FUNCTION APPROXIMATION USING BACK PROPAGATION ALGORITHM IN ARTIFICIAL NEURAL NETWORKS

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENTS FOR THE DEGREE OF

Bachelor of Technology

In

Electrical Engineering

By

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CERTIFICATE

This is to certify that the thesis entitled, **"FUNCTION APPROXIMATION USING BACK PROPAGATION ALGORITHM IN ARTIFICIAL NEURAL NETWORKS"** submitted by Mr. Gaurav Uday Chaudhari, Mr. V. Manohar, Mr. Biswajit Mohanty in partial fulfillment of the requirements of the award of Bachelor of Technology Degree in Electrical Engineering at the National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by them under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university / institute for the award of any Degree or Diploma.

Date:

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A C K N O W L E D G E M E N T

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C O N T E N T S

A B S T R A C T

Inspired by biological neural networks, Artificial neural networks are massively parallel computing systems consisting of a large number of simple processors with many interconnections. They have input connections which are summed together to determine the strength of their output, which is the result of the sum being fed into an activation function. Based on architecture ANNs can be feed forward network or feedback networks. Most common family of feed-forward networks, called multilayer perceptron, neurons are organized into layers that have unidirectional connections between them. These connections are directed (from the input to the output layer) and have weights assigned to them.

The principle of ANN is applied for approximating a function where they learn a function by looking at examples of this function. Here the internal weights in the ANN are slowly adjusted so as to produce the same output as in the examples. Performance is improved over time by iteratively updating the weights in the network. The hope is that when the ANN is shown a new set of input variables, it will give a correct output.

To train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back-propagation algorithm is the most widely used method for determining EW.

We have started our program for a fixed structure network. It’s a 4 layer network with 1 input, 2 hidden and 1 output layers. No of nodes in input layer is 9 and output layer is 1. Hidden layer nodes are fixed at 4 and 3. The learning rate is taken as 0.07. We have written the program in MAT LAB and got the output of the network. The graph is plotted taking no of iteration and mean square error as parameter. The converging rate of error is very good.

Then we moved to a network with all its parameter varying. We have written the program in VISUAL C++ with no. of hidden layer, no of nodes in each hidden layer, learning rate all varying. The converging plots for different structure by varying the variables are taken.

Chapter 1

ADAPTIVE SYSTEMS

INTRODUCTION

LINEAR& NONLINEAR MODELS

INTRODUCTION

ADAPTIVE SYSTEMS

In the recent years engineers are motivated to design adaptive systems which give a better performance amidst changing environment and system requirements. The adaptive systems (Fig 1.1) provide an optimal and robust solution when the system is subjected to a process called *learning*. The main advantage of the adaptive systems over the non-adaptive schemes lies in their self adjusting and time varying capabilities. Thus we find the application of adaptive systems in a range of applications like prediction, function approximation, system identification (modelling), adaptive equalization of digital channels and interference cancellation. In most cases the system is modelled using a linear FIR filter (tapped delay line referred to as TDL) or a nonlinear filter (say, neural networks, fuzzy logics or a combination of both).

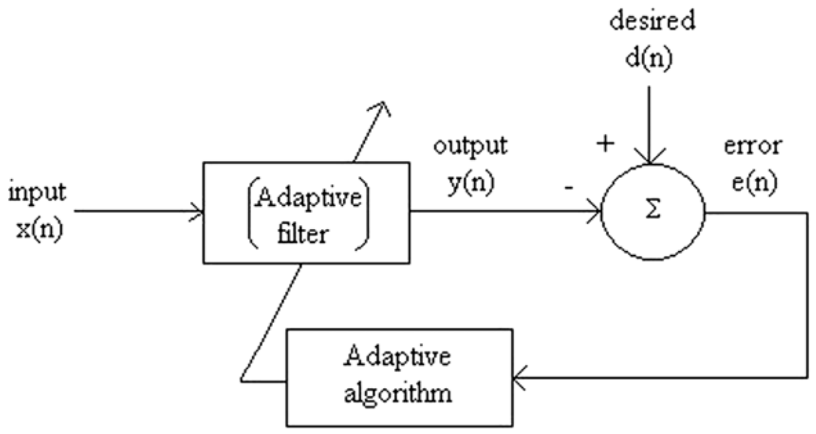


Fig. 1.1: Adaptive system

In each case the parameters of the adaptive filter are initialized to small random values and updated iteratively using an adaptive algorithm. The learning may be supervised (training data is known) or unsupervised (training data is not present). The learning process involves the minimization of a cost function with respect to the parameters of the adaptive filter. The cost function E is chosen to be the mean squared difference between the target value (desired output) $d(n)$ and the adaptive filter output $y(n)$. The learning may be facilitated by choosing an appropriate adaptive algorithm. Various adaptive algorithms like the least mean square (LMS) algorithm, recursive least squares (RLS) or the Kalman filter algorithm may be applied for learning. For instance the LMS algorithm provides robust performance by iteratively minimizing the mean square error in the direction opposite to the gradient of the cost function with respect to the parameters $w_i(n)$ of a TDL filter (see Fig.1.2). This can be expressed as

$$E = \sum_{n=1}^{P} e^2(n) \tag{1.1}$$

where the error over P ensembles of a training data set is given by

$$e(n) = d(n) - y(n) \tag{1.2}$$

If the output of the adaptive filter is given as

$$y(n) = \sum_i w_i(n) * x(n-i) \tag{1.3}$$

then the parameters $w_i(n)$ are updated using a learning rate η as

$$w_i(n+1) = w_i(n) - \eta * \frac{\partial E}{\partial w_i(n)} \tag{1.4}$$

LINEAR FILTER:

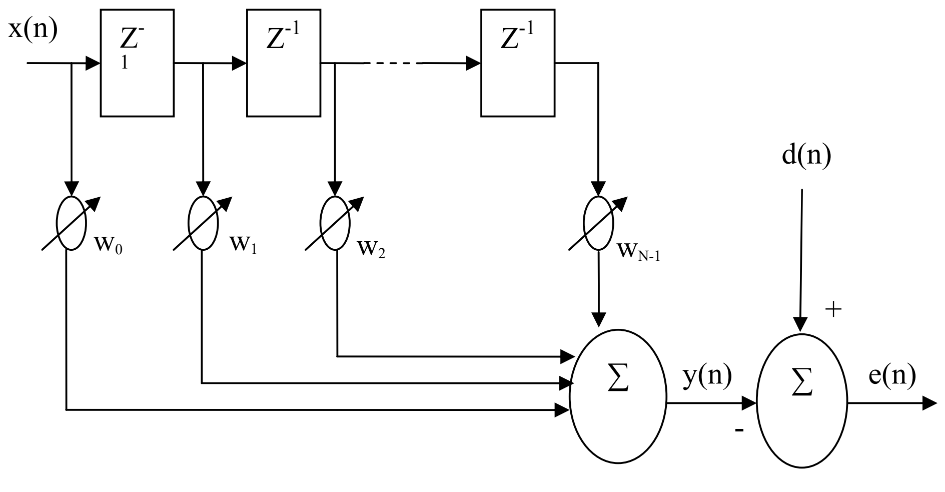


Fig 1.2: Tapped Delay Line Filter

LINEAR& NON-LINEAR MODELS

The models may be classified as linear or nonlinear depending on the architecture. Linear systems are modelled on the tapped delay line filter. They are the simplest structures that can be realized. They require least computational complexity and training period. But such systems can never approach the optimal performance since they can at the best provide a linear classification of the received data. This may be compensated by increasing the filter length and employing a nonlinear cost function as the criterion. In most cases it has been observed that an increase in the filter length (or order) enhances the additive white Gaussian noise.

This leads to the definition of an optimal performance since nonlinear process involving the construction of a nonlinear decision boundary between the received data points (channel states) belonging to the various classes of data symbols used in transmission. Thus an optimal model operates with the least number of misclassifications. Due to the above said drawbacks of the linear models we used here the nonlinear models (ARTIFICIAL NEURAL NETWORKS, ANN) for our function approximation problem.

Chapter 2

ARTIFICIAL NEURAL NETWORKS

INTRODUCTION

ARTIFICIAL NEURAL NETWORKS

Numerous advances have been made in developing intelligent systems, some inspired by biological neural networks. Researchers from many scientific disciplines are designing artificial neural networks (ANN) to solve a variety of problems in pattern recognition, function approximation, prediction, optimization, associative memory, and control.

Conventional approaches have been proposed for solving these problems. Although successful applications can be found in certain well-constrained environments, none is flexible enough to perform well outside its domain. ANNs provide exciting alternatives, and many applications could benefit from using them.

We discuss the motivations behind the development of *ANNs* , describe the basic biological neuron and the artificial computational model, outline network architectures and learning processes, and present some of the most commonly used ANN models. We conclude with function approximation a successful ANN application.

WHY ARTIFICIAL NEURAL NETWORKS?

The long course of evolution has given the human brain many desirable characteristics that are not present in Von Neumann system or in modern parallel computers. These include

- massive parallelism,
- distributed representation and computation,
- learning ability,
- generalization ability,
- adaptivity,
- inherent contextual information processing,
- fault tolerance, and
- low energy consumption.

It is hoped that devices based on biological neural networks will possess some of these desirable characteristics.

Modern digital computers outperform humans in the domain of numeric computation and related symbol manipulation. However, humans can effortlessly solve complex perceptual problems (like recognizing a man in a crowd from a mere glimpse of his face) at such a high speed and extent as to dwarf the world's fastest computer. Why is there such a remarkable difference in their performance? The biological neural system architecture is completely different from the von Neumann architecture. This difference significantly affects the type of functions each computational model can best perform.

Numerous efforts to develop "intelligent" programs based on von Neumann's centralized architecture have not resulted in general-purpose intelligent programs. Inspired by biological neural networks, ANNs are massively parallel computing systems consisting of an extremely large number of simple processors with many interconnections. ANN models attempt to use some "organizational" principles believed to be used in the human brain.

Modelling a biological nervous system using ANNs can also increase our understanding of biological functions. State-of-the-art computer hardware technology (such as VLSI and optical) has made this modelling feasible.

A thorough study of ANNs requires knowledge of neurophysiology, cognitive science/psychology, physics (statistical mechanics), control theory, computer science, artificial intelligence, statistics/mathematics, pattern recognition, computer vision, parallel processing, and hardware (digital/analog/VLSI/optical). New developments in these disciplines continuously nourish the field. On the other hand, ANNs also provide an impetus to these disciplines in the form of new tools and representations. This symbiosis is necessary for the vitality of neural network research. Communications among these disciplines ought to be encouraged.

HISTORICAL OVERVIEW

ANN research has experienced three periods of extensive activity. The first peak in the 1940s was due to McCulloch and Pitts' pioneering work. The second occurred in the 1960s with Rosenblatt's perceptron convergence theorem and Minsky and Papert's work showing the limitations of a simple perceptron. Minsky and Papert's results dampened the enthusiasm of most researchers, especially those in the computer science community. The resulting lull in neural network research lasted almost 20 years. Since the early 1980s, ANNs have received considerable renewed interest. The major developments behind this resurgence include Hopfield's energy approach in 1982 and the back-propagation learning algorithm for multilayer perceptrons (multilayer feed forward networks) first proposed by Werbos, reinvented several times, and then popularized by Rumelhart et aL in 1986. Anderson and Rosenfeld provide a detailed historical account of ANN developments.

BIOLOGICAL NUERAL NETWORKS

A *neuron* (or nerve cell) is a special biological cell that processes information. It is composed of a cell body, and two types of out-reaching tree-like branches: the *axon* and the *dendrites.* The cell body has a nucleus that contains information about hereditary traits and plasma that holds the molecular equipment for producing material needed by the neuron. A neuron receives signals (impulses) from other neurons through its dendrites (receivers) and transmits signals generated by its cell body along the axon (transmitter), which eventually branches into strands and sub strands. At the terminals of these strands are the *synapses.* A synapse is an elementary structure and functional unit between two neurons (an axon strand of one neuron and a dendrite of another), When the impulse reaches the synapse's terminal, certain chemicals called neurotransmitters are released. The neurotransmitters diffuse across the synaptic gap, to enhance or inhibit, depending on the type of the synapse, the receptor neuron's own tendency to emit electrical impulses. The synapse's effectiveness can be adjusted by the signals passing through it so that the synapses can *learn* from the activities in which they participate. This dependence on history acts as a memory, which is possibly responsible for human memory.

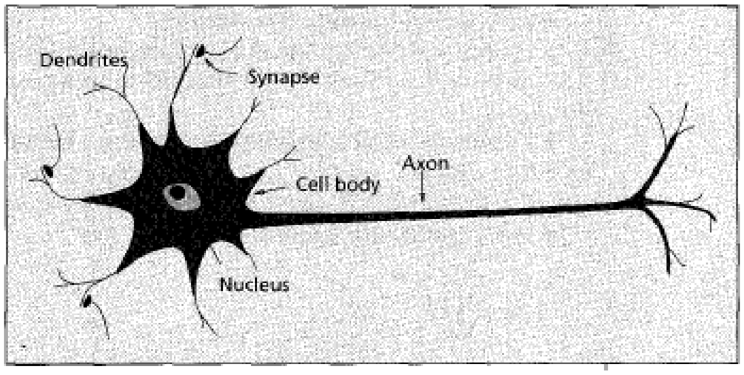


Fig 2.1: A SKETCH OF BIOLOGICAL NEURON

The cerebral cortex in humans is a large flat sheet of neurons about 2 to **3** millimeters thick with a surface area of about 2,200 cm^2, about twice the area of a standard computer keyboard. The cerebral cortex contains about 10^{11} neurons, which is approximately the number of stars in the Milky Way. Neurons are massively connected, much more complex and dense than telephone networks. Each neuron is connected to 10^3 to 10^4 other neurons. In total, the human brain contains approximately 10^{14} to 10^{15} interconnections.

Neurons communicate through a very short train of pulses, typically milliseconds in duration. The *message* is modulated on the pulse-transmission frequency. This frequency can vary from a few to several hundred hertz, which is a million times slower than the fastest switching speed in electronic circuits. However, complex perceptual decisions such as face recognition are typically made by humans within a few hundred milliseconds. These decisions are made by a network of neurons whose operational speed is only a few milliseconds. This implies that the computations cannot take more than about 100 serial stages. In other words, the brain runs parallel programs that are about 100 steps long for such perceptual tasks. This is known as the *hundred step rule.* The same timing considerations show that the amount of information sent from one neuron to another must be very small (a few bits). This implies that critical information is not transmitted directly, but captured and distributed in the interconnections-hence the name, *connectionist* model, used to describe *ANNs.*

ARTIFICIAL NEURAL NETWORKS

Artificial neurons are similar to their biological counterparts. They have input connections which are summed together to determine the strength of their output, which is the result of the sum being fed into an activation function. Though many activation functions exist, the most common is the sigmoid activation function, which outputs a number between 0 (for low input values) and 1 (for high input values). The resultant of this function is then passed as the input to other neurons through more connections, each of which are weighted. These weights determine the behaviour of the network.

In the human brain the neurons are connected in a seemingly random order and send impulses asynchronously. If we wanted to model a brain this might be the way to organize an ANN, but since we primarily want to create a function approximator, ANNs are usually not organized like this.

When we create ANNs, the neurons are usually ordered in layers with connections going between the layers. The first layer contains the input neurons and the last layer contains the output neurons. These input and output neurons represent the input and output variables of the function that we want to approximate. Between the input and the output layer a number of hidden layers exist and the connections (and weights) to and from these hidden layers determine how well the ANN performs. When an ANN is learning to approximate a function, it is shown examples of how the function works and the internal weights in the ANN are slowly adjusted so as to produce the same output as in the examples. The hope is that when the ANN is shown a new set of input variables, it will give a correct output. Therefore, if an ANN is expected to learn to spot tumours in an X-ray image, it will be shown many X-ray images containing tumours, and many X-ray images containing healthy tissues. After a period of training with these images, the weights in the ANN should hopefully contain information which will allow it to positively identify tumours in X-ray images that it has not seen during the training.

Chapter 3

STRUCTURE OF ANN

NETWORK ARCHITECTURE

MULTILAYER PERCEPTRONS

STRUCTURE OF A NEURON

NETWORK ARCHITECTURE

Based on the connection pattern (architecture), ANNs can be grouped into two categories:

1. *feed-forward* networks, in which graphs have no loops, and

2. *Recurrent* (or *feedback)* networks, in which loops occur because of feedback connections.

In the most common family of feed-forward networks, called multilayer perceptron, neurons are organized into layers that have unidirectional connections between them.

Different connectivities yield different network behaviours. Generally speaking, feed-forward networks are *static,* that is, they produce only one set of output values rather than a sequence of values from a given input. Feed forward networks are memory-less in the sense that their response to an input is independent of the previous network state. Recurrent, or feedback, networks, on the other hand, are dynamic systems. When a new input pattern is presented, the neuron outputs are computed. Because of the feedback paths, the inputs to each neuron are then modified, which leads the network to enter a new state.

