neural networks. The quiet years of 1970s were mainly due to lack of a general method for the training of multilayer networks.A method for propagating information about the errors at the output units back to hidden units has been discovered in the previous decade (Werbos, 1974), but had not gained wide publicity. The method was also discovered independently by David Parker (1985) and by Lecun (1986) before it became widely known.Another key player in the increased visibility of and respect for neural networks is Nobel prize winner John Hopfield of California Institute of Technology. Together with David Tank, Hofield has developed a numberof neural networks based on fixed weights and adaptive activations (Hopfield, 1982, 1984; Hopfield and Tank 1985, 1986, 1987). Kunihiko Fukushima and his colleagues at N.H.K laboratories in Tokyo have developed a series of specialised neural networks for character recognition.(Fukushima et al., 1983, 1988). A number of researchers have been involved in the development of non deterministic neural nets,that is,nets in which weights and activations are changed on the basis of a probability density function(Vecchi et al., 1983; Geman, 1984; Hinton et al., 1985; Szu et al., 1987).

Another reason for the renewed interest in the neural nets is availbility of improved computational capability. Optical neural nets (Farhat et al., 1985) and VLSI implementation (Sivilatti et al., 1987) are being developed.Several digital neurocomputers are also developed(Hecht-Nielson, 1990).

1.2.2 <u>Neural Networks For Optimization</u>:

Hopfield gave a model for a large network of neurons with graded response which was shown to have collective properties in very close correspondence to Mcculloch-

Pitts neurons(Hopfield, 1984). A neural network for a difficult but well defined problem the travelling salesman problem was presented by Hopfield and Tank(Hopfield & Tank, 1985) based upon Hopfields continous network. The further applications of this network to several problems ,which can be expressed as optimization problems are illustrated by Hopfield and Tank(Hopfield & Tank, 1985). However, earlier Boltzmann machine, a binary neural network, was used earlier to solve travelling salesman problem(Hinton et al., 1983; Aarts et al., 1989). But this problem was found to be difficult for these type of networks. Two variants of Hopfield model(wilson et al., Szu, 1988) were also applied to the optimization problems. A general framework that includes the Boltzmann machine, Hopfield net and other neural networks is known as Gaussian machine(Akiyama et al., 1989). Another network called Cauchy mahine, a modification of Boltzmann machine, is based on adding more noise to the net input to increase the likelihood of escaping from a neighbourhood of a local minimum(Szu et al., 1987).

1.2.3 Artificial neural networks in agriculture

In recent years there has been a spurt in the applications of the neural networks and agriculture is no exception.Most of the applications reported in the agriculture involve forecasting, classification or identification and control.

Related to forecasting the findings reported are on soil erosion forecasting (Cai, 1995), characterization of acquifer properties (Rizzo et al., 1994), runoff hydrograph estimation(Wang et al., 1993), predicting flowering and physiological maturity of soyabean(Elizondo et al., 1994), modelling individual tree moartality (Guan et al., 1991).

Classification and identification involved crop classification (Foody et al., 1994), locating melons (Engels et al., 1992), insect identification in flight (Moore, 1991), inspection of produce(Dect et al., 1992), recognition of chrysanthemum nodes (Davis et al., 1991), classifiers for machine vision(Deck et al.,1991), diagnosis of fruits using artificial neural networks (Hashimoto et al., 1994).

The control appliications involving artificial neural networks are related

The control application involving artificial neural networks are realted mostly to agricultural processing industry. Some of the reported applications are neural networks in dairy industry (Zhou et al., 1994), system identification and intelligent control of plant growth in hydroponics (Morimoto, 1993), simulated neural networks in machine vision research of the control engineering group (Davis, 1989),analysis of transcription control signals using artificial neural networks (Nair et al., 1995).

1.2.4 <u>Performance of artificial neural networks</u>

The performance of artificial neural networks has been compared with other available techniques in different fields. Some of the studies are enumerated here.

The neural networks achieved better interclass seperatability in the training data than discriminant analysis (Yates et al., 1994). Neural nets performed better than Bayesian classifiers for grading carrots (Howarth, 1991). The results obtained from artificial neural networks were in the close agreement with the statistical model for the performance of skidder tires in swamps (Tohmaz et al., 1995). The neural networks applied for the test scenario in optimization involving weapon to target assignment problem were found to produce best solution (Tagliarini et al., 1991).

In almost all the experiments the results obtained from artificial neural networks were in close agreement, if not better than the traditional techniques.

1.3 The Objectives Of Investigation

The study of the artificial neural networks show that they have the following prominent features.

1. Refinement of their responses
2. Ability to identify from the partial description of the object.
3. High computational power.
4. The "decision" of a particular neuron is not as a result of localized activity but is a joint decision having influence of all the neurons.
5. Are suitable for the dynamic systems involving uncertainty.
6. Ability to handle non linear functions.

These are also the properties which must also be incorporated in any decision support system related to agriculture.

This is because the environment in which the farming community operates is complicated, unpredictable and requires ingenuity on the part of farmers to make their venture successful. The artificial neural networks look promising for this application.As has been seen from the studies not much work has been done for the application of artificial neural networks to the field of the decision support systems in agriculture.This work was undertaken as an attempt to bring the aritificial neural networks to enhance the decision taking capabilities in agriculture.

The objectives of this investigation is to make use of artificial neural network for resource allocation in farm planning.The resources can be physical, financial or human.

The work consists of studying artificial neural networks, design of neural network for the resource allocation and its implementation on computer.

1.4 Organization Of Thesis

The study undertaken in this project has been arranged in the following manner.

The introduction to neural networks is given in chapter 2.

Design and Development of the model is presented in Chapter 3. Chapter 4 describes the software implementation of the neural model.

The performance is evaluated in chapter 5. The brief summary of the work done is given in chapter 6. Chapter 6 also includes the scope for the future work,which can lead to the hardware implementation of the model and develoomment of the integrated model for the decision support system for the crop management.

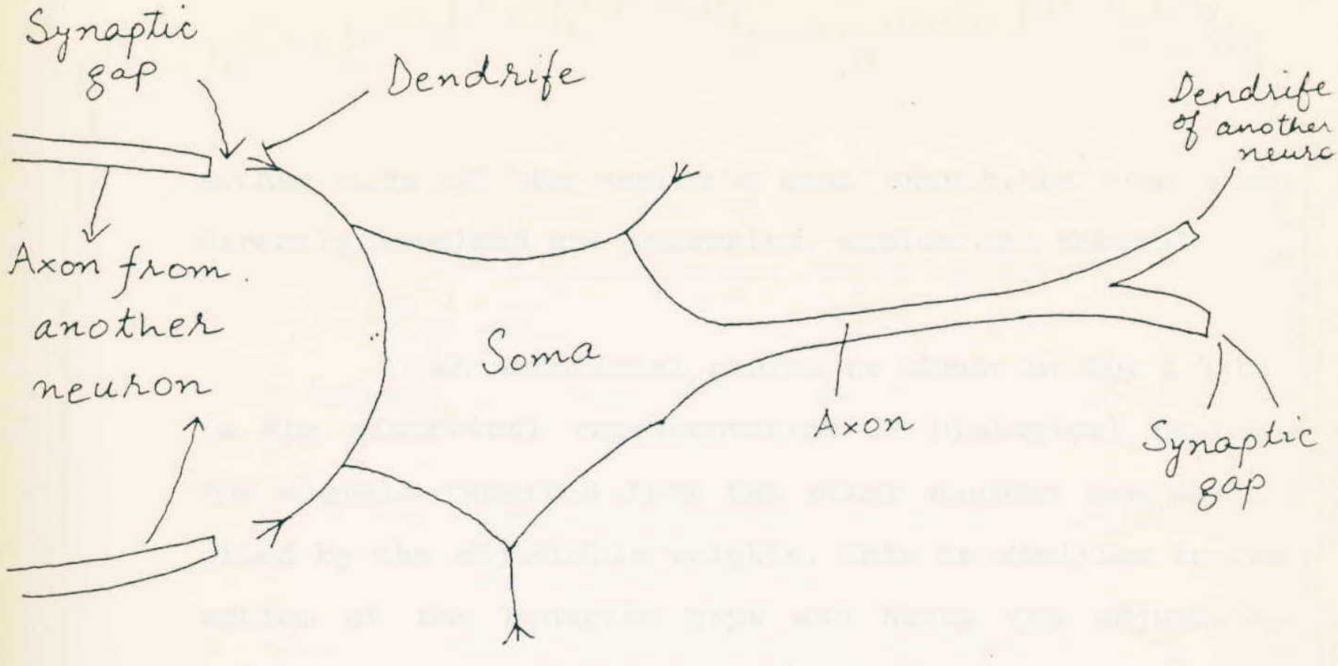
CHAPTER 2

INTRODUCTION TO THE NEURAL NETWORKS

2.1 Introduction

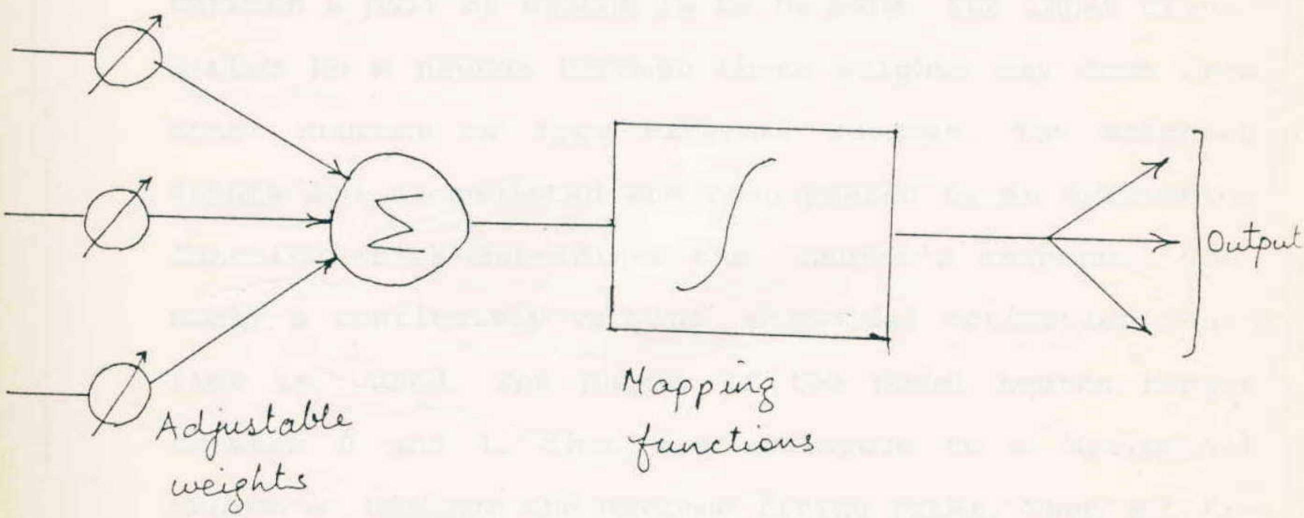
Artificial neural networks is an information processing system that has certain performance characteristics in common with the biological neural networks.