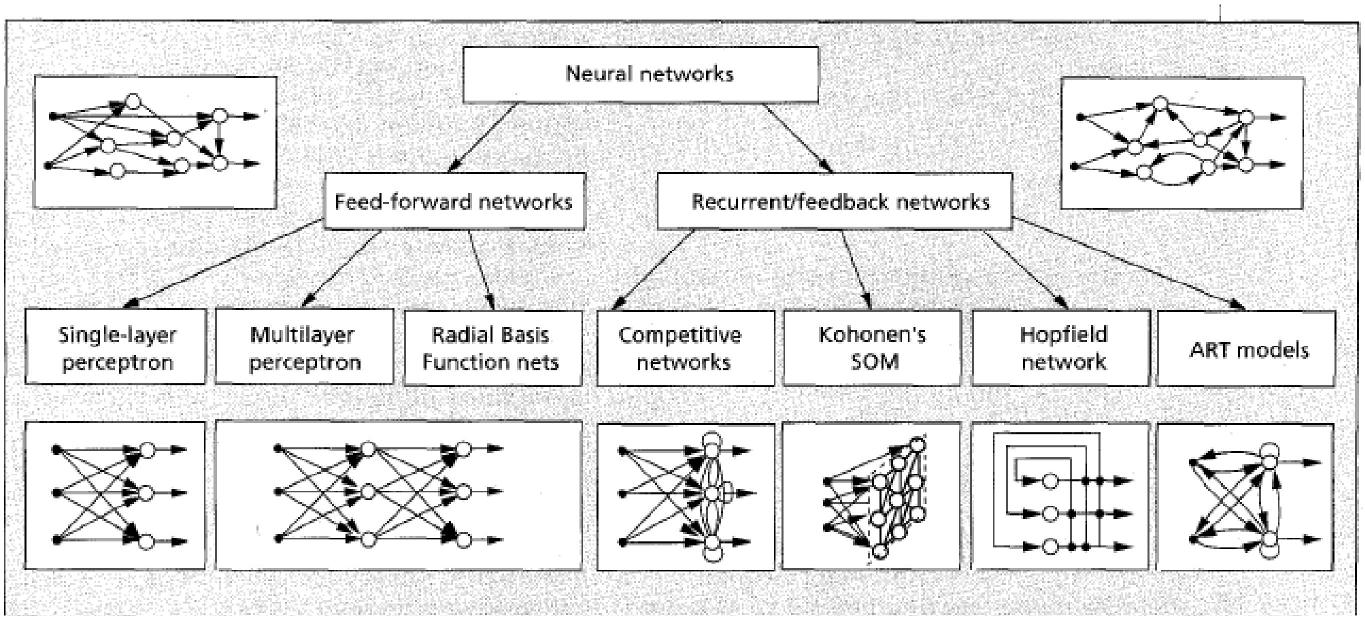


Fig 3.1: A taxonomy of feed-forward and feedback network architectures

MULTILAYER PERCEPTRONS

MLPs consist of a number of neurons (or perceptrons) that have inputs and generate an output using nonlinearity. Neurons in a MLP can be categorized into input neurons, output neurons and neurons that are neither of the two – so called hidden neurons. An MLP network is grouped in layers of neurons, i.e. input layer, output layer and hidden layers of neurons that can be seen as groups of parallel processing units. Each neuron of a layer is connected with all neurons of the following layer. These connections are directed (from the input to the output layer) and have weights assigned to. The operation of a MLP can be divided into two phases:

1. The training phase: Here the MLP is trained for its specific purpose using learning algorithms (e.g. Back propagation training).

2. The retrieve phase: The previously trained MLPs are used to generate outputs.

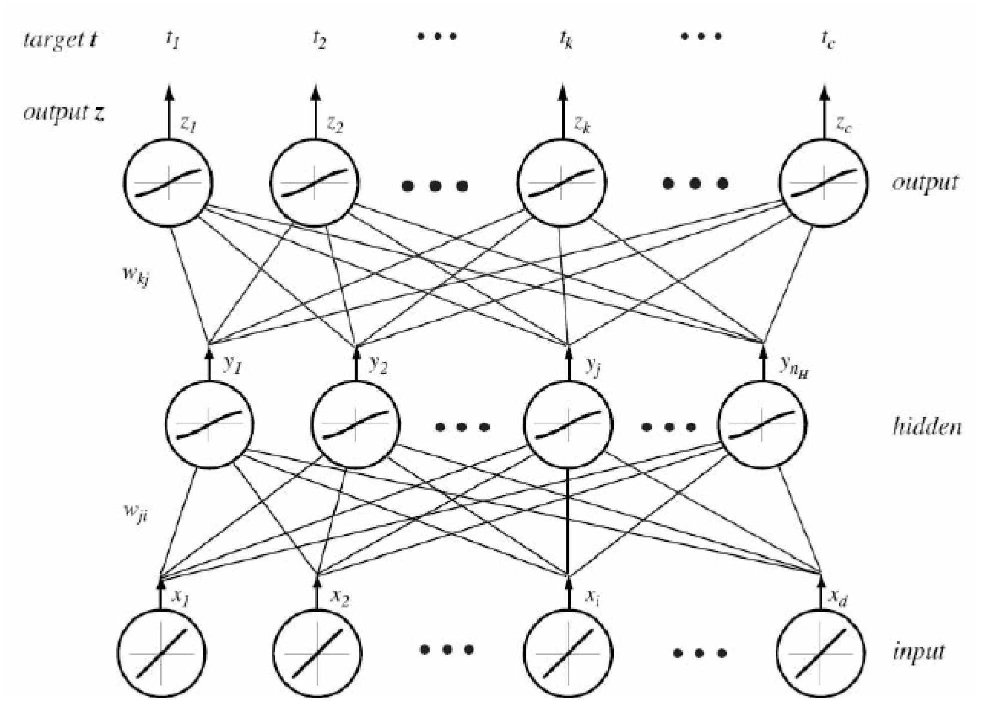


Fig 3.2: A structure of MLP

STRUCTURE OF A NEURON

A neuron *n* has a number of inputs and one output, the so called activation state of the neuron. The activation states of the *R* neurons *p(1)...p(R)* from the previous layer that are connected to *n* are multiplied with their respective weights *w(1),...,w(R)* and then summed up by the neuron in order to generate the neural input.

$$ni = \sum_{i=1}^{R} p(i) \cdot w(i) \qquad (3.1)$$

To the neural input a bias value *b* is added. The output of the neuron *is* determined using the transfer function *T*. This transfer function is usually sigmoid. Typical transfer functions are tangents, hyperboles and the logistic function:

$$T(x) = \tanh(x) \qquad (3.2)$$

$$T(x) = \frac{1}{1+e^{-x}} \qquad (3.3)$$

The output *no* of the neuron is defined as

$$no = T(ni + b) \qquad (3.4)$$

The values *w (1)... w(R)* of the connection weights and the bias *b* are determined during the training phase and used in the retrieve phase. For a supervised learning approach for control purposes, building the respective learning algorithm into hardware is not necessary. The training data is generated by numerically or analytically solving the control task. For this study we will be focusing on networks that are trained by software simulation.

Chapter 4

BACK PROPAGATION ALGORITHM

LEARNING

The ability to learn is a fundamental trait of intelligence. Although a precise definition of learning is difficult to formulate, a learning process in the ANN context can be viewed as the problem of updating network architecture and connection weights so that a network can efficiently perform a specific task. The network usually must learn the connection weights from available training patterns. Performance is improved over time by iteratively updating the weights in the network. ANNs' ability to automatically *learn from examples* makes them attractive and exciting. Instead of following a set of *rules* specified by human experts, ANNs appear to learn underlying rules (like input-output relationships) from the given collection of representative examples. This is one of the major advantages of neural networks over traditional expert systems.

To understand or design a learning process, you must first have a model of the environment in which a neural network operates, that is, you must know what information is available to the network. We refer to this model as a learning paradigm. Second, you must understand how network weights are updated, that is, which *learning rules* govern the updating process.

A *learning algorithm* refers to a procedure in which learning rules are used for adjusting the weights. There are three main learning paradigms: supervised, unsupervised, and hybrid. In supervised learning, or learning with a “teacher,” the network is provided with a correct answer (output) for every input pattern. Weights are determined to allow the network to produce answers as close as possible to the known correct answers. Reinforcement learning is a variant of supervised learning in which the network is provided with only a critique on the correctness of network outputs, not the correct answers themselves. In contrast, unsupervised learning, or learning without a teacher, does not require a correct answer associated with each input pattern in the training data set. It explores the underlying structure in the data, or correlations between patterns in the data, and organizes patterns into categories from these correlations. Hybrid learning combines supervised and unsupervised learning.

THE BACK PROPAGATION ALGORITHM

To train a neural network to perform some task, we must adjust the weights of each unit in such a way that the error between the desired output and the actual output is reduced. This process requires that the neural network compute the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is increased or decreased slightly. The back-propagation algorithm is the most widely used method for determining EW.

Algorithm:

1. Initialize the weights to small random values
2. Randomly choose an input pattern $x^{(u)}$.
3. Propagate the signal forward through the network.
4. Compute δ_i^l in the output layer ($o_i = y_i^l$).

$$\delta_i^L = g'(h_i^L)\left[d_i^u - y_i^L\right], \qquad (4.1)$$

where h_i^l represents the net input to the ith unit in the Ith
layer, and g' is the derivative of the activation function g.
5. Compute the deltas for the preceding layers by propagating the errors backwards;

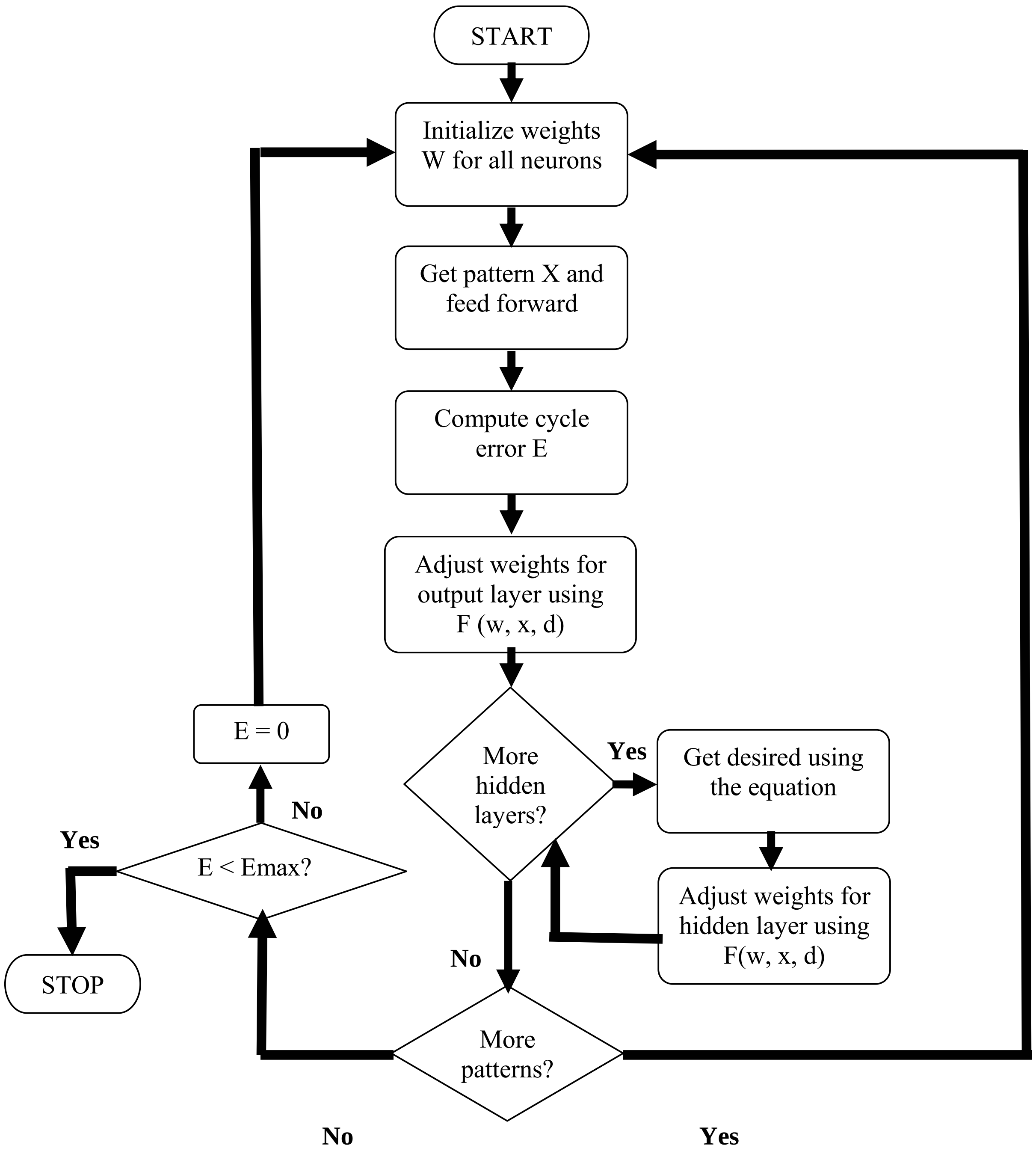
$$\delta_i^l = g'(h_i^l)\sum_j w_{ij}^{l+1}\,\delta_j^{l-1}, \qquad (4.2)$$

6. Update weights using

$$\Delta w_{ji}^l = \eta\,\delta_i^l\,y_j^{l-1} \qquad (4.3)$$

7. Go to step 2 and repeat for the next pattern until the error in the output layer is below a prespecified threshold or a maximum number of iterations is reached.

FLOW CHART:


START
Initialize weights W for all neurons
Get pattern X and feed forward
Compute cycle error E
Adjust weights for output layer using F (w, x, d)
More hidden layers?
Yes
Get desired using the equation
Adjust weights for hidden layer using F(w, x, d)
No
More patterns?
No
Yes
E < Emax?
No
Yes
E = 0
STOP

DATA FLOW DESIGN

Many data flow designs for neural networks have been developed for various purposes with varied successes, such as that for the committee machine. We report our design in this paper and omit a full review of them. For distributed computation, the network training procedure has to be deconstructed such that each neuron can be trained separately. A back-propagation algorithm trains network layer by layer doing forward and backward computations. According to the algorithm the updation formulas are

Forward computation

$$y_j^1 = \sigma\left(\sum_{i=0}^{m_0} w_{ji}^1 x_i + b_j^1\right) \qquad (4.4)$$

for the $j'th$ neuron of the first layer,

$$y_j^l = \sigma\left(\sum_{i=0}^{m_{l-1}} w_{ji}^l y_i^{l-1} + b_j^l\right), \{l = 2 \ldots L\} \qquad (4.5)$$

for the $j'th$ neuron of the $l'th$ layer;

Backward computation

$$\delta_j^L = (d_j^L - y_j^L)(y_j^L)' \qquad (4.6)$$

for the $j'th$ neuron of the output layer,

$$\delta_j^l = (y_j^l)' \sum_i^{m_{l+1}} \delta_i^{l+1} w_{ij}^{l+1}, \{l = 1 \ldots L\} \qquad (4.7)$$

for the $j'th$ neuron of the $l'th$ hidden layer,

$$w_{ji}^l = w_{ji}^l + \Delta w_{ji}^l = w_{ji}^l + \eta \delta_j^l y_i^{l-1} \qquad (4.8)$$

updation equation.

In the above equations w denotes the weight between two neurons. d is the desired response. x is the input. y denotes the neuron's output. σ is the active function. η is a tunable learning rate. l denotes the number of layer, where 1 denotes the first hidden layer and L is the output layer. i or j denote the number of neuron in each layer. So, y^l_j is the output of the j'th neuron in the l'th hidden layer, w^l_{ji} is the weight between the j'th neuron in the l'th layer and the I'th neuron in the (l − 1)'th layer. B^l_j is the j'th neuron's bias. d^l_j is the desired response of the j'th neuron in the l'th layer. δ^l_j is the j'th neuron's delta value for weight correction. m_0 is the number of neurons in input layer, m_{l-1} is the number of neurons in the (l − 1)'th layer . All neurons use these equations to improve their weights. Each neuron uses the outputs of all neurons in the next precedent layer as inputs. We will isolate each neuron with all its weights, inputs, desired response, and output. This allows us to implement the BP algorithm on distribute parallel machine.

Chapter 5

CHALLENGING PROBLEMS

PATTERN RECOGNITION

CLUSTERING

PREDICTION/FORECASTING

OPTIMIZATION

CONTENT ADDRESSABLE MEMORY

FUNCTION APPROXIMATION

CHALLENGING PROBLEMS

INTRODUCTION

Let us consider the following problems of interest to computer scientists and engineers.

PATTERN CLASSIFICATION

The task of pattern classification is to assign an input pattern (like a speech waveform or handwritten symbol) represented by a feature vector to one of many prespecified classes. Well-known applications include character recognition, speech recognition, EEG waveform classification, blood cell classification, and printed circuit board inspection.

CLUSTERING& CATEGORIZATION

In clustering, also known as unsupervised pattern classification, there are no training data with known class labels. A clustering algorithm explores the similarity between the patterns and places similar patterns in a cluster. Well-known clustering applications include data mining, data compression, and exploratory data analysis.

PREDICTION& FORECASTING

Given a set of n samples {y(t1), y(t2) y(t,,)} in a time sequence, t, t2, t,,, the task is to predict the sample y(t1) at some future time Prediction/forecasting has a significant impact on decision-making in business, science, and engineering. Stock market prediction and weather forecasting are typical applications of prediction/forecasting techniques.

OPTIMIZATION

A wide variety of problems in mathematics, statistics, engineering, science, medicine, and economics can be posed as optimization problems. The goal of an optimization algorithm is to find a solution satisfying a set of constraints such that an objective function is maximized or minimized. The Travelling Salesman Problem (TSP), an NP- complete problem, is a classic example.

CONTENT ADDRESSABLE MEMORY

In the von Neumann model of computation, an entry in memory is accessed only through its address, which is independent of the content in the memory. Moreover, if a small error is made in calculating the address, a completely different item can be retrieved. Associative memory or content-addressable memory, as the name implies, can be accessed by their content. The content in the memory can be recalled even by a partial input or distorted content. Associative memory is extremely desirable in building multimedia information databases.

FUNCTION APPROXIMATION

Suppose a set of n labelled training patterns (input-output pairs),{(x1,y1),(x2,y2),..., (x,y,,)}, have been generated from an unknown function i(x) (subject to noise). The task of function approximation is to find an estimate, say $\hat{u}$, of the unknown function u. Various engineering and scientific modelling problems require function approximation. Since our project is corresponding to the function approximation problem, let us look into this problem thoroughly by the application of the non-linear model of ADAPTIVE SYSTEM namely ARTIFICIAL NEURAL NETWORKS.

ANNs apply the principle of function approximation by example, meaning that they learn a function by looking at examples of this function. One of the simplest examples is an ANN learning the XOR function, but it could just as easily be learning to determine the language of a text, or whether there is a tumour visible in an X-ray image.

If an ANN is to be able to learn a problem, it must be defined as a function with a set of input and output variables supported by examples of how this function should work. A problem like the XOR function is already defined as a function with two binary input variables and a binary output variable, and with the examples which are defined by the results of four different input patterns. However, there are more complicated problems which can be more difficult to define as functions. The input variables to the problem of finding a tumour in an X-ray image could be the pixel values of the image, but they could also be some values extracted from the image. The output could then either be a binary value or a floating point value representing the probability of a tumour in the image. In ANNs this floating-point value would normally be between 0 and 1, inclusive.

Chapter 6

CHANNEL EUALIZATION

INTRODUCTION

NEED FOR EQUALIZATION

CLASSIFICATION OF EQUALIZER

NEURAL NETWORK EQUALIZER

INTRODUCTION

First we will understand the reasons that distort the pulses that we transmit over a communication channel. Then we go to different equalizer structures that were developed over the decades. The primary being linear transversal equalizer. Then we will observe the drawbacks in the linear equalizers and why we go for nonlinear structures. Then we concentrate on the need for decision feedback in an equalizer.

NEED FOR EQUALIZATION

INTERSYMBOL INTERFERENCE (ISI)

Ideally, the impulse response of a linear transmission medium is defined by

$$h(t) = A\delta(t-\tau) \qquad (6.1)$$

where t denotes continuous time,

$h(t)$ designates the impulse response,

A is an amplitude scaling factor,

$\delta(t)$ is the Dirac delta function

τ denotes the propagation delay incurred in the course of transmitting the signal over the channel.

Equivalently, in frequency domain the above equation can be written as

$$H(j\omega) = A\exp(-j\omega\tau) \qquad (6.2)$$

Where $H(j\omega)$ is the frequency response of the transmission media. In practice, it is impossible for any physical channel to satisfy the stringent requirements embodied in equations (1) and (2). The best we can do is to approximate equation (2) over a band of frequencies representing the essential spectral content of the transmitted signal, which makes the channel '*dispersive*' [1]. This channel impairment gives rise to '*Inter-symbol Interference*'. - A smearing of the successive pulses into one another with the result that they are no longer distinguishable.

NOISE

Some form of noise is always present at the output of every communication channel. The noise can be internal to the system, as in case of thermal noise generated by the amplifier at the front end of the receiver or external to the system, due to interfering signal originated from other sources.

The net result of the two impairments is that the signal received at the channel output is a noisy and distorted version of the signal that is transmitted. The function of the receiver is to operate on the received signal and deliver a reliable estimate of the original message signal to a user at the output of the system.

Hence there is a need for adaptive equalization. By equalization we mean the process of correcting channel induced distortion. This process is said to be adaptive when it adjusts itself continuously during data transmission by operating

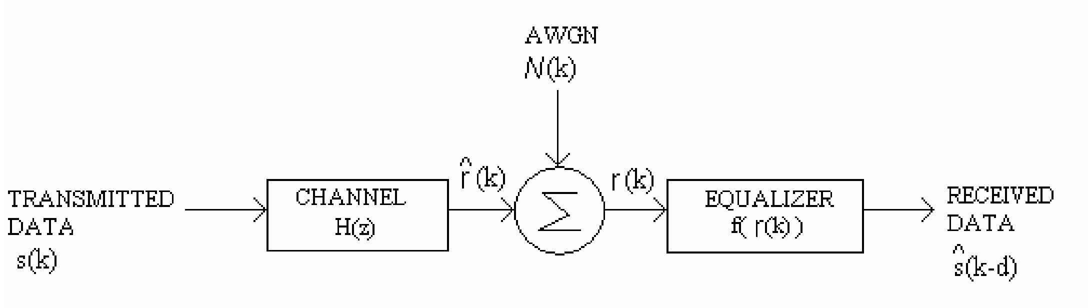


Fig 6.1: Schematic of Digital communication system

CLASSIFICATION OF ADAPTIVE EQUALIZERS

In general adaptive equalizers are either supervised or unsupervised. The equalizers with unsupervised training are called blind equalizers. The classification of the equalizers is shown in the figure.

$$\begin{tikzcd}
 & \textit{Adaptive equalizers} \arrow[dl] \arrow[dr] & \\
\textit{Supervised training} \arrow[d] \arrow[dr] & & \textit{Unsupervised or blind training} \\
\begin{array}{c}\textit{Sequence estimation}\\ \textit{(MLSE)}\end{array} & \textit{Symbol estimation} \arrow[d] \arrow[dr] & \\
 & \begin{array}{c}\textit{Nonlinear equalizers}\\ \textit{(ANN)}\\ \textit{(Fuzzy systems)}\end{array} & \begin{array}{c}\textit{Linear equalizers}\\ \textit{Transversal, Lattice}\\ \textit{(LMS, RLS...)}\end{array}
\end{tikzcd}$$

NEURAL NETWORK EQUALIZERS

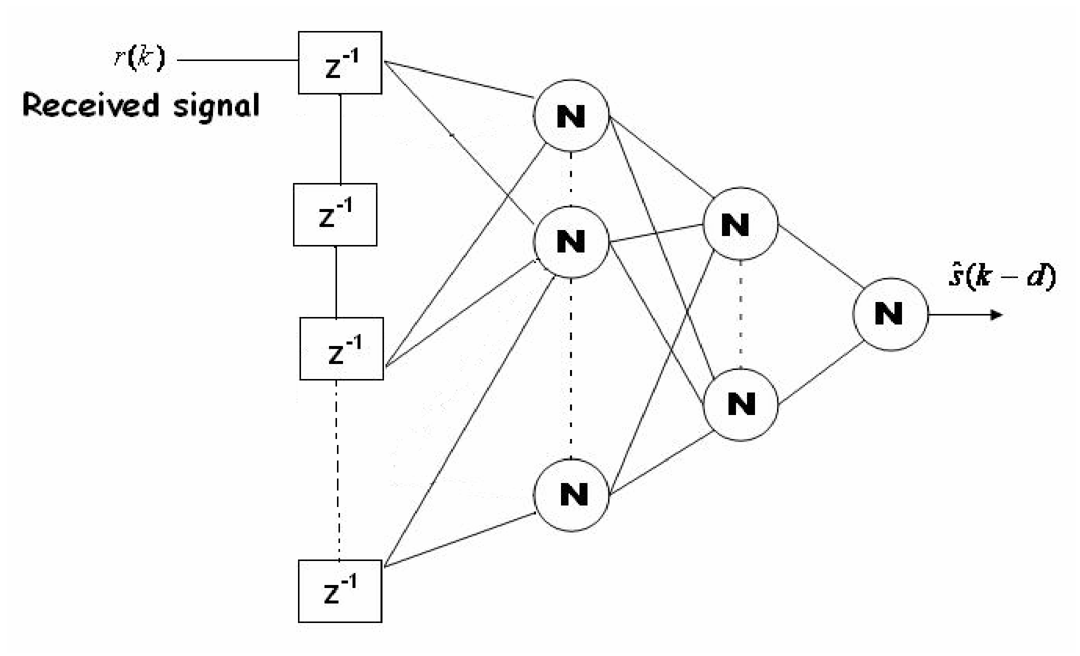


Fig 6.2: Neural network equalizer

Back-propagation algorithm is used to train the neural network. The algorithm may be stated as follows.

Firstly, the correction $\Delta w_{ji} = \eta * \delta_j(n) * y_i(n)$.

Where η is the learning rate parameter

$\delta_j(n)$ is the local gradient

$y_i(n)$ is the input signal of neuron j.

Second, the local gradient $\delta_j(n)$ depends on whether neuron j is an input node or a hidden node:

If neuron j is an output node, $\delta_j(n)$ equals the product of the derivative $\varphi'_j(v_j(n))$ and the error signal $e_j(n)$, both of which are associated with neuron *j.*

If neuron *j* is a hidden node, $\delta_j(n)$ equals the product of the associated derivative $\varphi'_j(v_j(n))$ and the weighted sum of the δ s computed for the neurons in the next hidden or output layer that are connected to neuron *j.*

The main disadvantage of using neural networks is that their convergence is slower compared to linear filters.

The performance of the equalizer is always better than those of linear equalizer. But there are some channels for which the negative centers and positive centers are very near and overlap in many cases due to the presence of additive noise. Such channels are called overlapping channels. One of the examples of such a channel is

$$H_6(z) = 0.4084 + 0.8164z^{-1} + 0.4084z^{-2} . \qquad (6.6)$$

Hence we need a decision feedback equalizer to classify these overlapping patterns. The advantage of the decision feedback equalizer is that ISI is eliminated without enhancement of noise by using past decisions to subtract out a portion of ISI in addition to the normal feed forward filter.

Chapter 7

FIXED STRUCTURE ANN

STRUCTURE OF ANN

RESULTS

FIXED STRUCTURE ANN

First we start the project by assuming a fixed structure for the ANN for our convenience. The structure is given by:

This ANN has 4 layers in total they include the input layer having 9 nodes, the output layer having 1 node, and the two hidden layers each having 4,3 nodes respectively. This means our structure can be defined in short as 9,4,3,1 structure. The main advantage of assuming a structure is to reduce considerably the number of variable parameters of the ANN.

The various variable parameters of an ANN include:

- No. of layers
- No. of neurons in each layer
- Activation function
- Learning factor
- Use of batch & sequential mode

So by choosing a fixed structure the other variable parameters get fixed except activation function which can be varied according to our convenience.

The reason for choosing 9,4,3,1 as the structure is that this structure is universally regarded as one of the best structure for convergence.

The results for the above structure for various functions and for various activation function are given in the pages to follow.

RESULTS

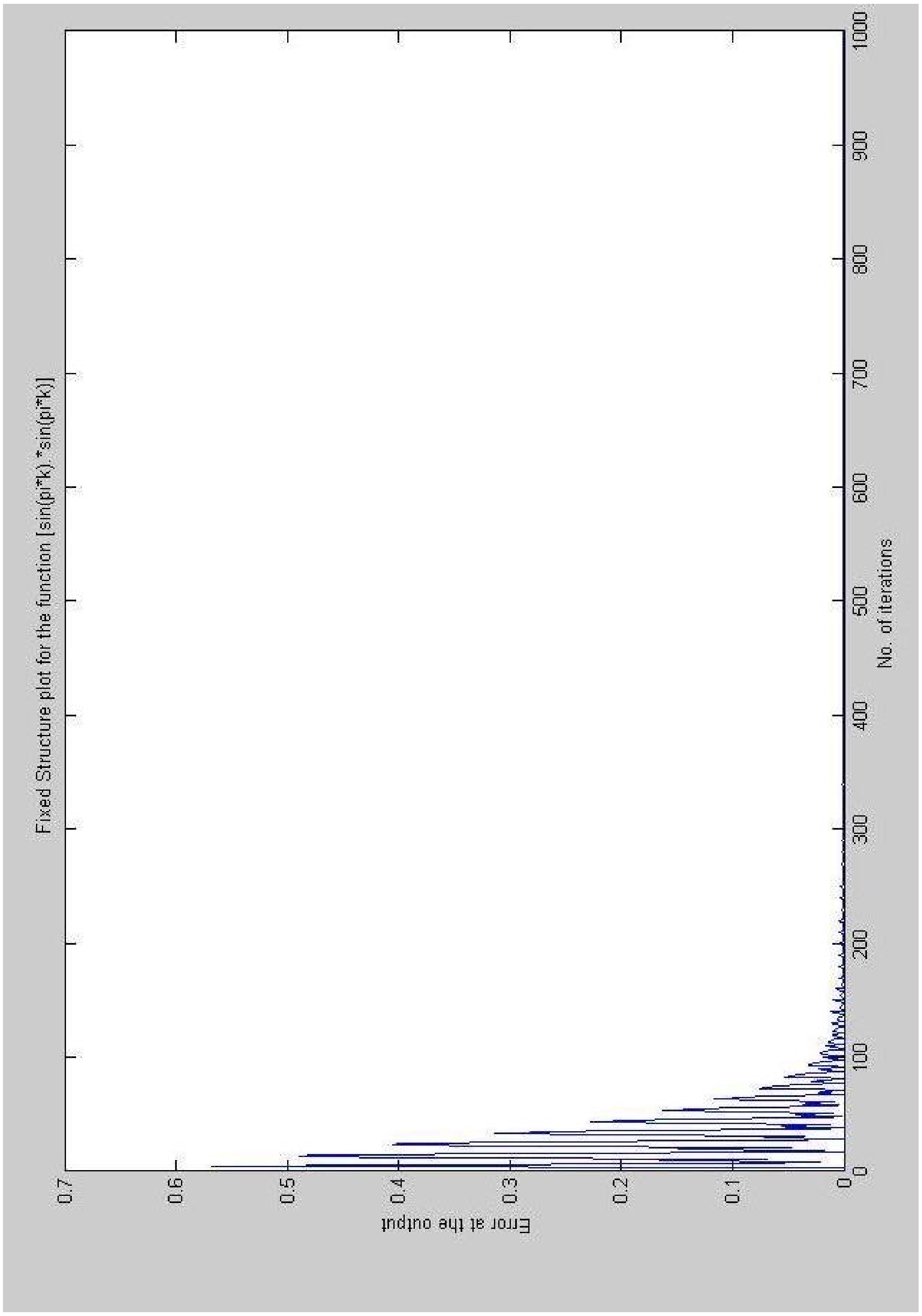


Fig. 7.1

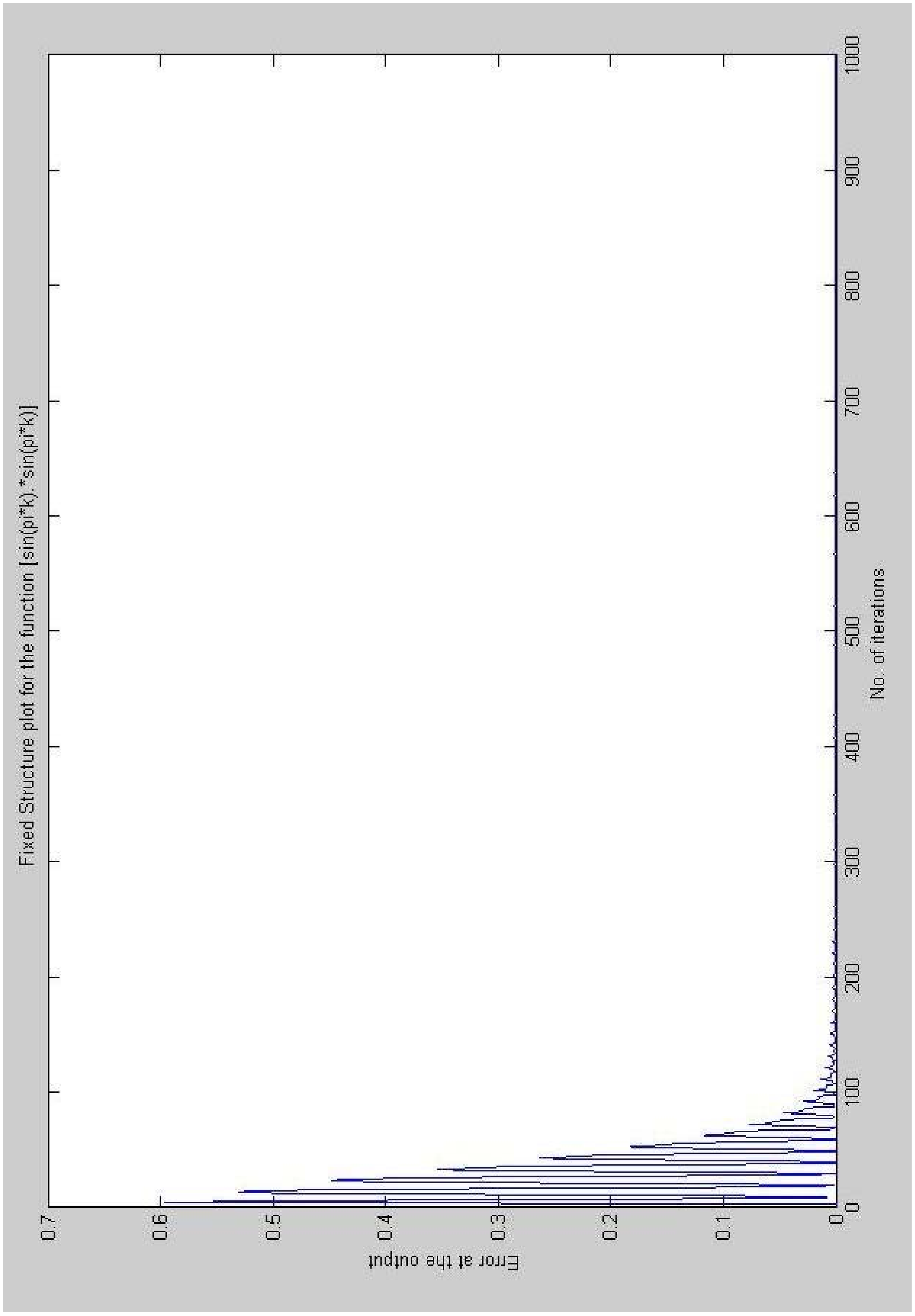

Fixed Structure plot for the function [sin(pi*k).*sin(pi*k)]
Error at the output
No. of iterations
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
100
200
300
400
500
600
700
800
900
1000