A biological neuron is shown in fig. 2.1 (a). A biological neuron has three types of components that are of particular interest in understanding an artificial neural networks. These components are dendrites, soma, axon. The dendrites receive signals from other neurons. The signals are electrical impulses that are transmitted across a synaptic gap by means of a chemical process.The action of chemical transmitter modifies the incoming signal. The soma or cell body, sums the incoming signals. When sufficient input is received, the cell fires i.e. it transmit its signal over its axon to other cells The transmission of signal from a particular neuron is accomplished by an action potential resulting from the differential concentration of ions on the



BIOLOGICAL NEURON

fig. 2.1 (a)



ARTIFICIAL NEURON

fig. 2.1(a)

either side of the neuron's axon sheath.the ions most directly involved are potassium, sodium and chloride.

An artificial neuron is shown in fig 2.1(b) is the electrical representation of biological neuron. The signals received from the other neurons are multiplied by the adjustable weights. This is similiar to the action of the synaptic gaps and hence the adjustable weights correspond to the biological synapses. For the purpose of analytical modelling it is often convenient to allow a positive weight to represent an excitatory connection and a negative weight to an inhibitory connection. A weight of zero is used when no connection between a pair of neuron is to be made. The input transmitted to a neuron through these weights may come from other neurons or from external sources. The weighted inputs are accumulated and then passed to an activation function which determines the neuron's response. Commonly a continously varying, sigmoidal activation function is used. The output of the model neuron ranges between 0 and 1, that are analogous to a biological neuron's minimum and maximum firing rates. When artificial neurons output is 0 the model neuron is said to be "off", and when its output is 1 the neuron is said to be on.

Several key features of processing elements of the artificial neural networks are summed up below.

1 The processing elements receives many signals.

2. The processing elements sums the weighted inputs.

3. The incoming signals might be modified by the weights.

4. Under appropriate circumstances (sufficient input), the neurons transmit a single signal.

5. The output from a particular neuron may be input to many other neurons.

6. Memory is distributed.

a. Long - term memory resides in the neuron weights.

b. Short term memory corresponds to the signals sent by the neurons.

7. Weights may be modified by the experience.

8. The transmitted signals may be excitatory or inhibitory.

9. Fault tolerance.

2.2 Neural Networks Application

The study of the neural networks is an extremely inter disciplinary field, both in its development and its application. A brief review of the some of the areas in which the neural networks are currently being applied suggests the breadth of their applicabilty.

2.2.1 Signal processing

There are many applications of the neural networks in the general areas of signal processing.One of the first commercial application was to suppress noise on a telephone line.The neural networks are being used for the noise suppression, data compression, speech analysis and speech synthesis. Specific networks which are available for these purposes are ADALINE, NETTALK, PHONETIC TYPEWRITER etc.

2.2.2 Control

A large number of the control applications ranging from the industrial process control to controller for backing up trailer has been developed.

2.2.3 Pattern Recognition

Many interesting problems fall in the general area of pattern recognition.Some of the important problems that are addressed by the neural networks include hand writing recognition,finger print recognition, image recognition etc.

2.2.4 Medicine

The applications in medicine ranges from developing diagnositic systems for various diseases to simulating the parts of the human brain to aid medical researchers.

2.2.5 Business

Neural networks are being applied for the number of the applications in business. These applications cover some of the complex problems remarkably well.They include predicting the behaviour of stock market ,mortgage assessment etc.

CHAPTER 3

DESIGN AND DEVELOPMENT OF THE NEURAL NETWORKS

3.1 INTRODUCTION TO PROBLEM

The problem addressed in this study is "Artificial Neural Network Application To Resource Allocation in Farm Planning".

The aim of any planning is to optimize the use of the resources for maximum gains. The majority of the resource allocation problems in the farm planning can be expressed in the above stated form, which are currently solved by the linear programming techniques.

Thus the problem has been viewed as that of maximizing the returns, subject to the availability of the resources. The objective function of the problem becomes that of maximizing the profits while limits on the resources become constraints. The resources can be physical, financial or the human resources. Since in the farm planning the most of the problems are bounded and consistent these conditions have been assumed.

3.2 Neural Networks for Optimization

Hopfield developed a continous neural network model which was shown to have computational properties similar to binary neurons. He applied it successfully to several optimization problems like travelling salesman problem, signal decision circuits etc. Earlier attempts with discontinous neural model did not yield satisfatory results. The success of the Hopfields network for these problems was due to the fact that it seeks minima for the energy function of the network. Optimization, in one way or the other, try to minimize or maximize a particular quantity or a function. As such these problems can be reduced to give objective functions resembling enegy functions of the Hopfield net. Once that is formulated the solution to the problem is guaranted. Therefore all the optimization problems are solved using Hopfield model. The same will be used for this work.

3.3 Hopfield Continuous Neural Model

Neural networks for optimization are fixed weight networks and are derived from Hopfield's continous network model. Discussed below is the theory behind the Hopfield's continous model.

Let

V_i -> output variable of neuron.

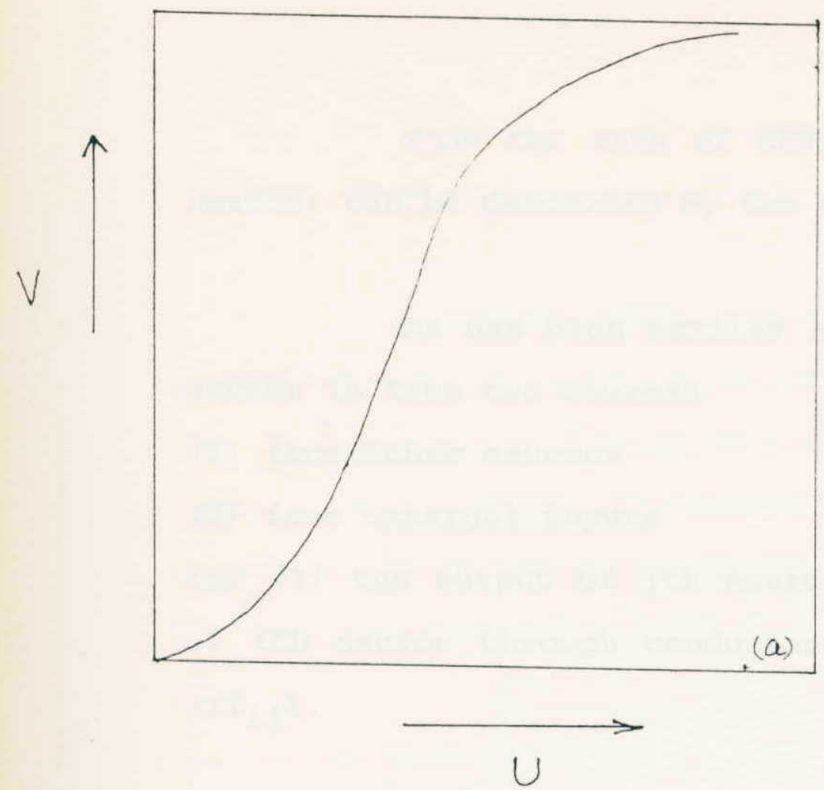
V_i has range [0,1].

and also V_i be a continous and monotonically increasing function of the instantaneous input ,U_i, to neuron i. The typical input output relationship($G_i(U_i)$) is a sigmoid with asymptotes tending to 0 and 1 as shown in fig 3.1.

For exhibiting action potentials, U_i, could be thought as the mean soma potential of a neuron from total effect of its excitatory and inhibitory inputs. V_i can be viewed as a short term average of the firing rate of cell i.

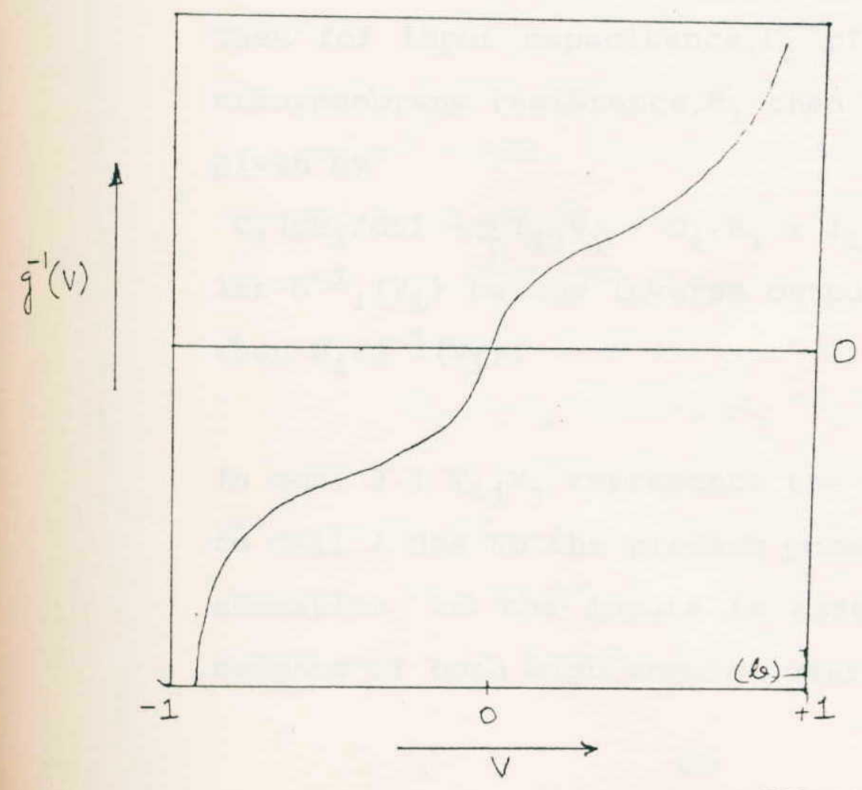
In terms of electrical circuits, $G_i(U_i)$ represents the input-output charateristics of a non linear amplifier with negligible response time.

In biological system, U_i(action potential or input of ith neuron) will lag behind V_j(output of jth neuron) of other cells because of the input capacitance C_i of the cell membranes, the transmembrane resistance R_i, and the finite impedance T_{ij} between the output V_j and the cell body of cell i.



SIGMOID INPUT-OUTPUT RELATIONSHIP FOR TYPICAL NEURON

fig. 3.1(a)



THE OUTPUT-INPUT RELATIONSHIP

$u = g^{-1}(V)$

fig (3.1(b)

Thus the rate of change of U_i (input to ith neuron) can be described by the equation derived below.

As has been earlier seen that the input to a neuron is from two sources

(1) from other neurons

(2) from external inputs

for (1) the output of jth neuron is connected to input of ith neuron through conductance T_{ij}(impedance $T'_{ij} = 1/T_{ij}$).

For (2) let I_i denotes external input to ith neuron in the form of current.

Then for input capacitance, C_i of the cell membrane and transmembrane resistance, R_i then rate of change of U_i is given by

$$C_i(dU_i/dt) = \sum_j T_{ij}V_j - U_i/R_i + I_i \quad - \qquad (3.1)$$

let $G^{-1}{}_i(V_i)$ be the inverse output-input relationship. then $U_i = G^{-1}(V_i)$.

In eqn. 3.1 $T_{ij}V_j$ represents the eletrical current input to cell i due to the present potential of cell j. Linear summation of the inputs is assumed. In neural network weights of both sign should occur.

Now eqn. 3.1 also represents the electrical circuit shown in the fig. 3.2.

Inverting amplifiers are there to provide inhibitory signals. The magnitude of T_{ij} is $1/R_{ij}$ where R_{ij} is the resistor connecting output of neuron j to the input line of neuron i, while the sign of T_{ij} is determined by the choice of the positive or negative amplifier j at the connection site.

R_i is then given by

$$1/R_i = 1/r_i + \sum_j 1/R_{ij} \text{-----} \qquad (3.2)$$

where r_i is the input resistance of amplifier i. C_i is the total input capacitance of the amplifier i and its associated leads. Output impedance of the amplifier is assumed to be negligible.With these assumptions eqn. 3.1 is also valid for the fig. 3.2.

Now consider the quantity

$$E = -1/2 \sum_i \sum_j T_{ij} V_i V_j + \sum_i (1/R_i) \int_0^{V_i} G_i'(V_i)\,dv - I_i V_i \text{----} \qquad (3.3)$$

for symmetric T(matrtix formed by T_{ij})

$$E = -1/2 \sum_i V_i [\sum_j T_{ij} V_j] + \sum_i (1/R_i) \int_0^{V_i} G'_i(V)\,dv - \sum_i I_i V_i \text{--} \qquad (3.4)$$

$$dE/dt = -\sum_i dV_i/dt (\sum_j T_{ij} V_j - U_i/R_i + I_i) \text{---} \qquad (3.5)$$

Using eqn. 3.1 in eqn. 3.5

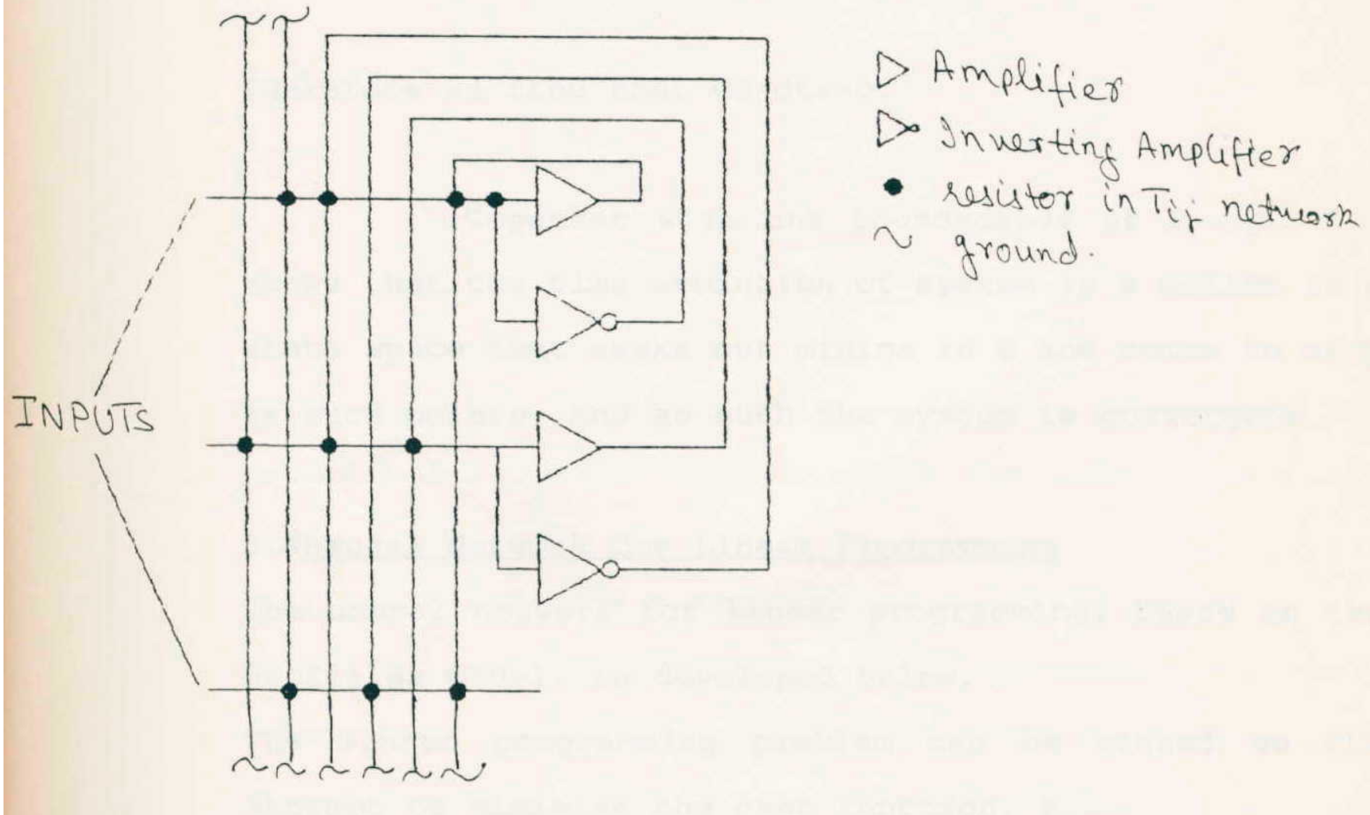

Amplifier
Inverting Amplifier
resistor in T_{ij} network
ground.
INPUTS

fig 3.2.

$$dE/dt = -\sum_i C_i (dU_i/dt)(dV_i/dt) \text{---} \tag{3.6}$$

using the derivative of $V_i = G_i\ (U_i)$ w.r.t. t

and eqn. 3.6 becomes

$$dE/dt = -\sum_i C_i G_i{}'(U_i)(dU_i/dt)^2 \text{--} \tag{3.7}$$

Since $G_i(U_i)$ are monotonically increasing function

i.e. $G'_i(U_i)>0$.

and C_i are positive, for all i and also

$(dU_i/dt)^2>=0$.

Therefore we find that $dE/dt<=0$.

Together with the boundedness of E eqn. 3.7 shows that the time evolution of system is a motion in a state space that seeks out minima in E and comes to stop at such points. And as such the system is convergent.

3.4 Neural Network for Linear Programming

The neural network for linear programming, based on the Hopfields model, is developed below.

The linear programming problem can be stated as the attempt to minimize the cost function, P.

$P = A_1V_1+.....+A_n0$

or $P = \mathbf{A.V}$

$\mathbf{A}=[A_1\ A_2.....A_n]$

$$\mathbf{V} = \begin{bmatrix} V_i \\ \\ \\ V_n \end{bmatrix}$$

A is an n dimensional vector of coefficients for n-variables which are the components of **V**.