Fig. 7.2

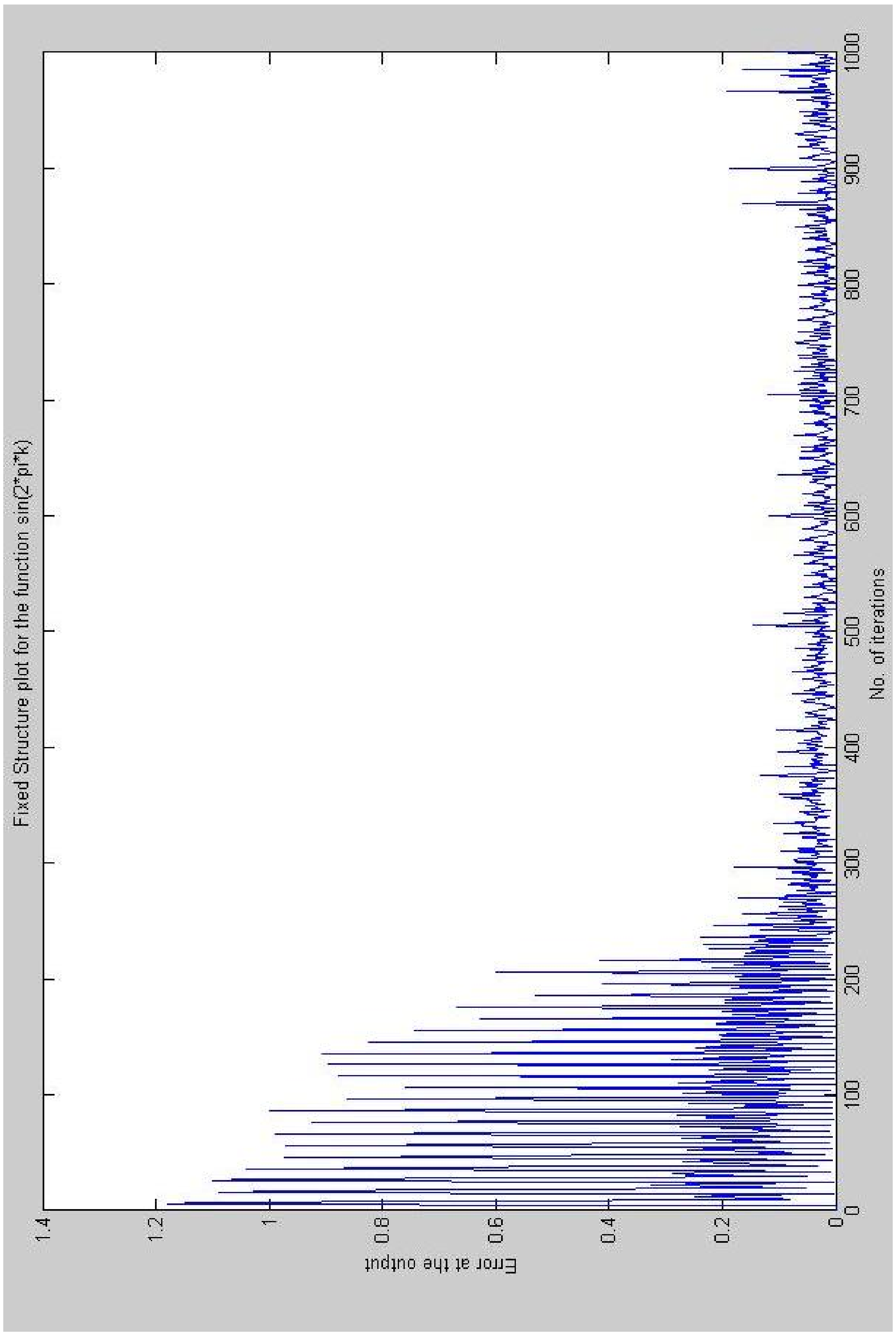

Fixed Structure plot for the function sin(2*pi*k)
Error at the output
No. of iterations
0
0.2
0.4
0.6
0.8
1
1.2
1.4
0
100
200
300
400
500
600
700
800
900
1000

Fig. 7.3

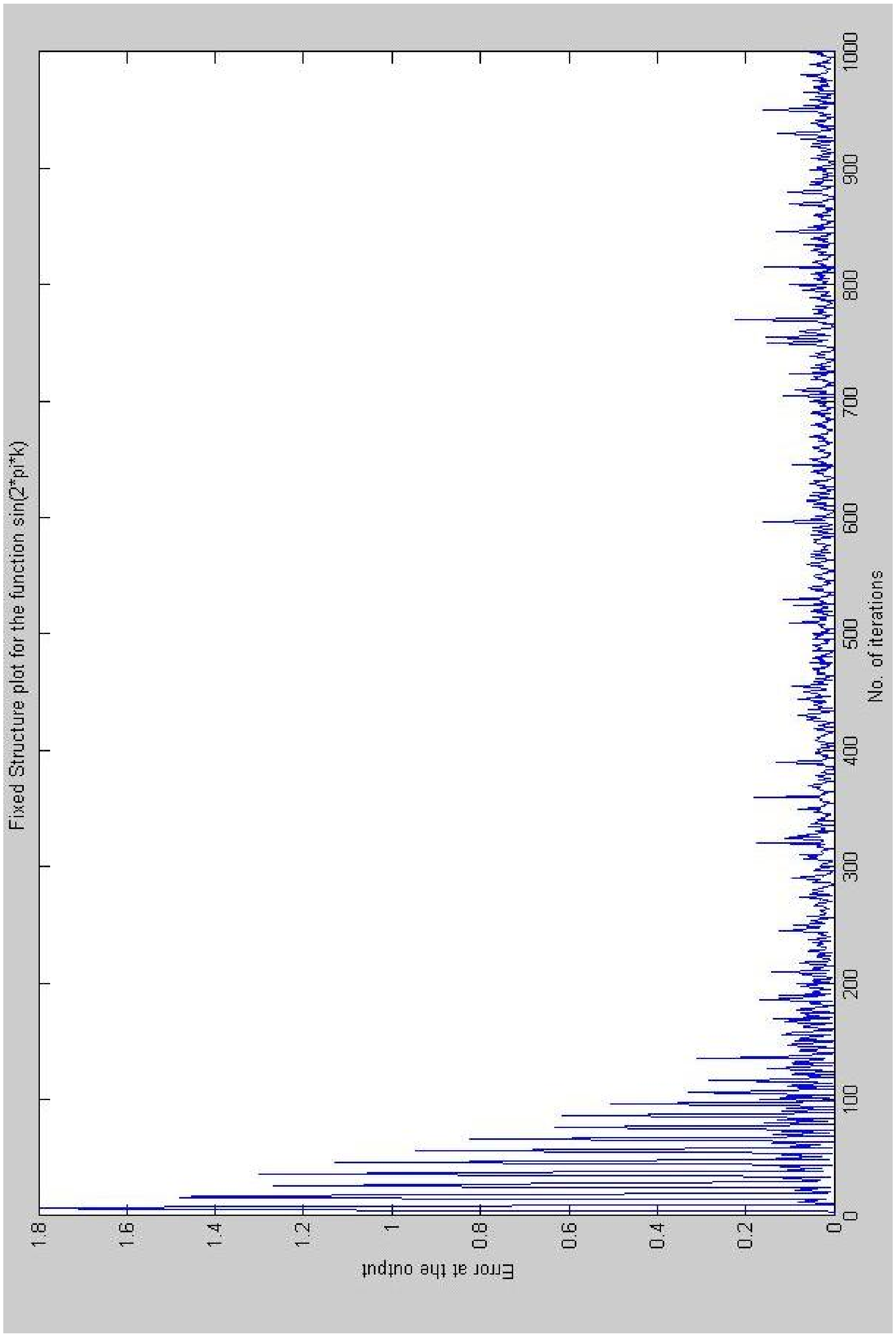

Fixed Structure plot for the function sin(2*pi*k)
Error at the output
No. of iterations
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
100
200
300
400
500
600
700
800
900
1000

Fig. 7.4

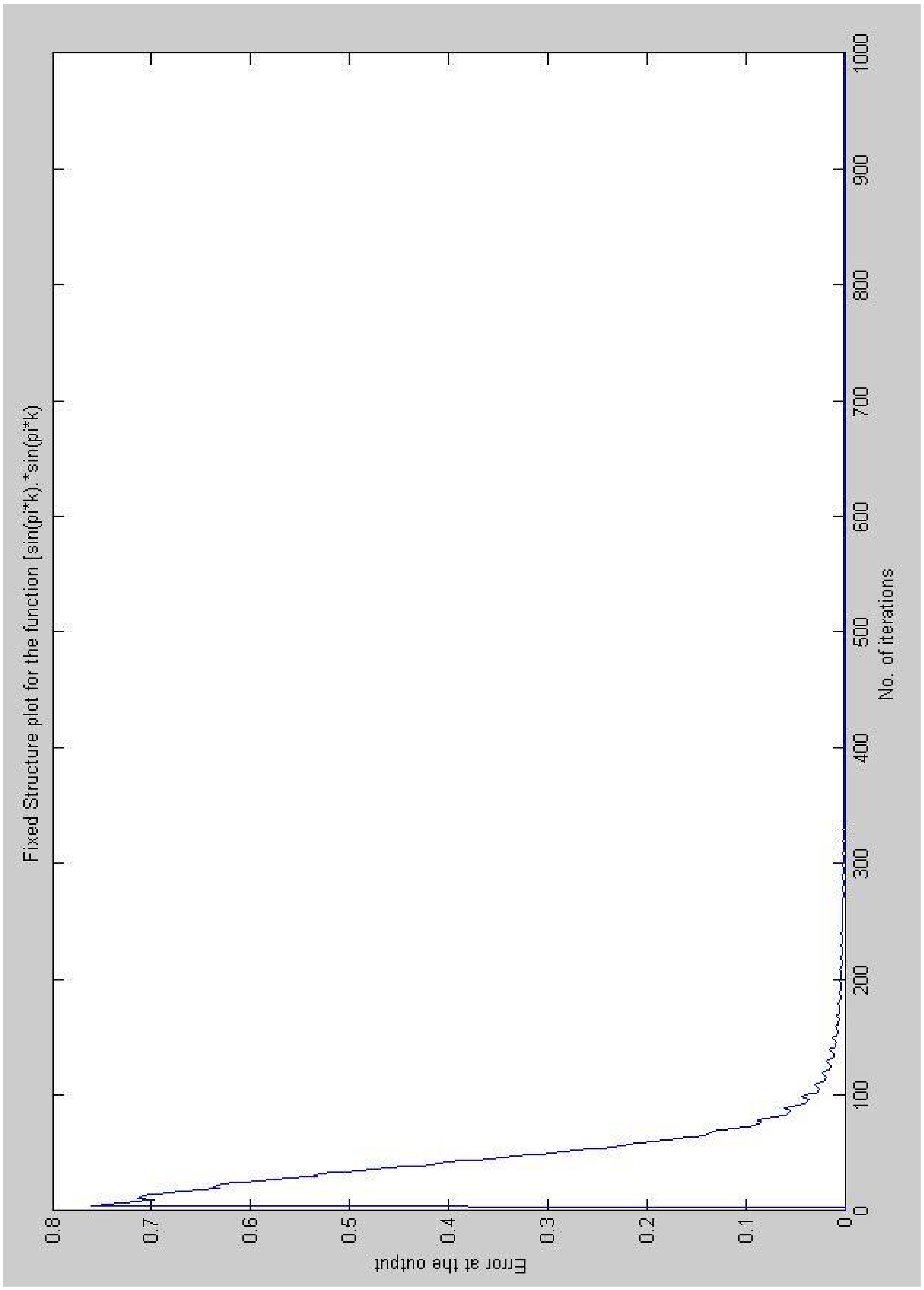

Fixed Structure plot for the function [sin(pi*k).*sin(pi*k)]
Error at the output
No. of iterations
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0
100
200
300
400
500
600
700
800
900
1000

Fig. 7.5

Chapter 8

GENERALIZED STRUCTURE ANN

STRUCTURE

RESULTS

STRUCTURE

As said in the chapter above the various variable parameters in the ANN include:

The various variable parameters of an ANN include:

- No. of layers
- No. of neurons in each layer
- Activation function
- Learning factor
- Use of batch & sequential mode

The function that we have approximated is a simple square function. The results of convergence plots for various structures of ANN i.e. for various no. of layers, for various no. of neurons in each layer, various values of learning rate are obtained and the conclusion for the optimum no. of layers, for the structure of the no. of neurons in each layer and for the optimum value of learning rate are deduced.

Here the comparisons are given in terms of groups of three having the same number of hidden layers and the same number of neurons in each layer for three different values of the learning factor. The first three graphs correspond to the results of the structure having one hidden layer, which in turn is having two neurons at three different learning rates. These learning rates are 0.075, 0.1, 0 .5

The results for the generalized model are shown in the pages to follow.