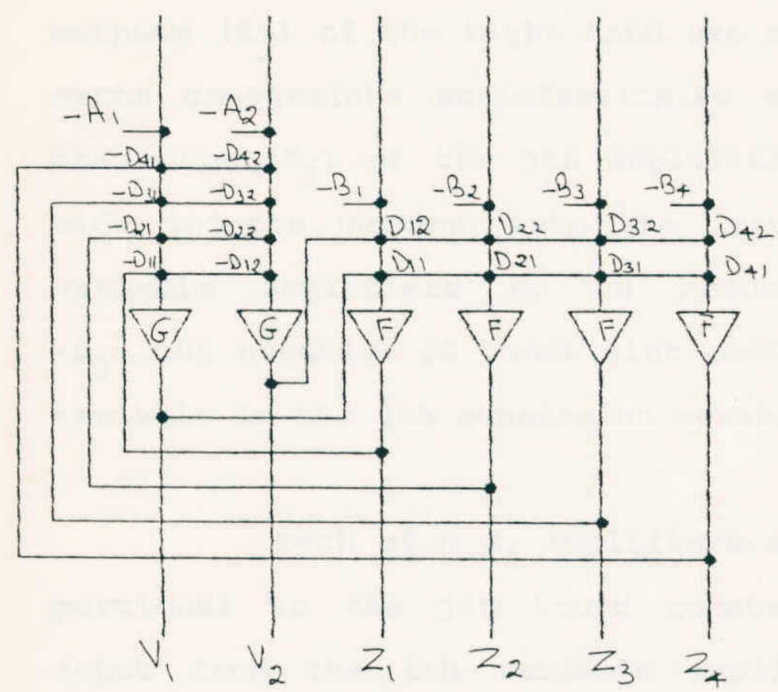
The minimization is to be accomplished subject to a set of m linear constraints among the variables.

$\mathbf{D_j}.\mathbf{V}>=\mathbf{B_j}$, $j=1.....m$.

$$\mathbf{D_j} = \begin{bmatrix} D_{ji} \\ . \\ . \\ D_{ji} \end{bmatrix}^T \qquad i=1.....N.$$

where $\mathbf{D_{ji}}$ are the coefficients in the j^{th} constraint equation and $\mathbf{B_j}$ are the bounds for the constraint equations.

Hopfield proposed a circuit shown in fig. 3.3 for the specific case of two variables and four constraints, which can be used to compute the solution of this optimization problem, by variation of the mathematical analysis done earlier.



The Organization of a network which will solve a 2-variable 4 constraint linear programming Problem.

fig. 3.3.

In the circuit of the fig. 3.3 the n outputs V_i of the left hand side of the amplifiers will represent the values of the variables in the linear programming problems. The components of **A**(A_1, A_2) are proportional to the input currents fed into these amplifiers. The m outputs (Z_j) of the right hand set of amplifiers represents constraints satisfaction. As shown in the figure the output (Z_j) of the jth amplifier on the right hand side injects current into the input lines of the V_i variable amplifiers by an amount proportional to $-D_{ji}$, the negative of constraint coefficient for the ith variable in the jth constraint equation.

Each of m Z_j amplifiers are fed current proportional to the jth bound constant (B_j) and receive input from the ith variable amplifier by an amount proportional to D_{ji}.

Each of V_i amplifier has an input capacitance C_i and input resistor r_i in parallel, which connects input to the ground. The input - output relationships of the V_i amplifiers are linearly characterised by a linear function G_i in the relationship $V_i = G(U_i)$. The Z_j amplifiers have the non linear input-output relation characterized by the function

$z_j = F(U_j)$, $U_j = \mathbf{D_j.V-B_j}$

where $F(x)=0, x>=0$

$F(x)=-x, x<0$

This function provides for large positive values of z_j when the corresponding constraint it represents is being violated.

Assuming that the response time of Z_j amplifiers is negligible as compared to the V_i amplifiers, then the circuit equation of the variable amplifiers can be written as

$$CdU_i/dt = -A_i - U_i/R - \sum_j D_{ji} F(U_j)$$

$$= \_A_i - U_i/R - \sum_j D_{ji} F(\mathbf{D_j.V}-_j)$$

-- (3.8)

Now consider an energy function of the form

$$E = (\mathbf{A.V}) + \sum_j F(\mathbf{D_j.V-B_j}) + \sum_i 1/R \int_0^{V_i} \mathbf{G^{-1}(V)\,dv}$$

then the time derivative of E is

$$dE/dt = \sum_i dV_i/dt\,[U_i/R + \mathbf{A} + \sum_j D_{ji} f(\mathbf{D_j.V-B_j})]$$

Where

$$f(x) = dF(x)/dx$$

Using the relation

$V_i = G_i\ (U_i)$ with equations (3.8 and 3.9)

$$dE/dt = -\sum_i C_i G'(U_i)(dU_i/dt)^2$$

Since C_i is positive ,$G'(U_i)$ is a positive monotone increasig function

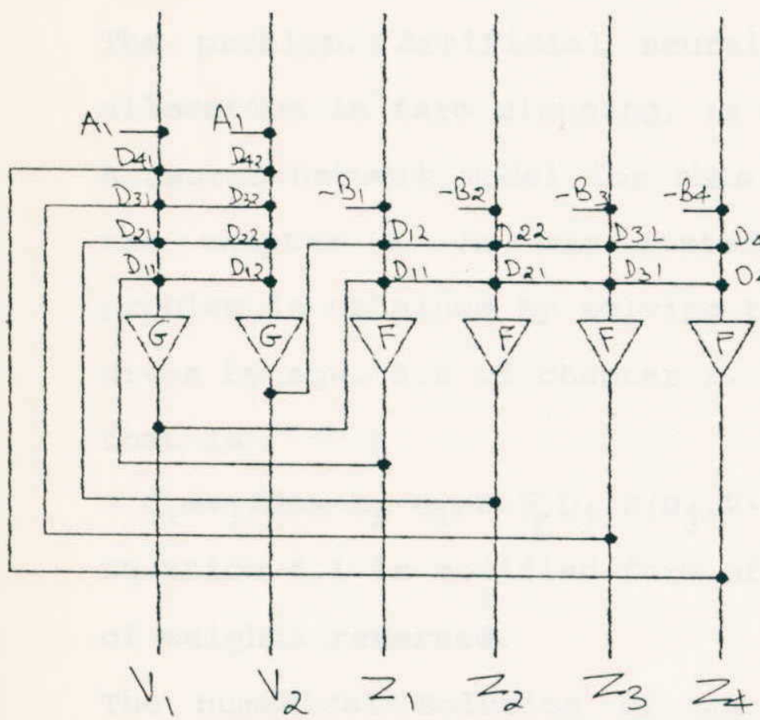
So $dE/dt <= 0$.

Thus the time evolution of the system is a motion in a state space which seeks out a minima to E and stops.

3.5 Neural Network for resource allocation in farm planning

The majority of resource allocation problems in the farm planning can be formulated as a linear programming problems.Since the aim of the planning is to maximize profits, the problem has been viewed as that of maximizing the returns subject to the availability of the resources which serve as constraints.

Since maximizing the cost function,P, is equivalent to minimizing -P, the neural network discussed in the previous section can be used for maximization problem by changing the sign of the weights and external inputs.the resultant network, shown, in the fig. 3.4 can be used for this problem.



The neural Network for optimization Maximization Problem.

fig. 3.4.

CHAPTER 4

IMPLEMENTATION

4.1 Defining The Problem

The problem, Artificial neural networks for resource allocation in farm planning, is an optimization problem. A neural network model for this problem is discussed in the chapter 3. As was stated, the solution of the problem is obtained by solving the differential equation given by eqn. 3.8 of chapter 3.

that is

$$C_i dv_i/dt = -A_i - U_i/R - \sum_j D_{ji} F(\mathbf{D_j}.\mathbf{V} - B_j) \text{ --} \quad (4.1)$$

Equation 4.1 is modified form of equation 3.1. with sign of weights reversed.

The numerical solution of the above equation can be obtained numerically by the method given below.

now,

dU_i/dt can be written as $\Delta U/\Delta t$

$\Delta U = U_{new} - U_{old}$

taking $U_{old} = U_i$.

$\Delta U = U_{new} - U_i$

therefore, $(U_{new} - U_i)/\ \Delta t \quad = -U_i/(R_i C_i) - A_i/C_i - 1/C_i \sum_j D_{ji} F(\mathbf{D_j}.\mathbf{V} - B_j)$

therefore,

$$U_{new}=[U_i(1-1/(R_iC_i))-A_i/C_i-1/C_i(\sum_j D_{ji}F(D_j.V-B_j))]dt$$

if

$1>>1/(R_iC_i)$.

then

$$U_{new}=[U_i-A_i/C_i-1/C_i\sum_j D_{ji}F(D_j.V-B_j)]dt \quad (4.2)$$

eqn. 4.2 gives the next predicted value of U_i.

These values can be mapped by the linear function as suggested by Hopfield to obtain the values of the variables V_is.Since for the physical problems the solution must lie in the first quadrant, and for this solution space the origin is the absolute minima,the mapping function must pass through the origin and should be linear.As such the mapping function so selected is

$$V_i=g*U_i \quad (4.3)$$

where g is gain.

Parameter g hastens the approach of the solution. A provision of gain varying from 1-10 is made. To meet the condition that $1>>1/(R_iC_i)$, the values of R_i and C_i must be selected accordingly. The value of R_i is taken as that predicted by (3.2) by taking internal resistance of amplifier equal to that of the operational amplifiers.While that of C_i is taken as 1.

Another important parameter is time increment, dt. Its value is important .If it is very small,the accuracy is more but time taken to reach the solution is more,while if it is large,the probability of stepping over the solution is more and the tolerance limit as such must be kept high. A trade of is made between the two extremes and thus the value of dt is so selected that contribution of coefficient of cost function is to second decimal place.

The important steps that are involved in the algorithm are

1. Read in the values of coefficients(a_is) of the cost function, P.

2. Read in the values of the coefficients(D_{ji}s) in the constraints.

3. Calculate dt.

4. Evaluate U_is from eqn.4.1.

5. Evaluate V_is from equation 4.2.

6. Evaluate the constraints violations using $z_i = D_j . V - B_j$.

7. set $z_i = -z_i$.

8. repeat steps 3-7 if the constraint violation are not within the prescribed limits else stop.

4.2 Software

The software has been divided into the series of the modules.The major steps that are performed are listed in the previous section.The main flowchart illustrating the essence of the problem is shown in fig.4.1.

The program begins by clearing all flags and arrays to zero.The important arrays that are used are

1. a[] for storing coefficients of cost function.A provision for 7 variables is made.
2. d[][] for storing coefficients and bounds for constraints. A provision for 7 constraints is made.
3. V[] for values of variables.
4. z[] for storing constraint violations.

The various functions written for this software are given below :

4.2.1 : Function INTLZ ()

This function clears all the arrays and flags to zero. The flow chart for this function is shown in Fig. 4.2. After this function, we read the number of variables, n, and constraints, m.

4.2.2. : Function COEFFS() :

This function reads in the coefficients of the cost function. The flow chart for this function is shown in Fig. 4.3.

4.2.3 : Function COEFFSD() :

This function reads in the coefficients and bounds of the constraints. The flow chart is shown in Fig. 4.4.

4.2.4 : Function CALDT() :

This function calculates the value of time increment dt. The flow chart for this function is shown in Fig. 4.5.

4.2.5. Function CALT() :

This function calculates the values of U_i and V_i. The flow chart for this function is shown in Fig. 4.6.

4.2.6. Function CALZ() :

This function calculates for constraint violation. The steps are illustrated in flow chart shown in Fig. 4.7.

Finally the check for termination condition is done in the main program.It is seen that if the constraint violations are within the prescribed limit, the program is termiated.The limit can be varied.In this case the tolerance limit is set to .1.

4.2.7. User Interface :

To facilitate the user a user friendly screen procesing is done. This interface provides the folowing facilities.

1. Seperate windows for entering the number of variables and constraints, coefficients of objective functions, coefficients and bounds for constraints, and results.

2. Editing functions, which includes facility to edit already entered values.

3. Error messages for illegal entries.

4.2.8 Programing language :

The entire software has been developed in C-language. C offers following advantages :

1. Convenience of programing.
2. Well structured.
3. Generates fast codes.
4. Easy to understand and maintain.
5. Easy portability.
6. Close control over hardware.

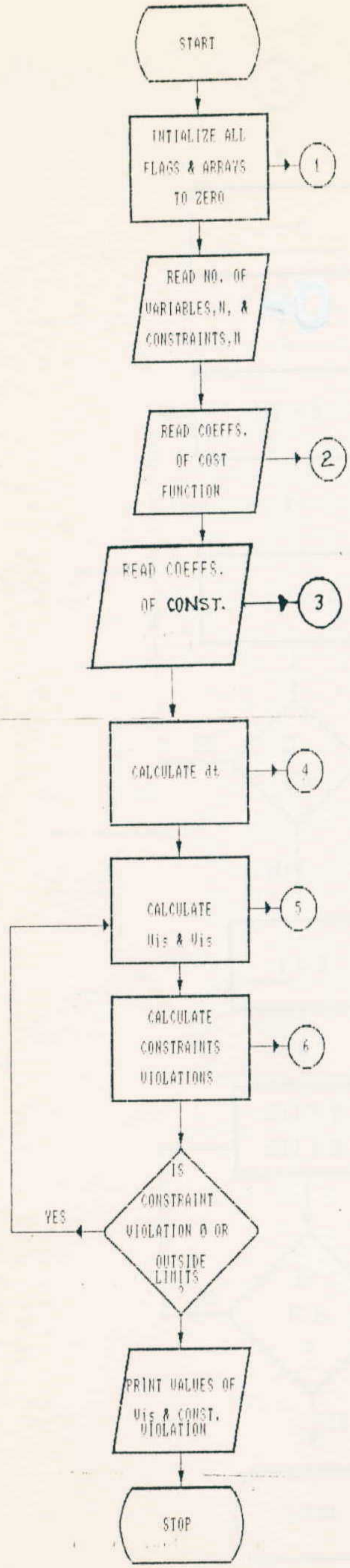


FIG. 4.1 MAIN FLOW CHART

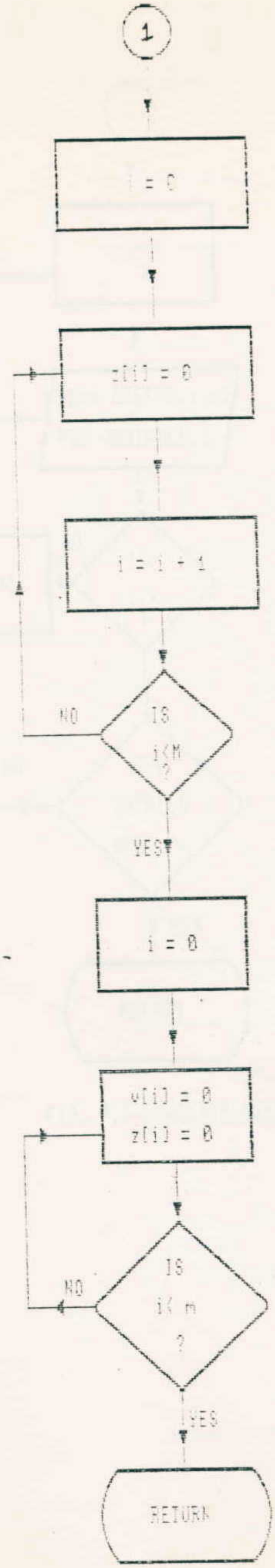


FIG 4.2 FUNCTION INTLZ()

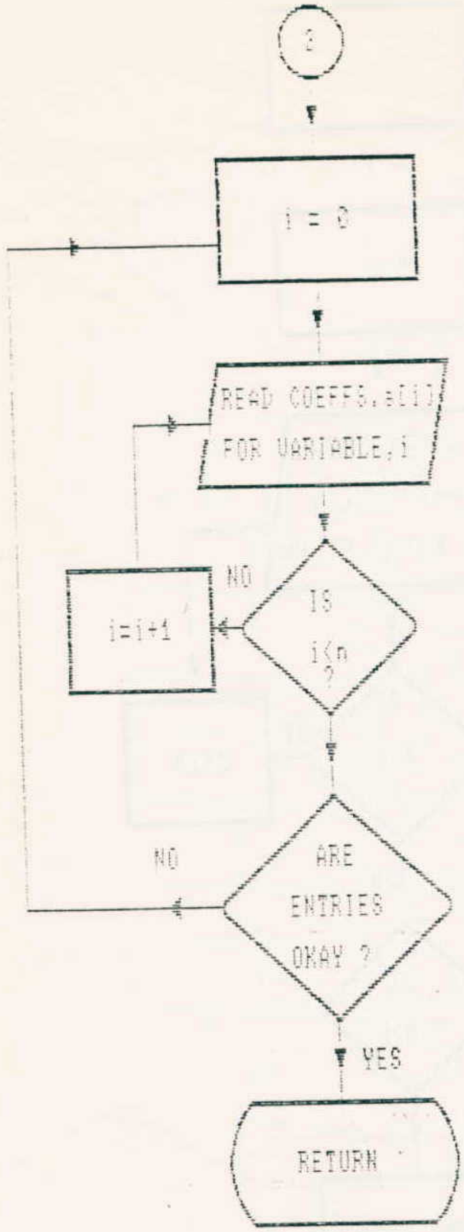


FIG. 4.3 FUNCTION COEFFS()

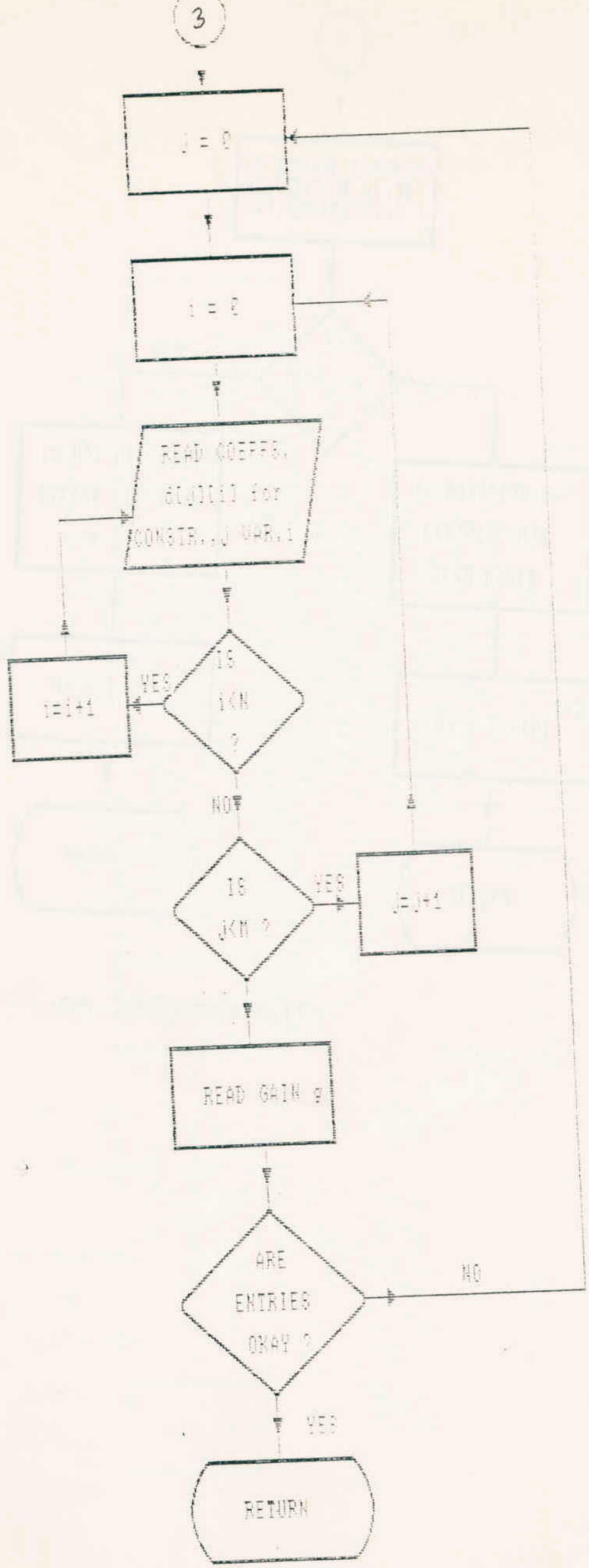


FIG. 4.4 FUNCTION COEFFSD()