RESULTS

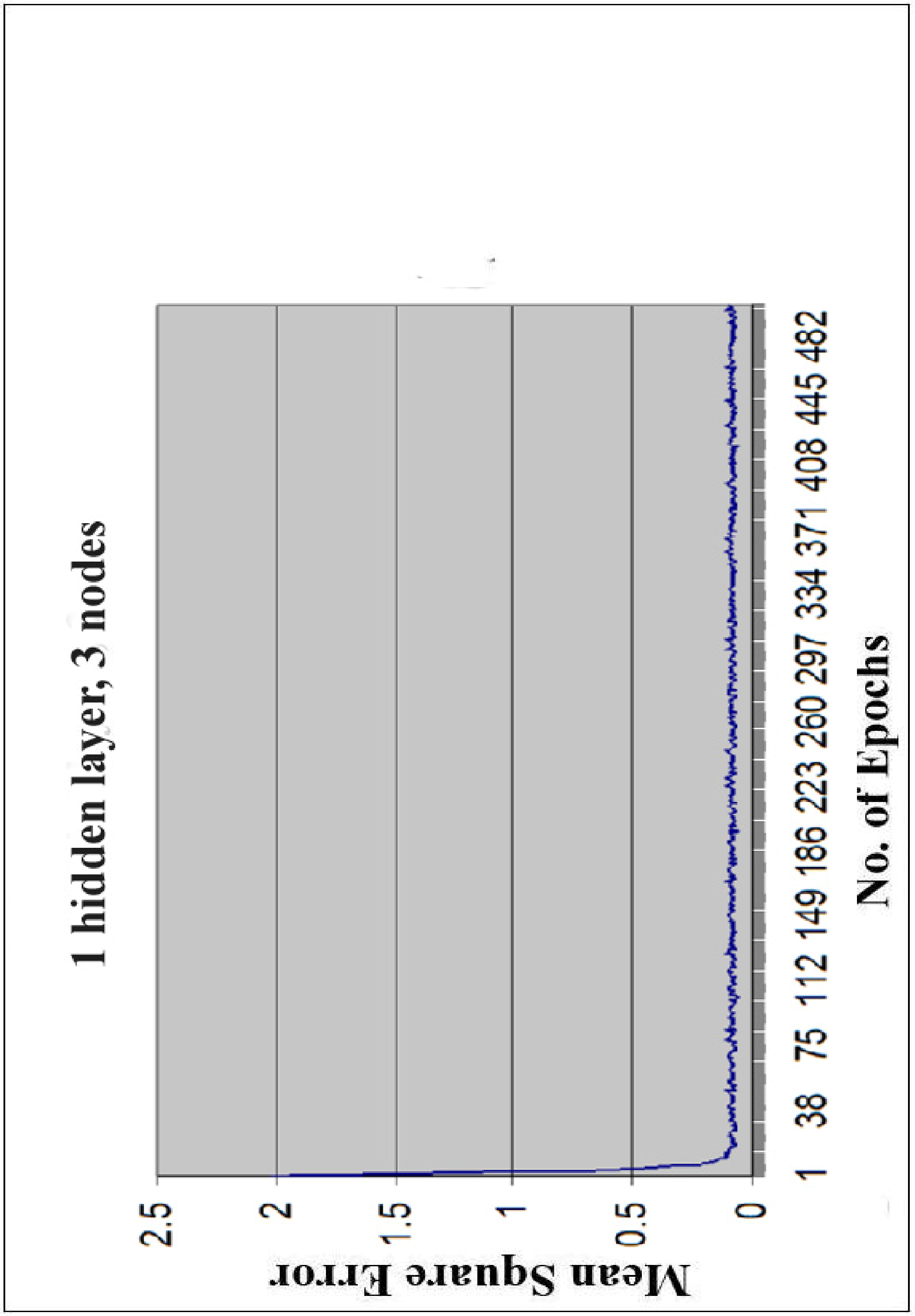


Fig. 8.1

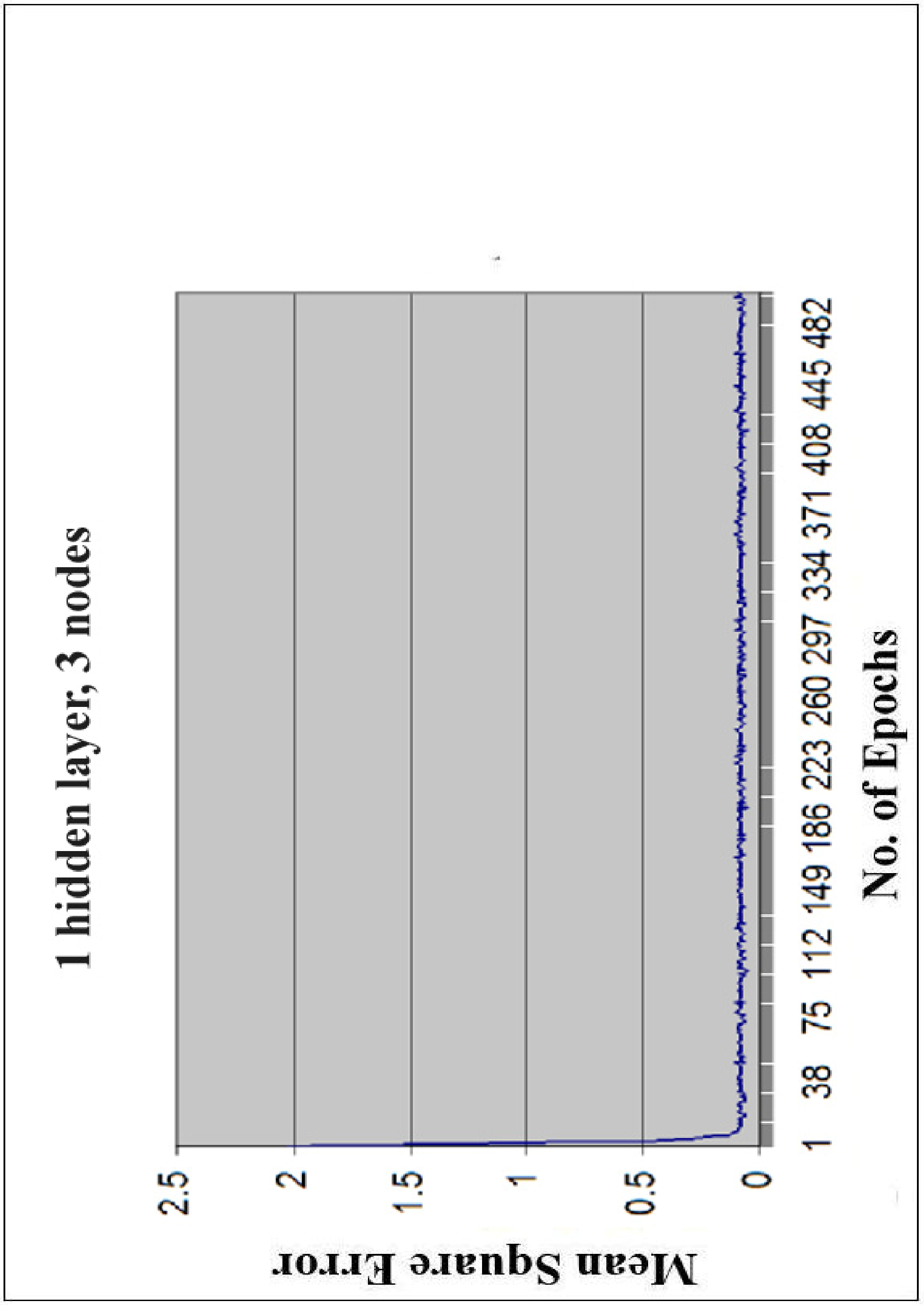

1 hidden layer, 3 nodes
Mean Square Error
2.5
2
1.5
1
0.5
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.2

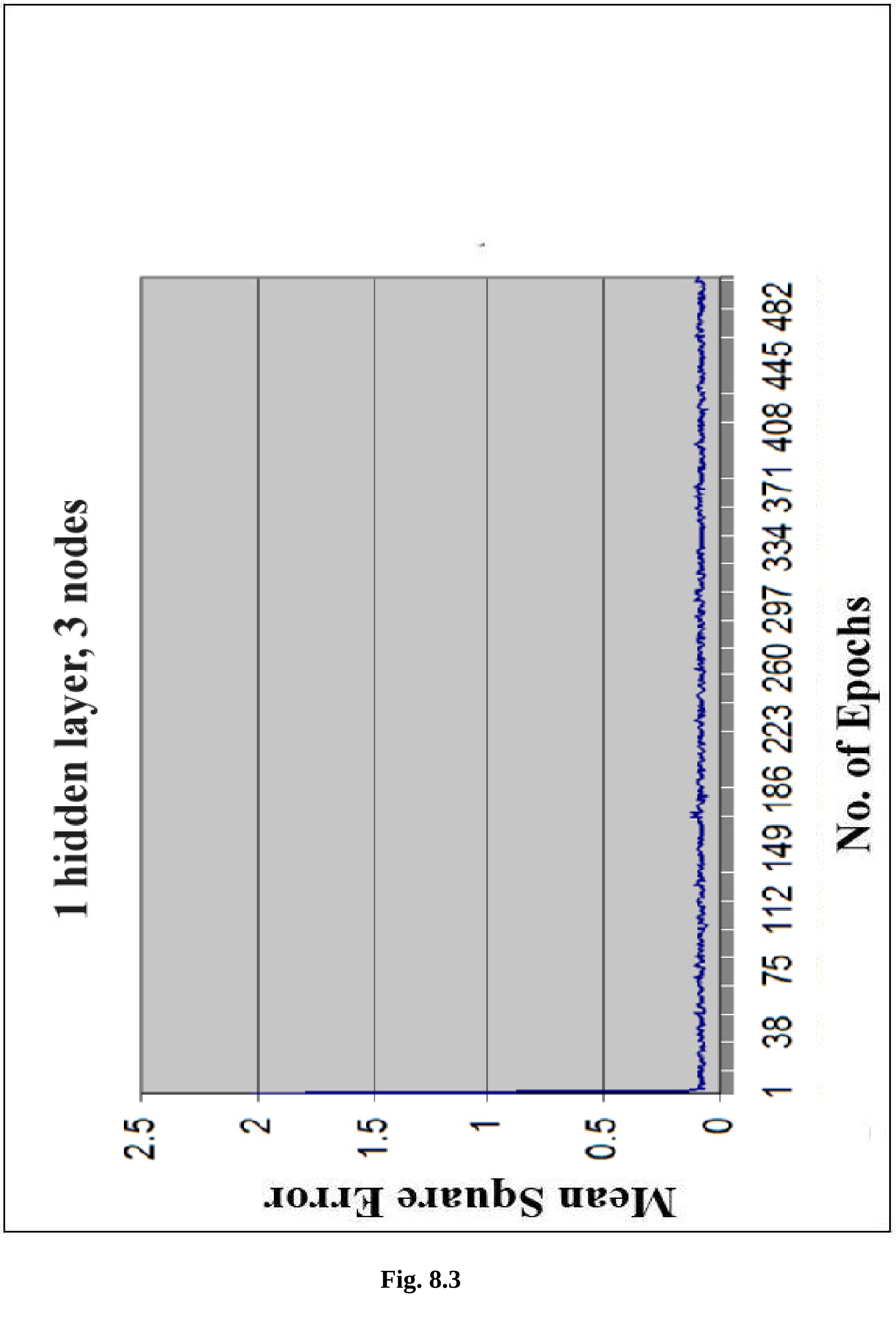

1 hidden layer, 3 nodes
Mean Square Error
2.5
2
1.5
1
0.5
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.3

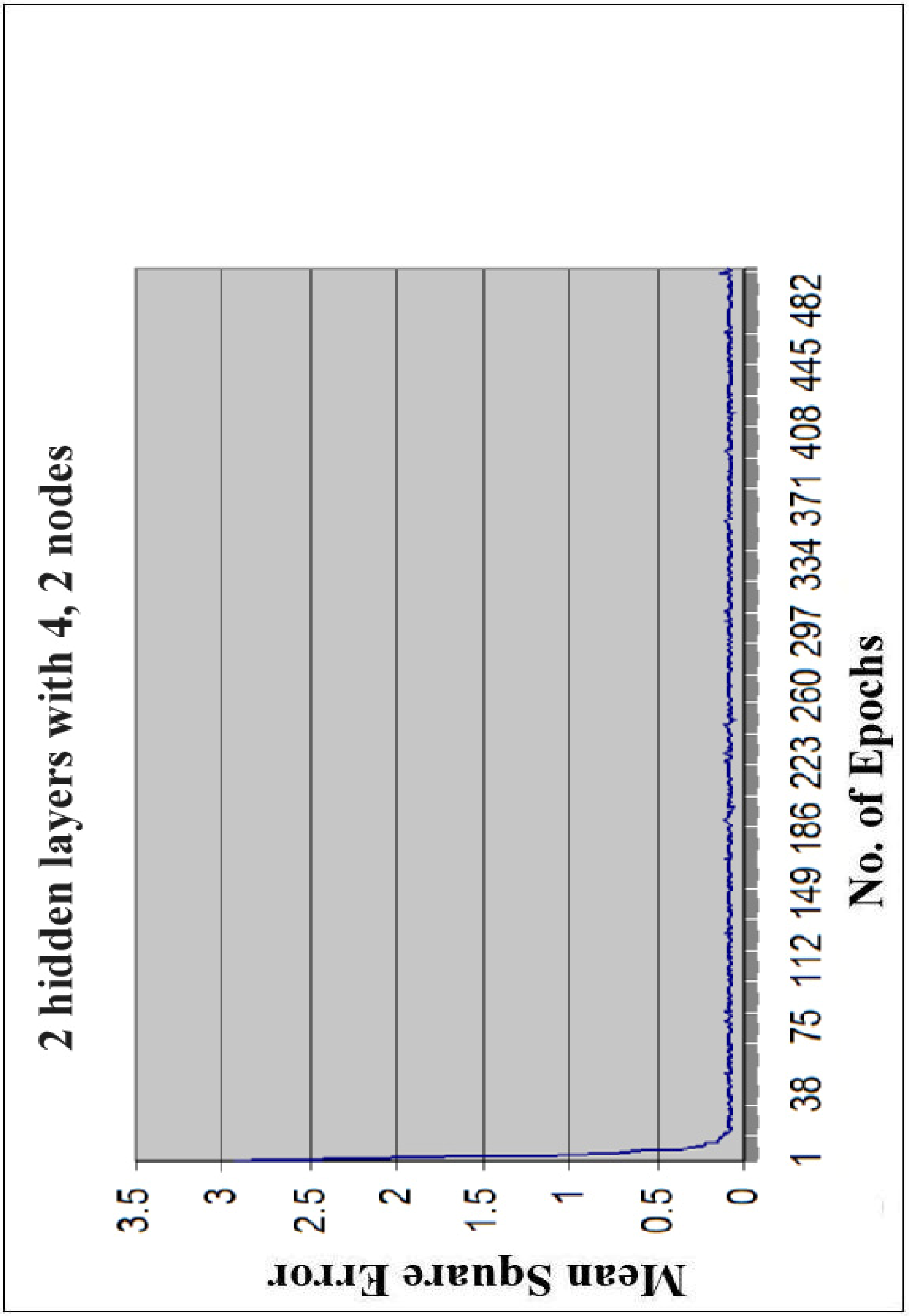

2 hidden layers with 4, 2 nodes
Mean Square Error
3.5
3
2.5
2
1.5
1
0.5
0
No. of Epochs
1
38
75
112
149
186
223
260
297
334
371
408
445
482

Fig. 8.4

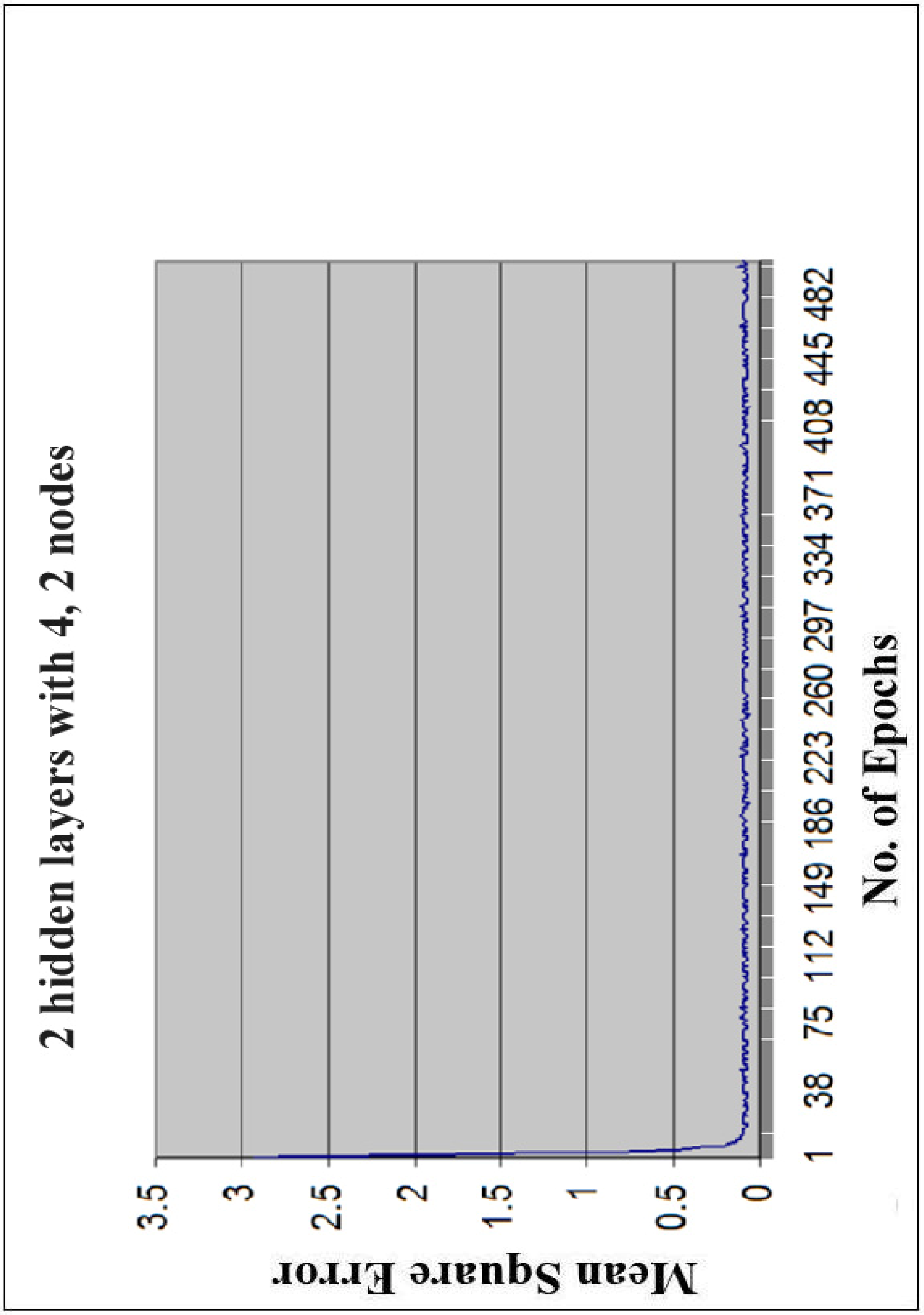

2 hidden layers with 4, 2 nodes
Mean Square Error
3.5
3
2.5
2
1.5
1
0.5
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.5