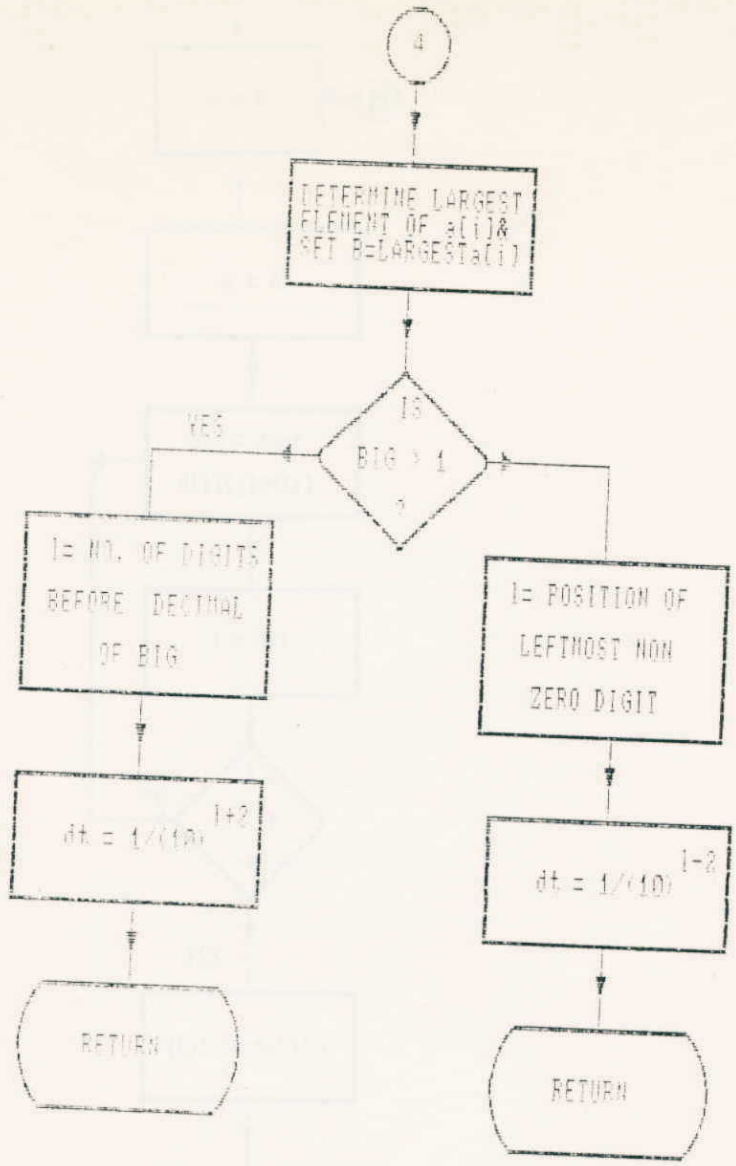
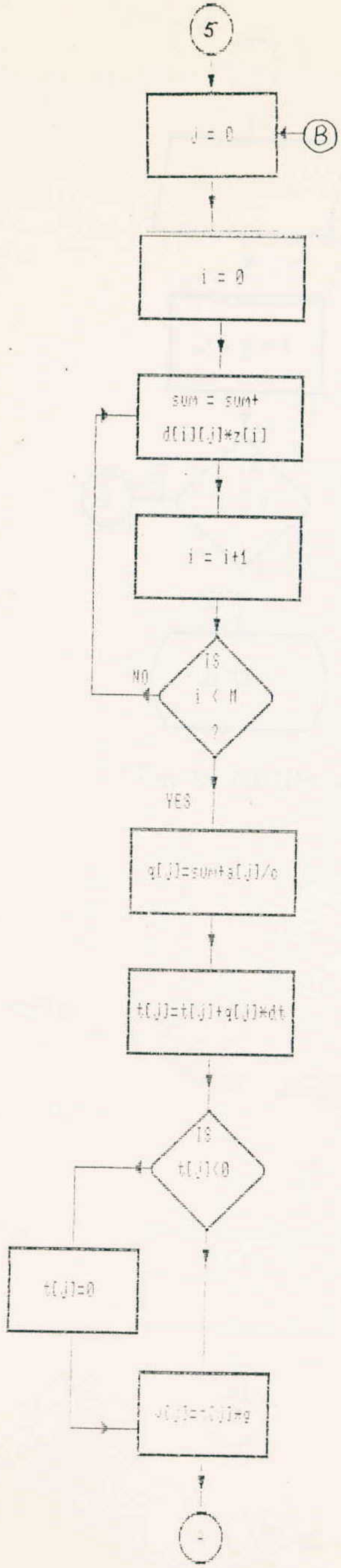


FIG. 4.5 FUNCTION CALDT()


5
j = 0
B
i = 0
sum = sum+
d[i][j]*z[i]
i = i+1
IS
i < M
?
NO
YES
q[j]=sum+s[j]/c
t[j]=t[j]+q[j]*dt
IS
t[j]<0
t[j]=0
-

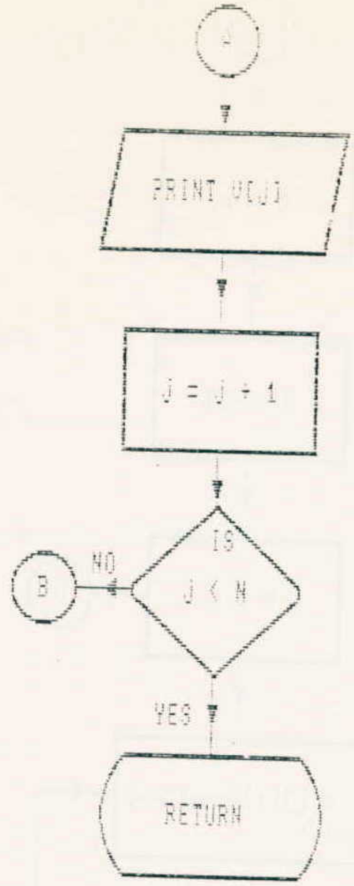
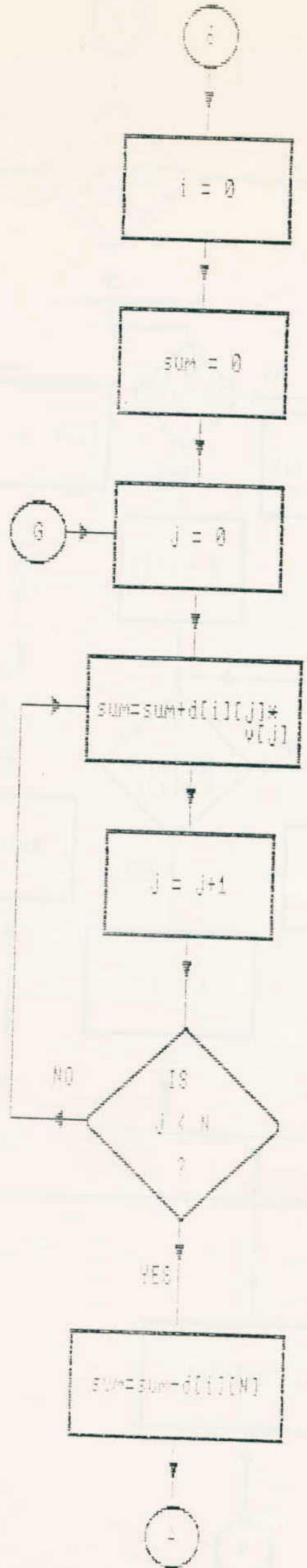
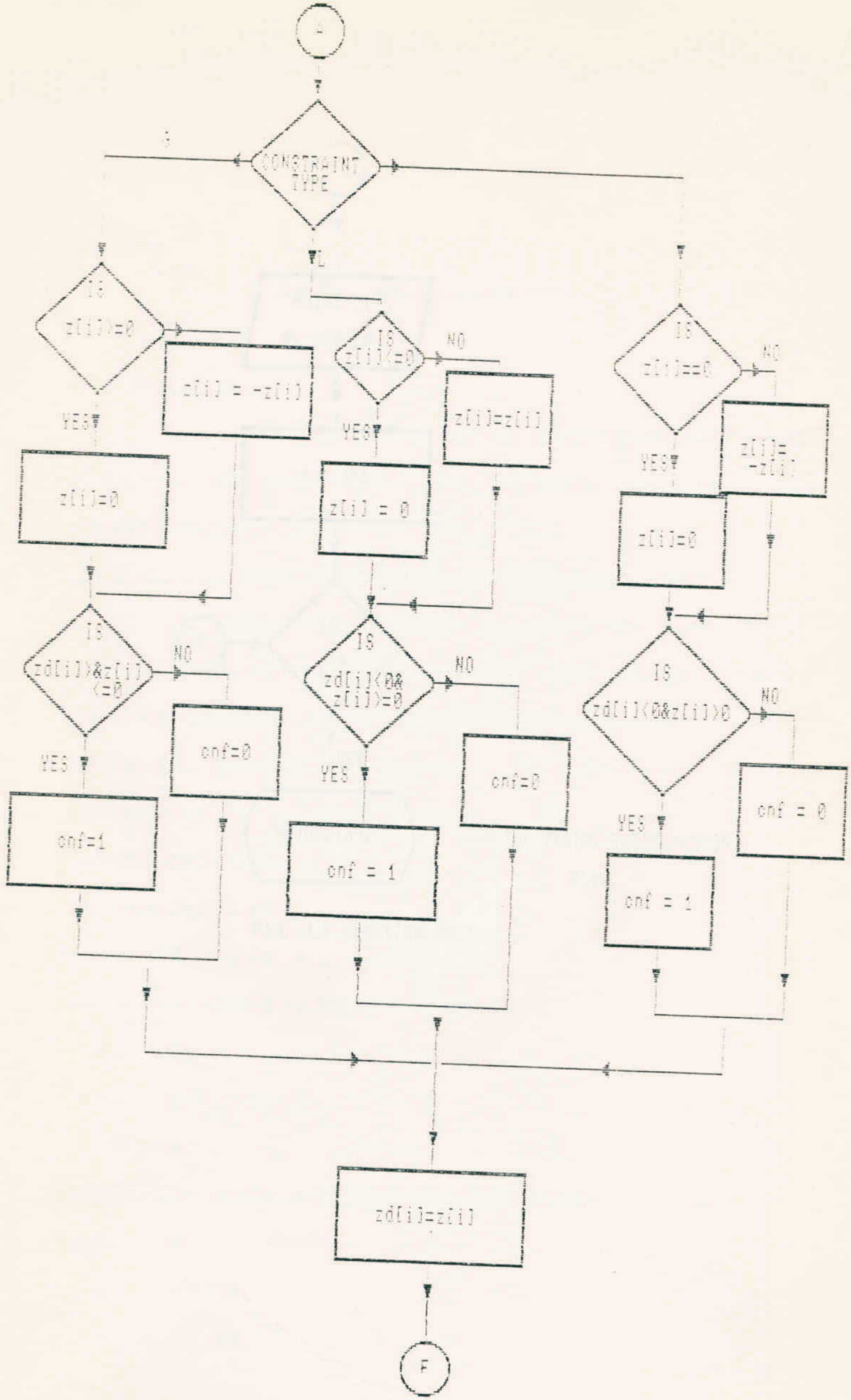