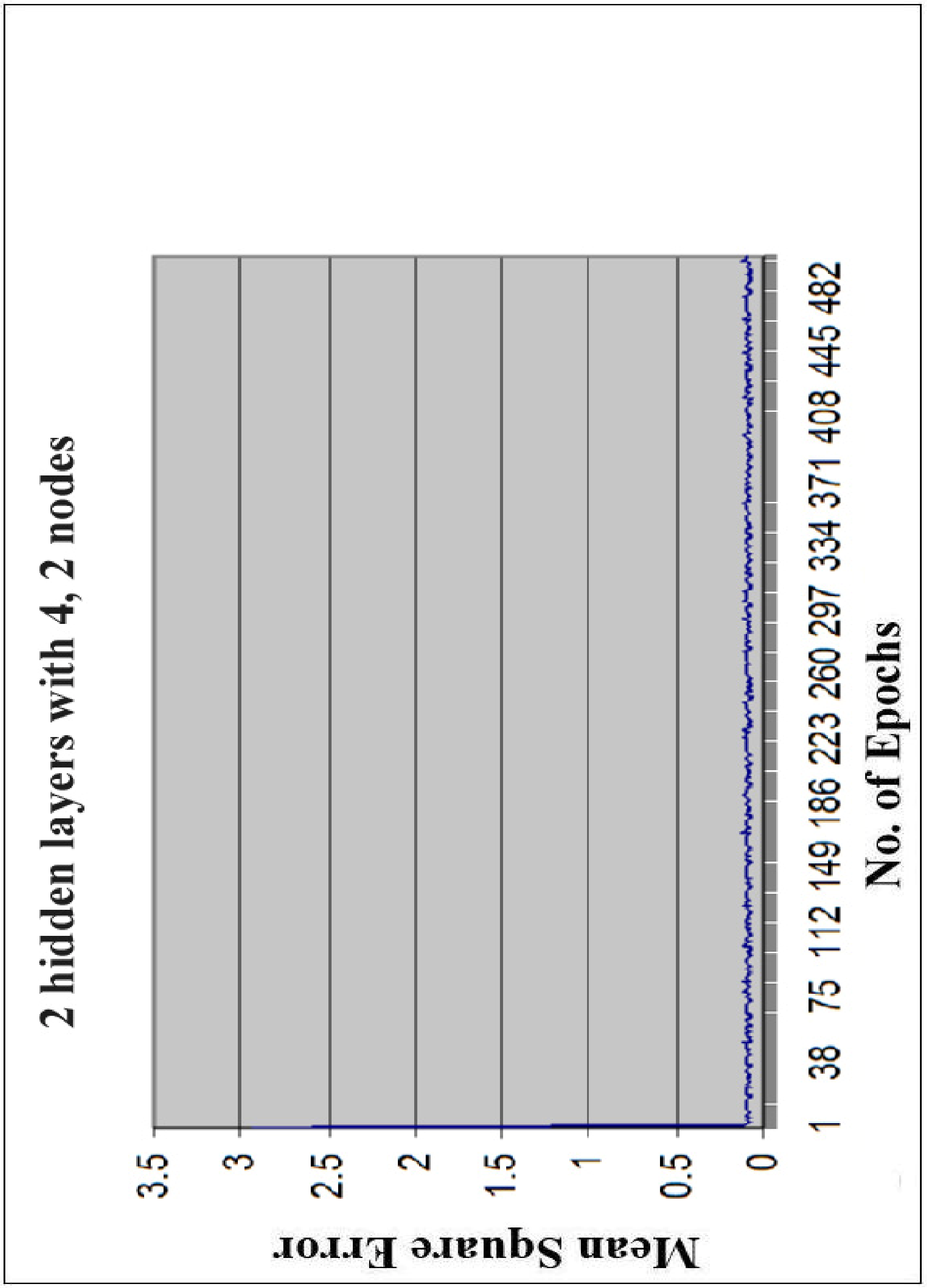
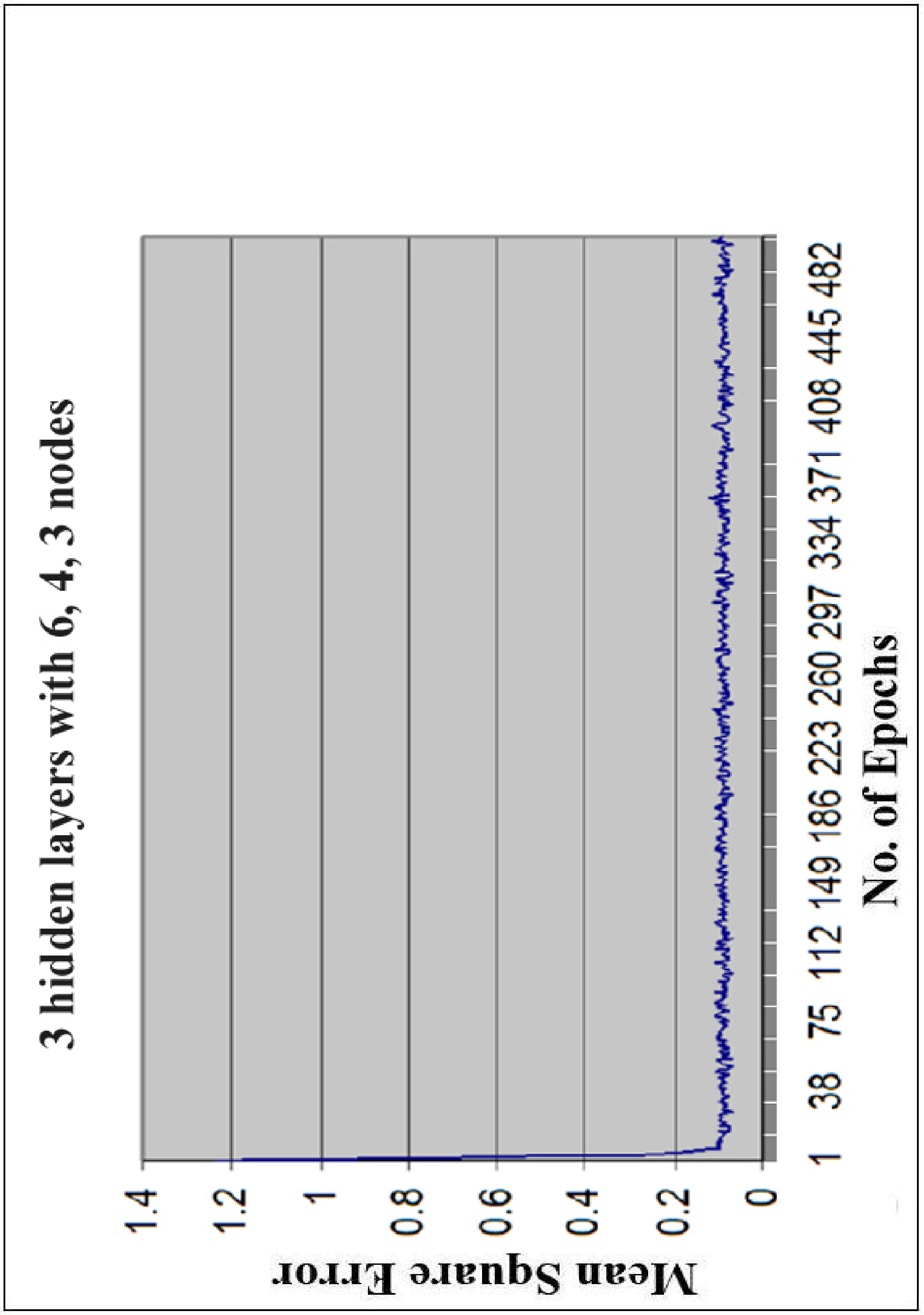

2 hidden layers with 4, 2 nodes
Mean Square Error
3.5
3
2.5
2
1.5
1
0.5
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.6



3 hidden layers with 6, 4, 3 nodes
Mean Square Error
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.7

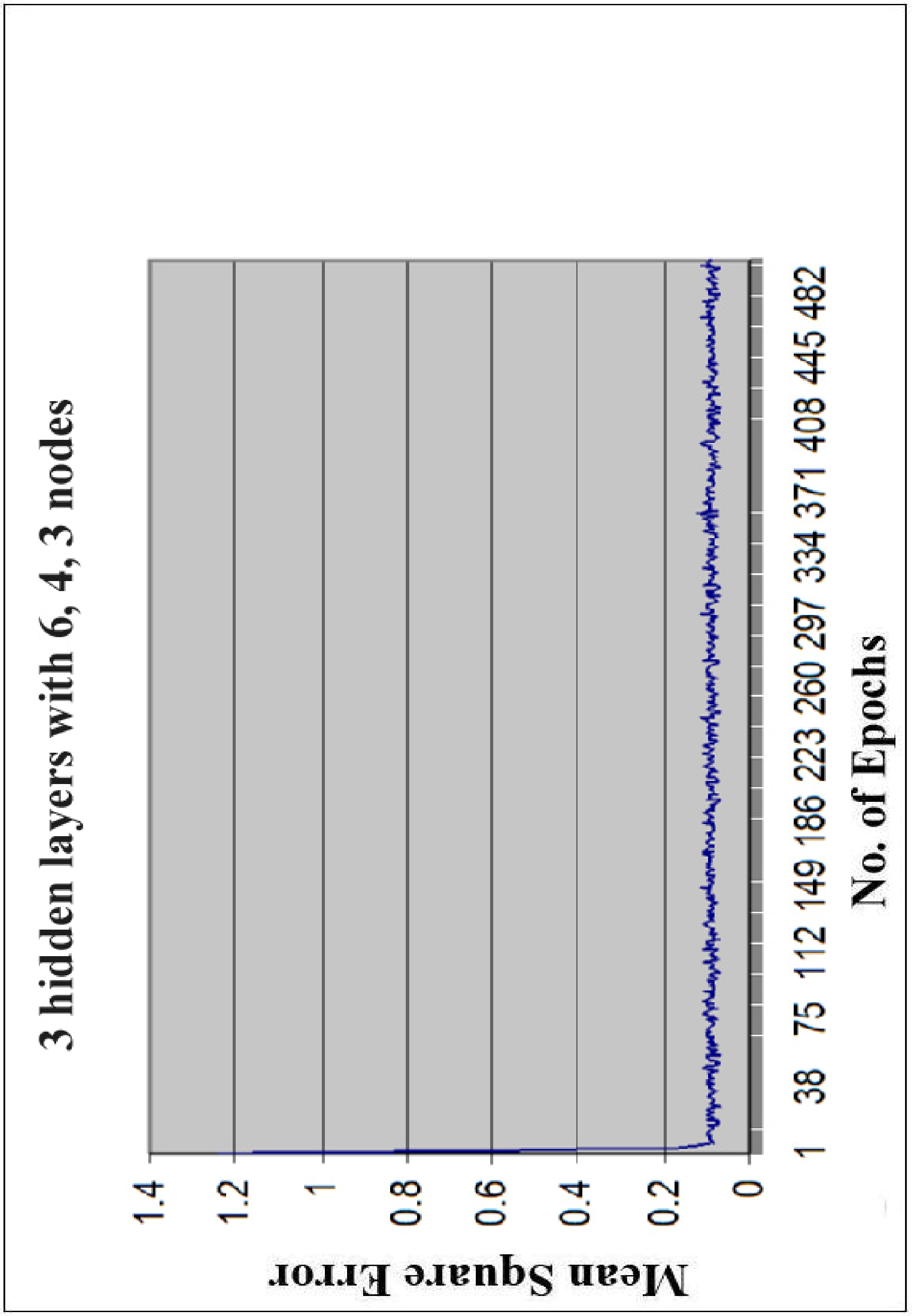

3 hidden layers with 6, 4, 3 nodes
Mean Square Error
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.8

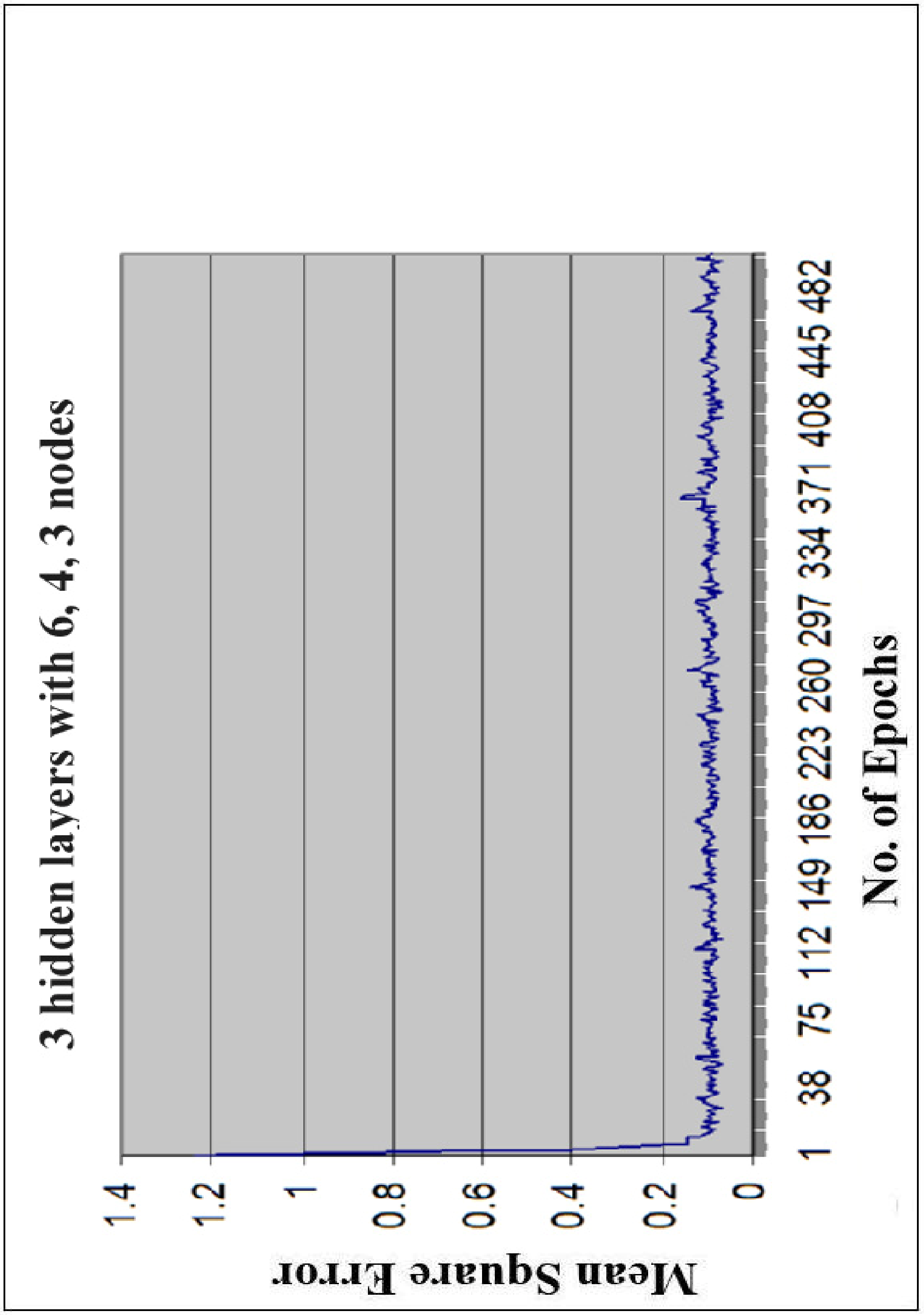

3 hidden layers with 6, 4, 3 nodes
Mean Square Error
1.4
1.2
1
0.8
0.6
0.4
0.2
0
1 38 75 112 149 186 223 260 297 334 371 408 445 482
No. of Epochs