FIG. 4.6 FUNCTION CALT()


i = 0
sum = 0
G
j = 0
sum=sum+d[i][j]*
v[j]
j = j+1
NO
IS
j < N
?
YES
sum=sum-d[i][N]


A
CONSTRAINT TYPE
IS z[i]>=0
YES
z[i]=0
z[i] = -z[i]
IS z[i]<=0
NO
YES
z[i] = 0
z[i]=z[i]
IS z[i]==0
NO
YES
z[i]=0
z[i]= -z[i]
IS zd[i]>&z[i] <=0
NO
YES
cnf=1
cnf=0
IS zd[i]<0& z[i]>=0
NO
YES
cnf = 1
cnf=0
IS zd[i]<0&z[i]>0
NO
YES
cnf = 1
cnf = 0
zd[i]=z[i]
F

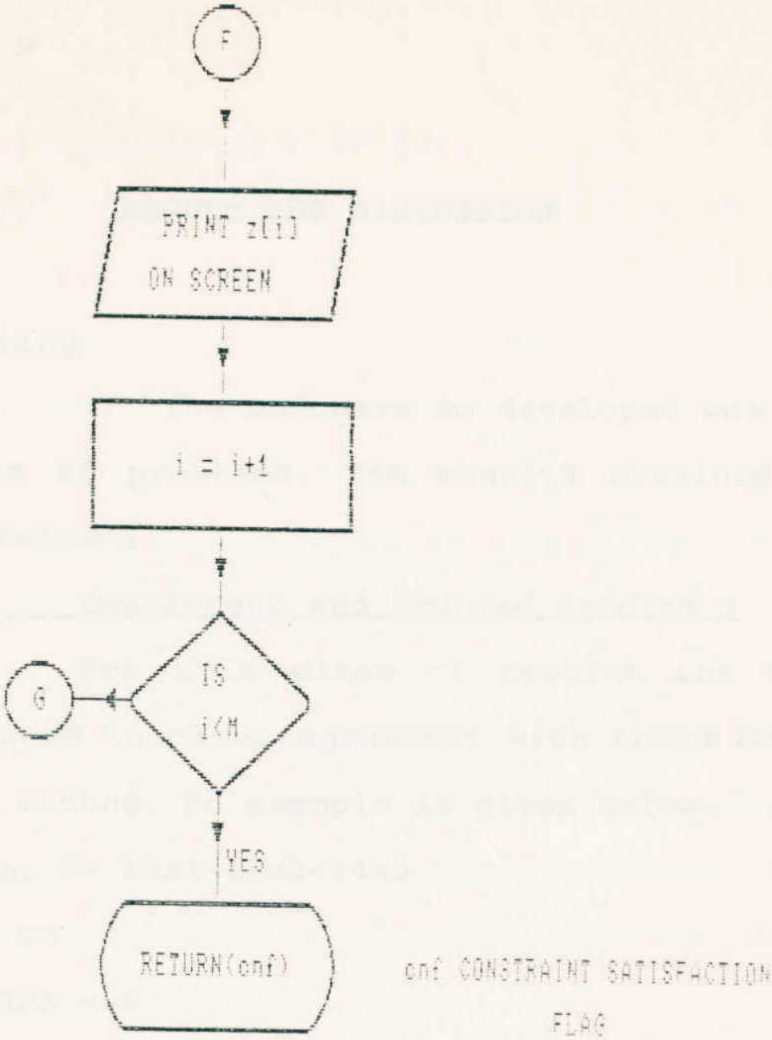


FIG. 4.7 FUNCTION CALZ()

CHAPTER 5

RESULT AND DISCUSSION

5.1 Testing

The software so developed was tested for a number of problems. The results obtained are discussed below :

5.1.1. Consistent and bounded problem :

For this class of problem the results obtained were in close agreement with those obtained from simplex method. An example is given below.

Maximize, Z= 12x1+15x2+14x3

subject to

-x1+x2+0x3 <=0

0x1-x2+2x3 <=0

x1+x2+x3 <=100

solution using simplex method

x1 = 40

x2 = 40

x3 = 20

solutions obtained by this software

gain = 1

x1 = 40.02

x2 = 40.03

x3 = 20.02

number of iterations = 10,039

gain = 10

x1 = 40.00

x2 = 40.02

x3 = 19.99

number of iterations = 1401

The solutions obtained are in the close agreement with those from the simplex method.

5.1.2. Two phase method problem :

The problem solved by two phase method in linear programing, did not give consistant results when solved by the single layer neural network. An example is given below :

Maximize

Z = -2x1-3x2=2x3+x4-x5.

Subject to constraints

3x1-3x2+4x3+2x4-x5 = 0

x1+x2+x3+3x4+x5 = 2

Results by two phase method

x1=x2=x3=0, x4=0.4, x5=0.8

Results by neural network

Number of iterations = 284

x1=x2=x3=0

$x4=0.48$, $x5=0.16$

For this type of problems, it is suggested to use two layer network. The first layer to minimize infeasibility form and second layer to minimize or maximize the give objective function.

5.1.3 Problems with unbounded solution

A typical example of this problem is

Maximize $Z=5z1+4x2$

Subject to constraints

$x1-2x2 <=1$

$x1+2x2 >=3$

5.1.4 Problems with no solution

For these porblems the neural networks outputs were continuously varying. Example is

$Z = 3x1+2x2$

Subjected to constraints

$-2x1+3x2 <= 9$

$3x1-2x2 < -20$

To evolve a method for the elimination of problems mention in section 5.1.3 & 5.1.4 by neural networks it is suggested that the behaviour of neural network for these types of problems should be future studied.

The software so developed is general, and could be applied for the problems which are bounded and consistent.

CHAPTER 6

CONCLUSION

6.1 Summary

Artificial neural network marks the latest break through in the field of computer science. Due to its similarity with the functioning of the human brain, it offers the advantage of learning,operating in the uncertain environment and handling non linear functions.These features make it attractive for applications to such biological systems as agriculture.

The objective of this project was to develop the artificial neural network based software for resource allocation in the farm planning.

The problem of the resource allocation in the farm planning was viewed as that of maximizing the profits subjected to the availability of the resources.

The software was developed in turbo-C environment.

It was tested for the number of problems .The results obtained were in the close agreement with those obtained from the simplex method.

6.2 Suggestions For The Further Scope of Work

1. Hopfield based model can be implementd using hardware.As such this work can form basis for the development of small handheld type computer for farmer.

2.The problem can be extended for the unbounded and inconsistent conditions.

3.Further work can be done for assignment and trasportation problem in farm planning.

6.3 Conclusion

Artificial neural network based model for resource allocation in farm planning is developed.The results obtained were satisfactory.

LITERATURE CITED

Abu-Mostafa, Y.S., and St Jacques, J.M., "Information capacity of the Hopfield Model, " IEEE Transaction on Informaation Theory, IT-31, 1989, pp. 461-464.

Ackley, D.H., Hinton, G.E., and Sejnowski, T.J., "A Learning Algorithm for Boltzmann Machines," Coginitive science, 9, 1985, pp. 638-649.

Anderson, J.A., "A Memory Storage Model Utilizing Spatial Correlation functions, " Cybernetics, 5, 1968, pp. 113-119.

Anderson, J.A., "A Simple Neural Network Generating an Interactive Memory, "Mathematical Biosciences, 14, 1972, pp. 197-220.