Fig. 8.9

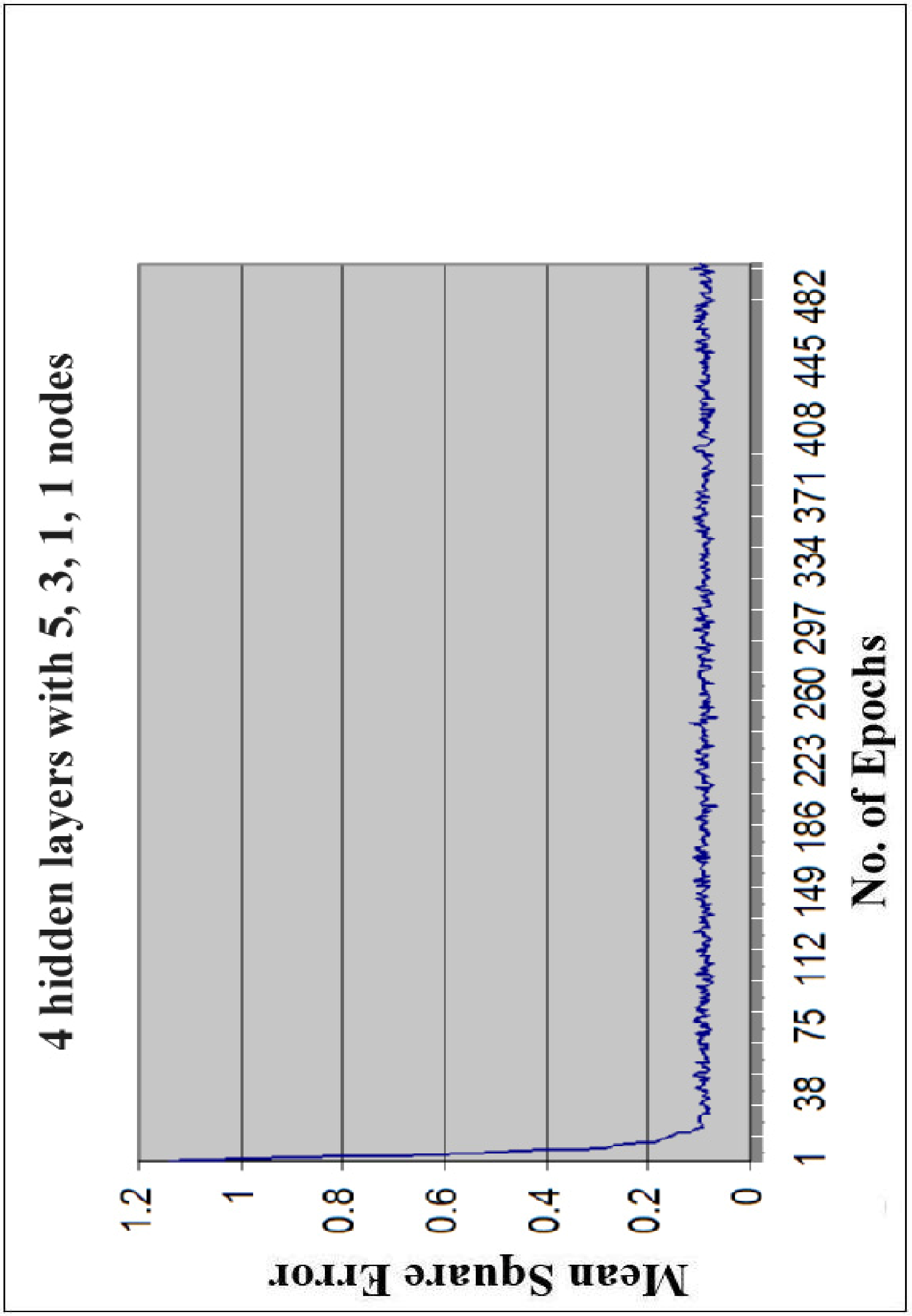

4 hidden layers with 5, 3, 1, 1 nodes
Mean Square Error
1.2
1
0.8
0.6
0.4
0.2
0
1 38 75 112 149 186 223 260 297 334 371 408 445 482
No. of Epochs

Fig. 8.10

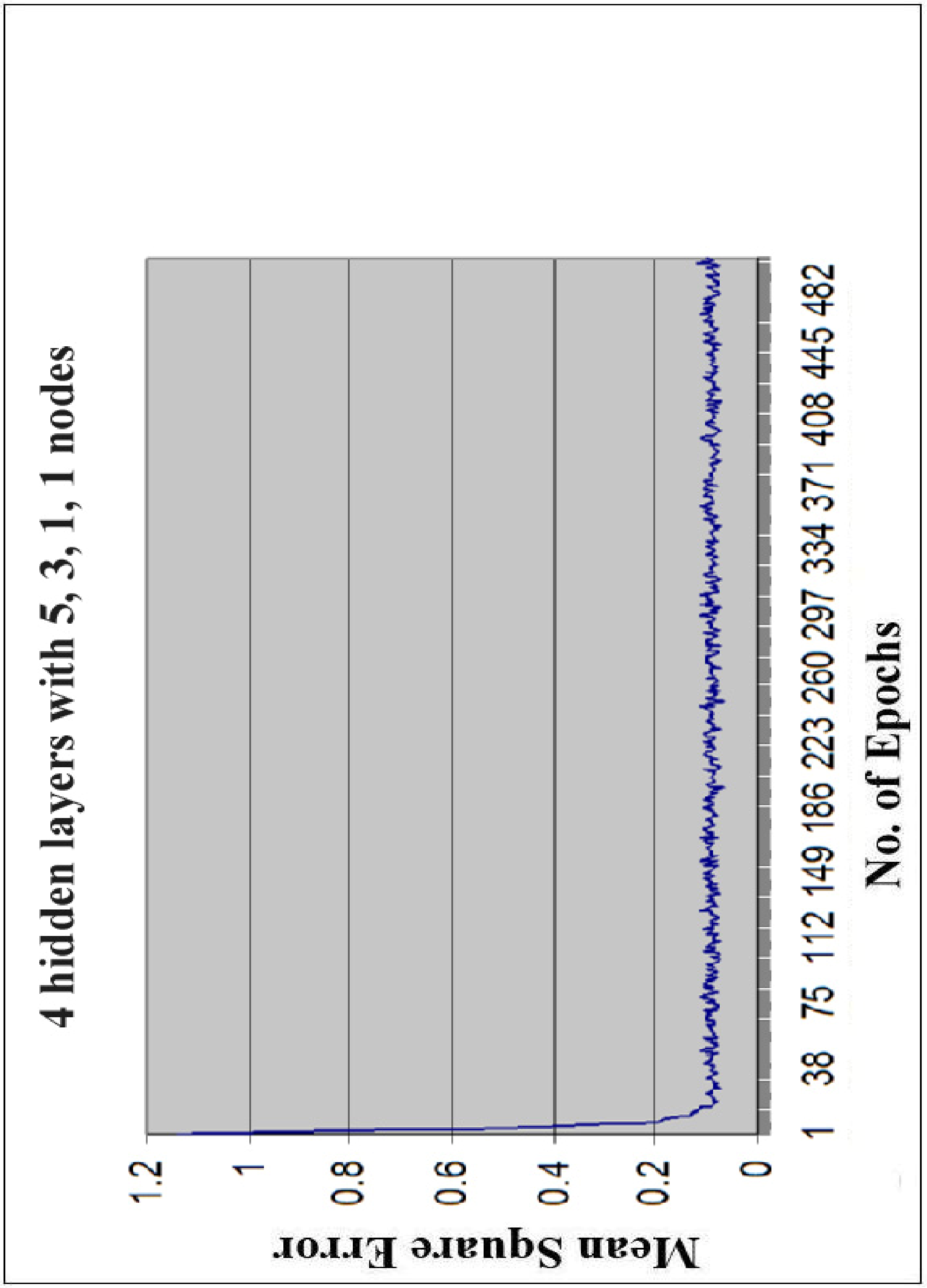

4 hidden layers with 5, 3, 1, 1 nodes
Mean Square Error
1.2
1
0.8
0.6
0.4
0.2
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.11

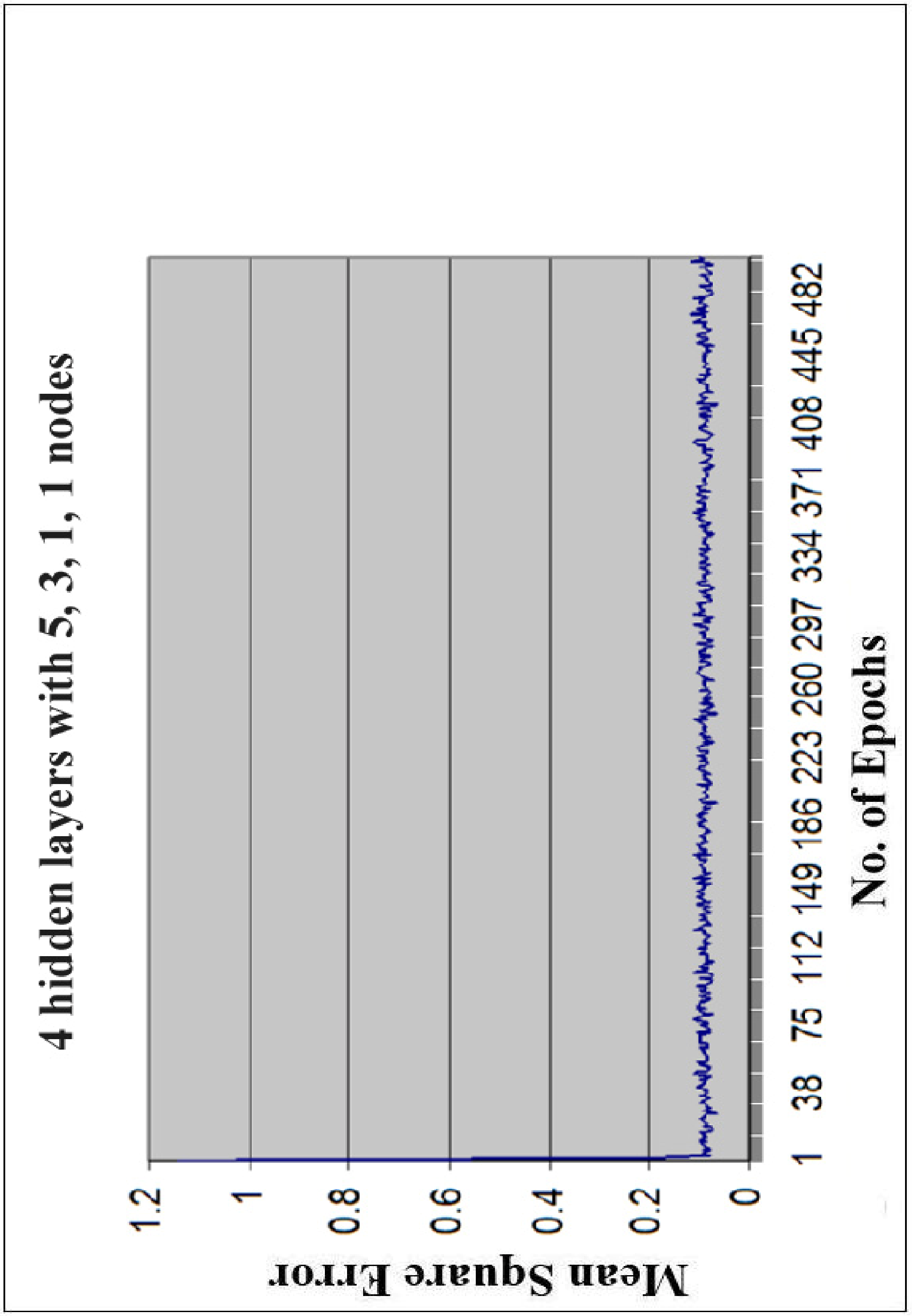

4 hidden layers with 5, 3, 1, 1 nodes
Mean Square Error
1.2
1
0.8
0.6
0.4
0.2
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.12

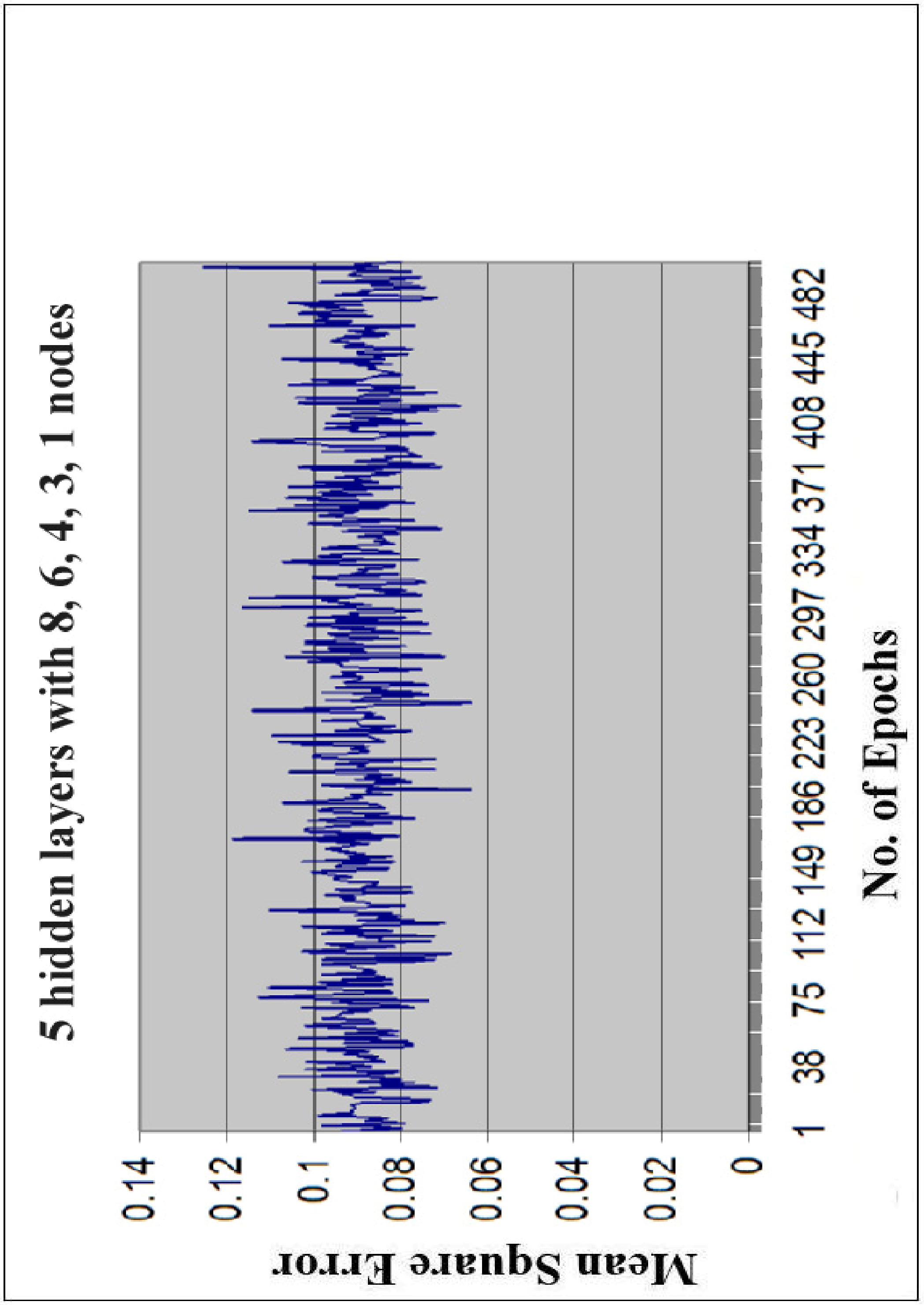

5 hidden layers with 8, 6, 4, 3, 1 nodes
Mean Square Error
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.13

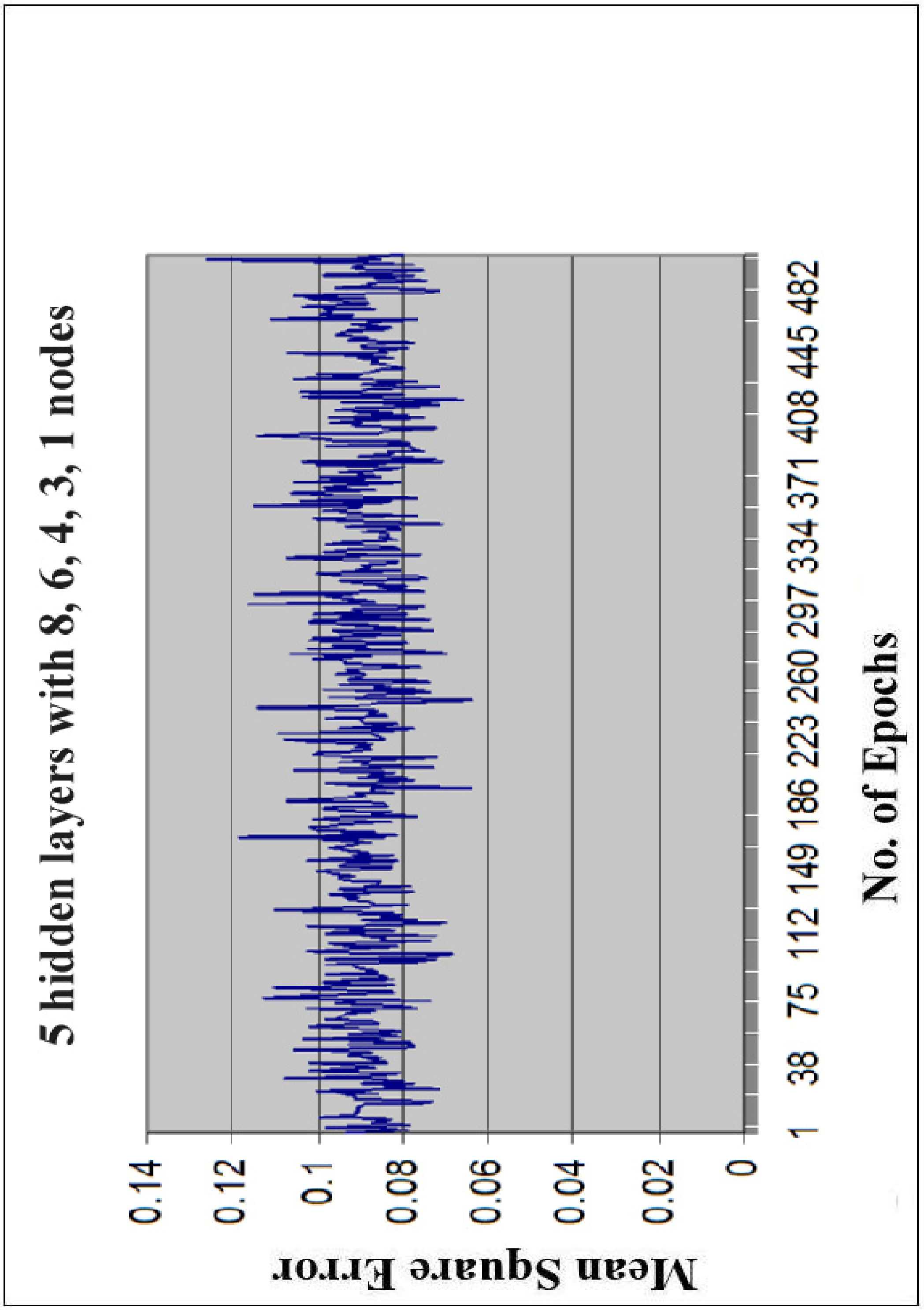

5 hidden layers with 8, 6, 4, 3, 1 nodes
Mean Square Error
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.14