Anderson, J.A., and Rosenfield, E., Neurocomputing: Foundations of Research, Cambridge, MA : MIT Press.

Beightler, C.S., Phillips, D.T., and Wilde, D.J., Foundations of Optimization 2nd ed. Englewood Cliffs, NJ: Prentice Hall, 1979.

Block, H.D., "The Perceptron : A Model for Brain Functioning, 1, " Reviews of Modern Physics, 34, 1962, pp. 123-135.

Cai, Y., "Artificial Neural Network Method for Soil Erosion Forecasting, " Bondenkultur, 1995, pp. 19-24.

Carpenter, G.A., and Grossberg,S., "Category Learning and Adaptive Pattern Recognition, a Neural Network Model," Proceedings of the Third Army Conference on Applied Mathematics and Computation,ARO Report 86-1, 1985, pp. 37-56.

Carpenter, G.A., and Grossberg, S., "A Massively Parallel Architecture for a self-Organizing Neural Pattern Recognition Machine," Computer Vision , Graphics, and Image Processing, 37:54, 1987a, pp. 54-115.

Carpenter, G.A., and Grossberg, S., "ART2 : Self-Oranization of Stable Category Recognition Codes for Analog Input Patterns, " Applied Optics, 26, 1987b, pp. 4919-4930.

Carpenter, G.A., and Grossberg, S., "ART3 : Hierarchical Search Using Chemical Transmitters in Self organizing Pattern Recognition Architectures ," Neural Networks, 1990, 3(4), pp. 129-152.

Cater, J.P., " Successfully Using Peak Learning Rates of 10 (and greater) in Backpropagation Networks with the Heuristic learning Algorithm, " IEEE First International Conference on Neural Networks, San Diego, CA, 1987, pp. 645-652.

Davis, P., "Orientation - independent Recognition of Chrysanthemum nodes by an Artificial Neural Network," Computers and Electronics in Agriculture, 5:4, pp. 305-314.

Davis, P.F., "Development and Applications of Simulated Neural Networks in the Machine Vision Research of the control engineering Group Of IER," Divisional Note AERC-Institute of Enginering Research, No. DN1546, 18pp.

Deck, S., Morrow, C.T., and Sommer, H.J., "Neural Network for Automated Inspection Of Produce," ASAE , No. 92-3594, 14 pp.

Deck, S., Morrow, C.T., Heinmann, P.H., and Sommer, H.S., "Neural Network Versus Traditional Classifiers for

Machine Vision Inspection," ASAE, No. 91-3502, 14pp.

Elizondo, D.A., Mcclendon, R.W., and Hoggenboom, G., "Neural Network Model for Predicting Flowering and Physiological Maturity of Soyabean", Transactions Of ASAE, 37:3, 1994, pp. 981-988.

Engel, B.A., Benady, M., and Zhuang, X., " Locating Melons using Artificial Neural Networks ," ASAE , No. 92-7014, 11 pp.

Farhat, N.H., Psaltis, D., Prata, A., and Paek, E., "Optical implementation of the Hoplield Model," Applied Optics, 24, 1985, pp. 1469-1475.

Foody, G.M., Mccullouch, M.B., and Yates, W.B., "Crop classification from C-Band Polarmetric Radar Data", International Journal of Remote Sensing, 15:14, 1994, pp. 1871-2885.

Fukushima, K., "Cognitron: A self Organizing Multilayer network, " Biological Cybernitics, 29(3/4) pp. 121-136.

Fukushima, K., " Neocognitron: A Hierarchial Neural Network Model Capable of Visiual Pattern Recognition," Neural Networks, 1(2), 1988, pp. 119-130.

Fukushima, K., Miyake, S., and Ito, T., "Necognitron: A Neural Network Model for a Mechanism of the Visual Pattern Recognition," IEEE Transtions on Systems, Man, and Cybernetics, 13, 1983, pp. 826-834.

Geman, S., and Geman, D., "Stochastic Relaxation, Gibbs Distributions, and the Bayesian Restoration of Images," IEEE Transtions on Pattern Analysis and Machine Intelligence, PAMI-6, 1984, pp. 721-741.

Grossberg, S., "Embedding Fields : A Theory of Learning with Physiological Implications," Journal Of Mathematical Psychology, 6, 1969, pp. 209-239.

Grossberg, S., " Adaptive Pattern Classification and Universal Recoding, 1 : Parallel Development and Coding of Neural Feature Detectors, " Biological Cybernetics, 23, 1976, pp. 121-134.

Grossberg, S., "How does a brain builds a coginitive code?," Psychological Review, 87,1980, pp. 1-51.

Grossberg, S., Studies of Man and Brain ,Boston : Reidel, 1982.

Grossberg, S., "The Adaptive Brain, 1 : Cognition Learning, Reinforcement, and Rhythm, and 2 : Vision, Speech, Language and Motor Control, Amsterdam : North-Holland, 1987-1988.

Guan, B.T., and Gertner, G., "Using a Perallel Distributed Processing Systems TO Model Individual Tree Mortality, " Forest-Science, 37:3, PP. 871-885.

Hashimoto, Y.,Hatou, K., and Morimoto, T., " Diagnosis of Fruits using Artificial Neural Network," Proceedings 5th Int. Congress for Computer Technology in Agriculture, 1994, pp. 102-104.

Hebb, D.O., The Organization Of Behaviour, New York : John Wiley and Sons, 1949.

Hoppfield, J.J., "Neural Networks and Physical Systems with Emergent Collective Computational Abilities," Proceedings of the National Academy of Sciences, 79, 1982, pp. 2554-2558.

Hopfield, J.J., "Neurons with Graded Response have Collective Computational Properties like those of Two -state Neurons," Proceedings of the National Academy of Sciences, 81, 1984, pp. 3088-3092.

Hopfield, J.J., and Tank, D.W., "Neural Computations of Decisions in Optimization Problems," Biological Cybernetics, 52, 1985, pp. 141-152.

Hopfield, J.J., and Tank, D.W., "Computing with the Neural Circuits," Science, 233, 1986, pp. 625-633.

Howarth, M.S., and Searchy, S.W., "Comparison of Bayesian and Neural Networks Classifiers for Grading Carrots," ASAE, no. 91-7012, 14 pp.

Kirpatrick, S., Gelatt, C.D., and Vecchi, M.P., "Optimization by Simulated annealing, " Science, 220, 1983, pp.671-680.

Kohonen, T., "Correlation Matrix Memories," IEEE Transtions on Computers, C-21, 1972, pp. 174-180.

Le Cun, Boser, Y.B., Denker, J.S., Henderson, D., Howard, R.E., Hubbard, W., and Jackel, L.D., "Handwritten

Digit Recognition with a Backpropagation network," 1990.

Moore, A., "Artificial Neural Network Trained to Identify Mosquitoes in Flight," Journal of Insect Behaviour, 4:3, 1991, pp. 391-396.

Mcculloch, W.S., and Pitts, W., "A Logical Calculas of the Idea Immanent in Nervous Activity," Bulletion Of Mathematical Biophysics, 1943, 5, pp. 115-133.

Morimoto, T., "System Identification and Intelligent Control of Plant Growth in Hydroponics," Memoirs of the College of Agriculture , Ehine-University, Japan, 38:1, 1-33.

Nair, T.M., Tambe, S.S., and Kulkarni, B.D., "Analysis of Transcription Control Signal Using ANNs," Computer applications in Biosciences, 11:3, pp. 93-300.

Parker, D., Learning Logic, Technical Report TR-87, Cambridge, MA : Centre for Computational Research in Economics and Management Sciences, MIT, 1985.

Rizzo, D., and Doughetry, D., "Charaterization of Aquifer Properties Using Artificial Neural Networks," Water

Resources Research,1994, 30:2, pp. 483-497.

Rochester, N., Holland, J.H., Haibt, L.H., and Duda, W.L., "Tests on a Cell Assembly Theory Of the Action of The Brain , Using a Large Digital Computer," IRE Transactions on information Theory, IT-2, 1956, pp. 80-93.

Sivilatti, M.A., Mahomald, M.A., and Mead, C.,A., "Real Time Visual Computations Using Analog CMOS processing Arrays," Proceedings of the 1987 Stanford Conference, pp. 295-312.

Szu, H.H., "Fast TSP Algorithm Based on Binary Neuron Output and Analog Neuron Input Using Diagonal Interconnect Matrix and Necessary and Sufficient Constraints of the Permutations Matrix," IEEE International conference on Neural networks, San Diego, CA, 1988, pp. 259-265.

Szu, H.H. and Hartley, R., "Fast Simulated Annealing," Physics Letters A, 122(3,4), 1987, pp. 157-162.

Werbos, P., Beyond Regression : New Tools for Prediction and Analysis in the Behavioural Sciences (Ph.D Thesis), Cambridge, 1974.

Tagliarni, G.A., Christ, J.F., and Page, E.W., "Optimization Using Neural Networks," IEEE Trans. on Computers, vol. 40, No. 12, 1991, pp. 1347-1358.

Tohmaz, A.S., and Hassan, A.E., "Performance Of Skidder Tires in Swamps - Comparison Between Statistical and Neural Network Models," ASAE, 38:5, 1995, pp. 545-1551.

Wang, M., Heatole, C.D., and Hijelmfelt, A.T., "Runoff Hydrograph Estimation Using Artificial Neural Networks," Proceedings of ASAE, 1993, pp. 315-320.

Widrow, B., and Hoff, M.E., "30 Years of the Adaptive Neural Networks : Perceptron, Madaline , and Backpropagation," Proceedings of IEEE ,78(9),1990, pp. 1415-1442.

Zhou, W., Tuck, D.L., Norback, J.P., and Hourigan, J.A., "Artificial Neural Networks in the Dairy Industry," Australian Journal of Dairy Technology, 49:2, pp. 110-124.