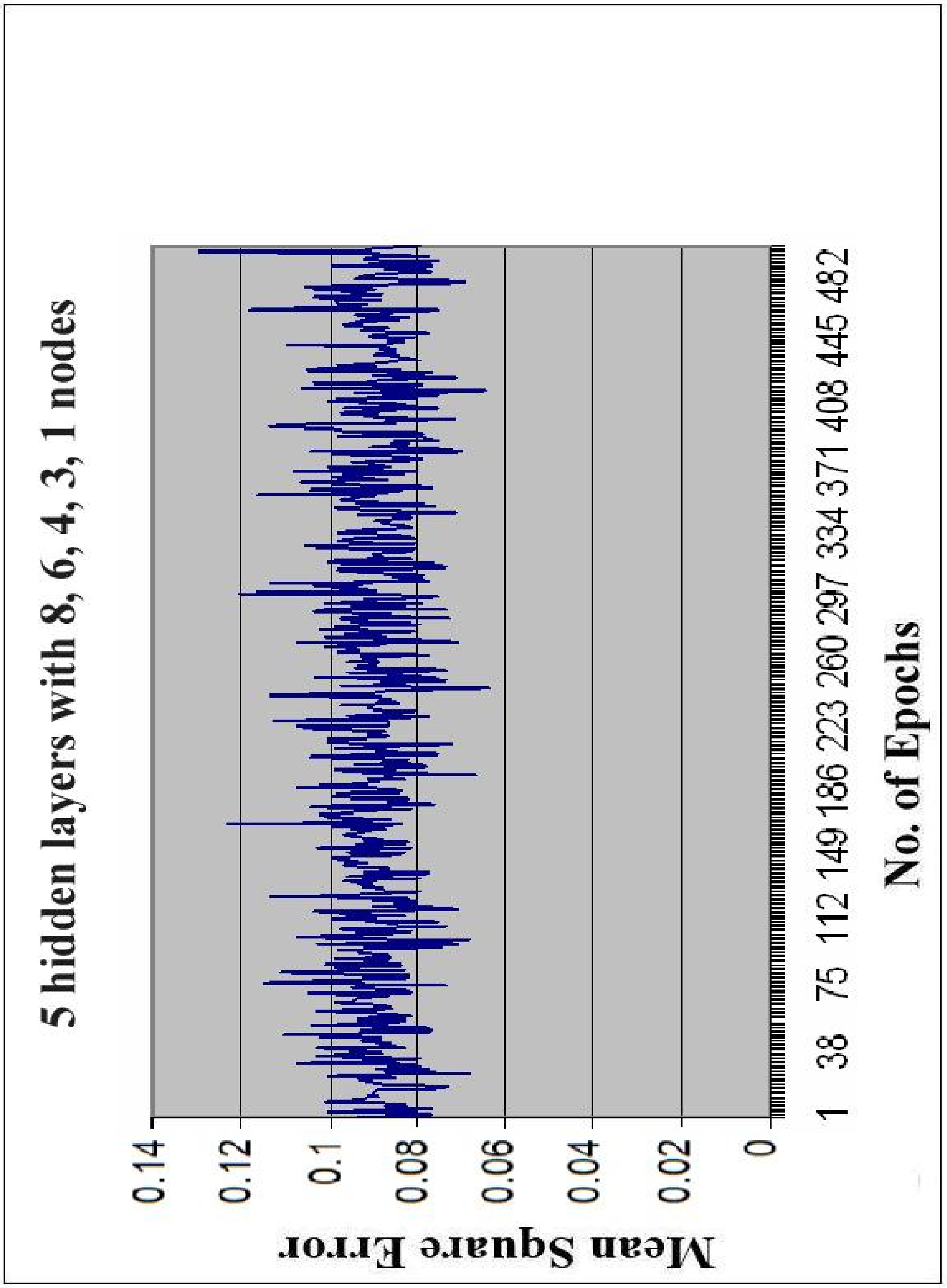

5 hidden layers with 8, 6, 4, 3, 1 nodes
Mean Square Error
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.15

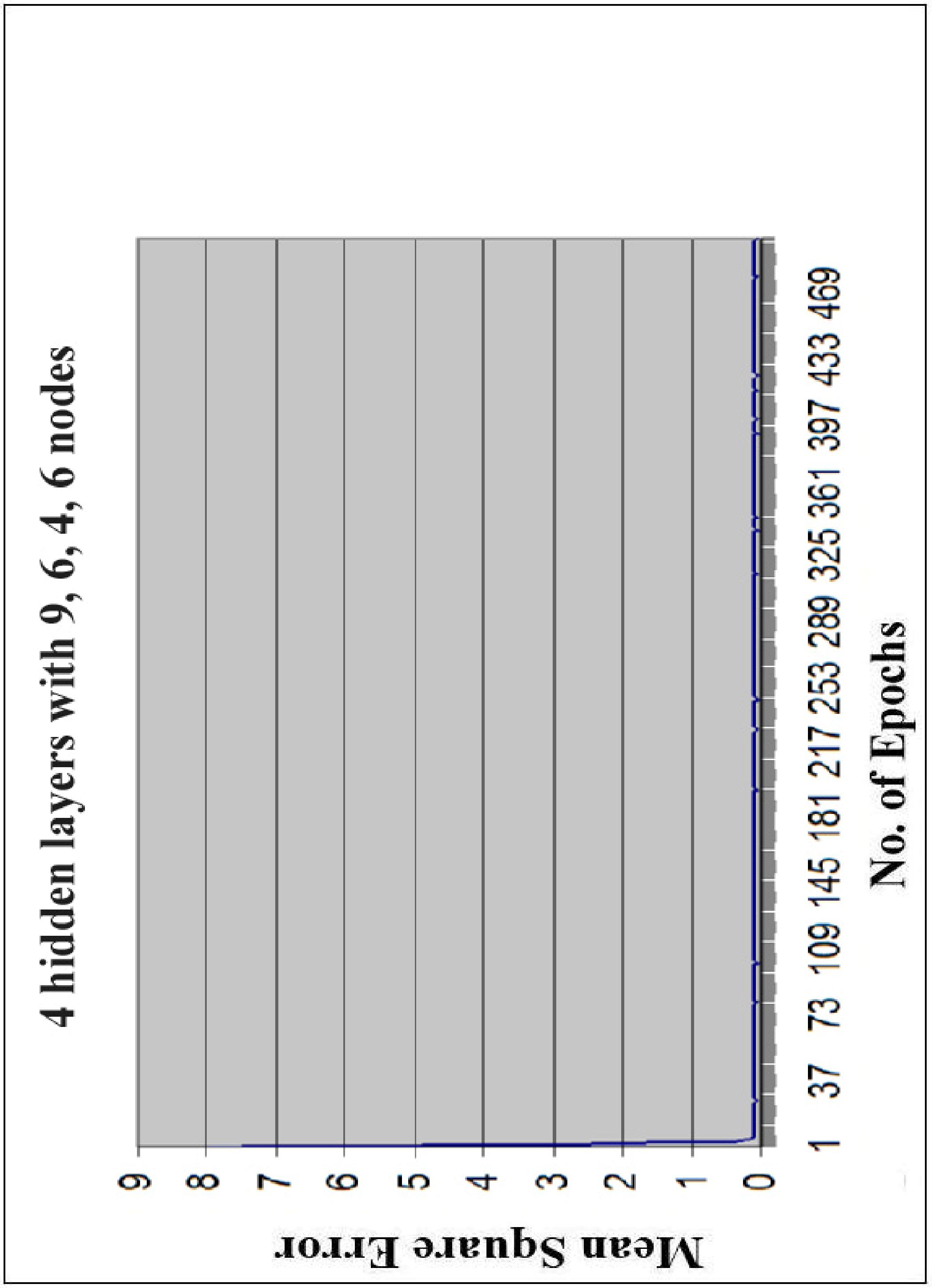

4 hidden layers with 9, 6, 4, 6 nodes
Mean Square Error
0
1
2
3
4
5
6
7
8
9
1
37
73
109
145
181
217
253
289
325
361
397
433
469
No. of Epochs

Fig. 8.16

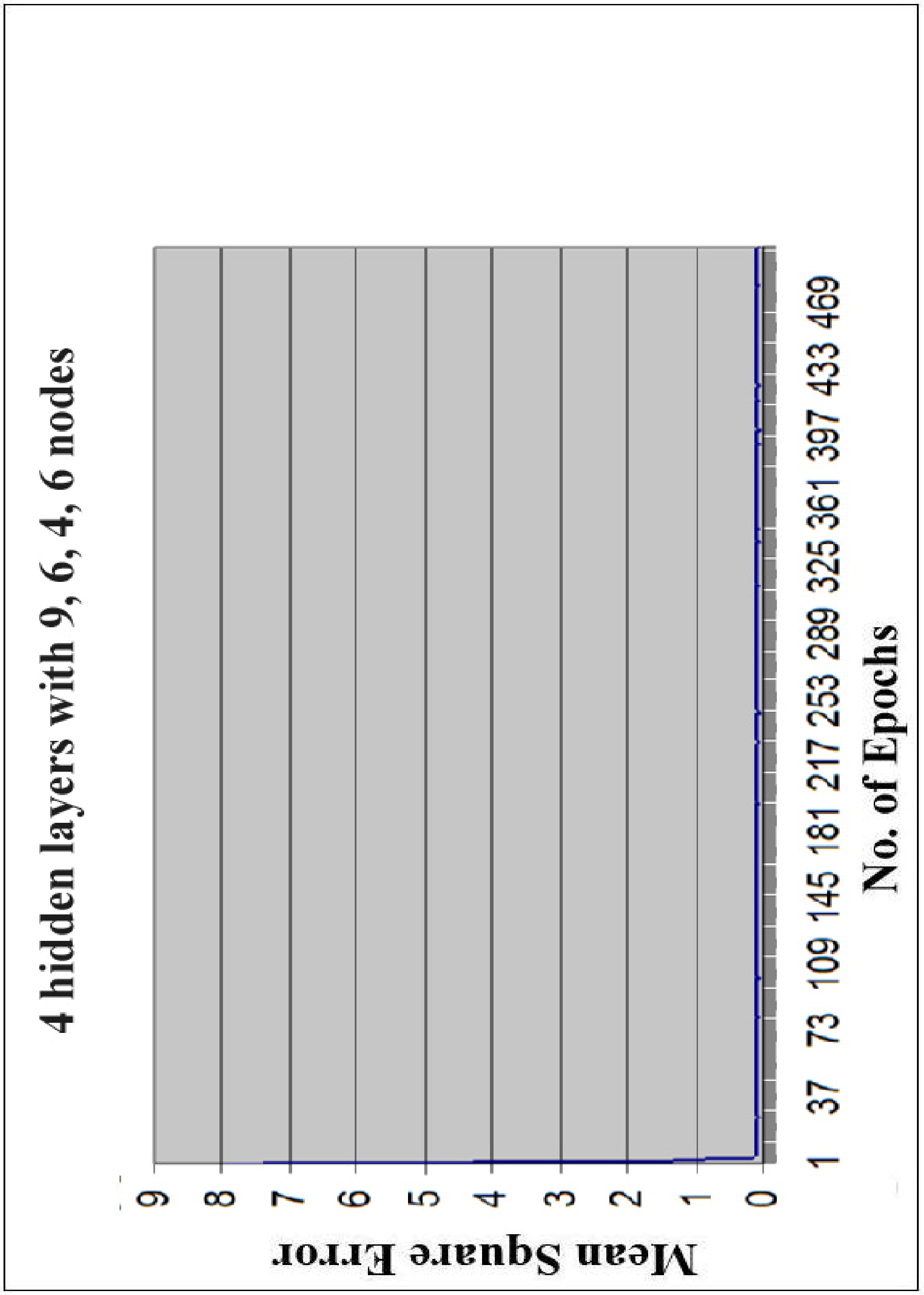

4 hidden layers with 9, 6, 4, 6 nodes
Mean Square Error
0
1
2
3
4
5
6
7
8
9
No. of Epochs
1
37
73
109
145
181
217
253
289
325
361
397
433
469

Fig. 8.17

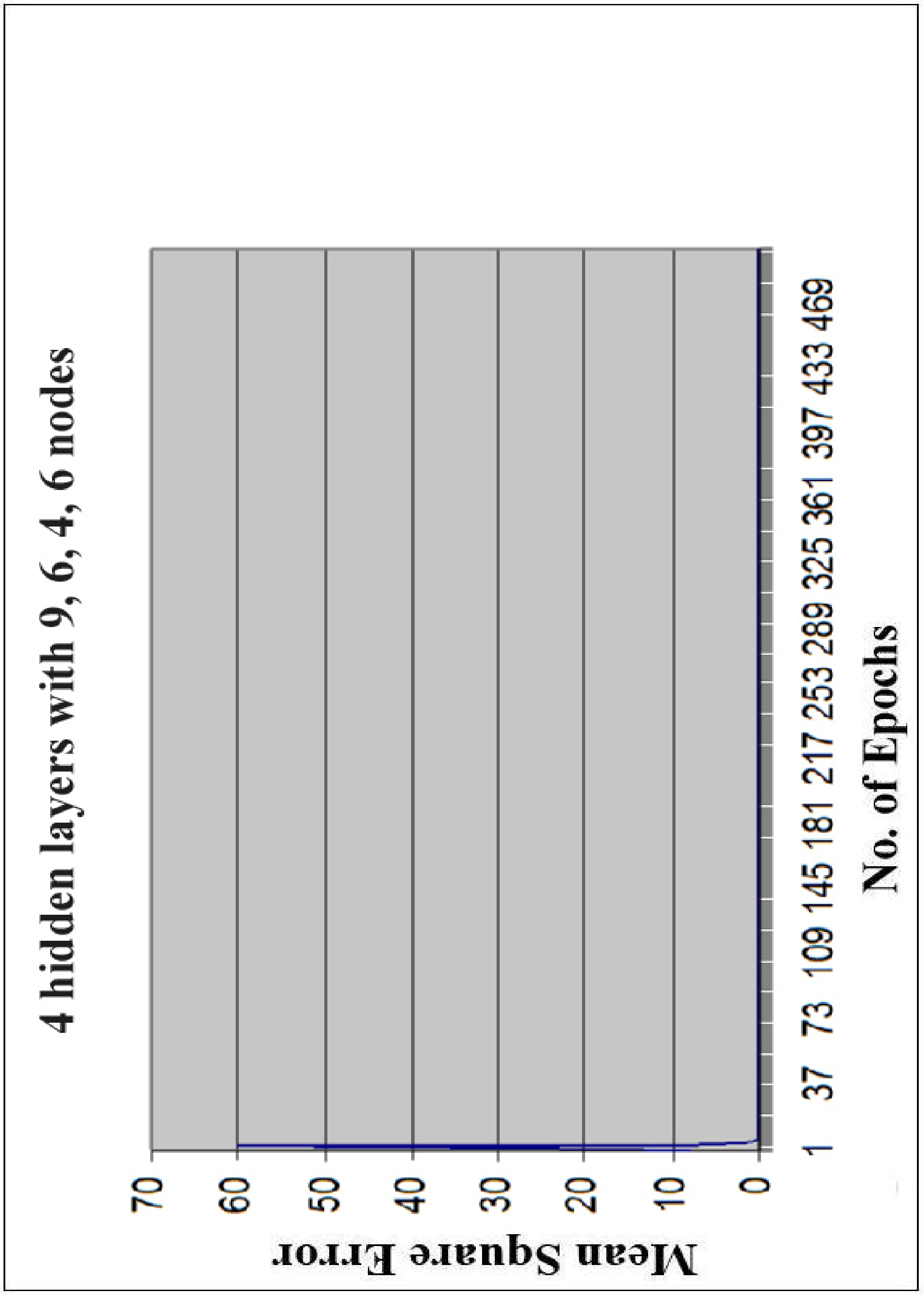

4 hidden layers with 9, 6, 4, 6 nodes
Mean Square Error
70
60
50
40
30
20
10
0
1
37
73
109
145
181
217
253
289
325
361
397
433
469
No. of Epochs

Fig. 8.18

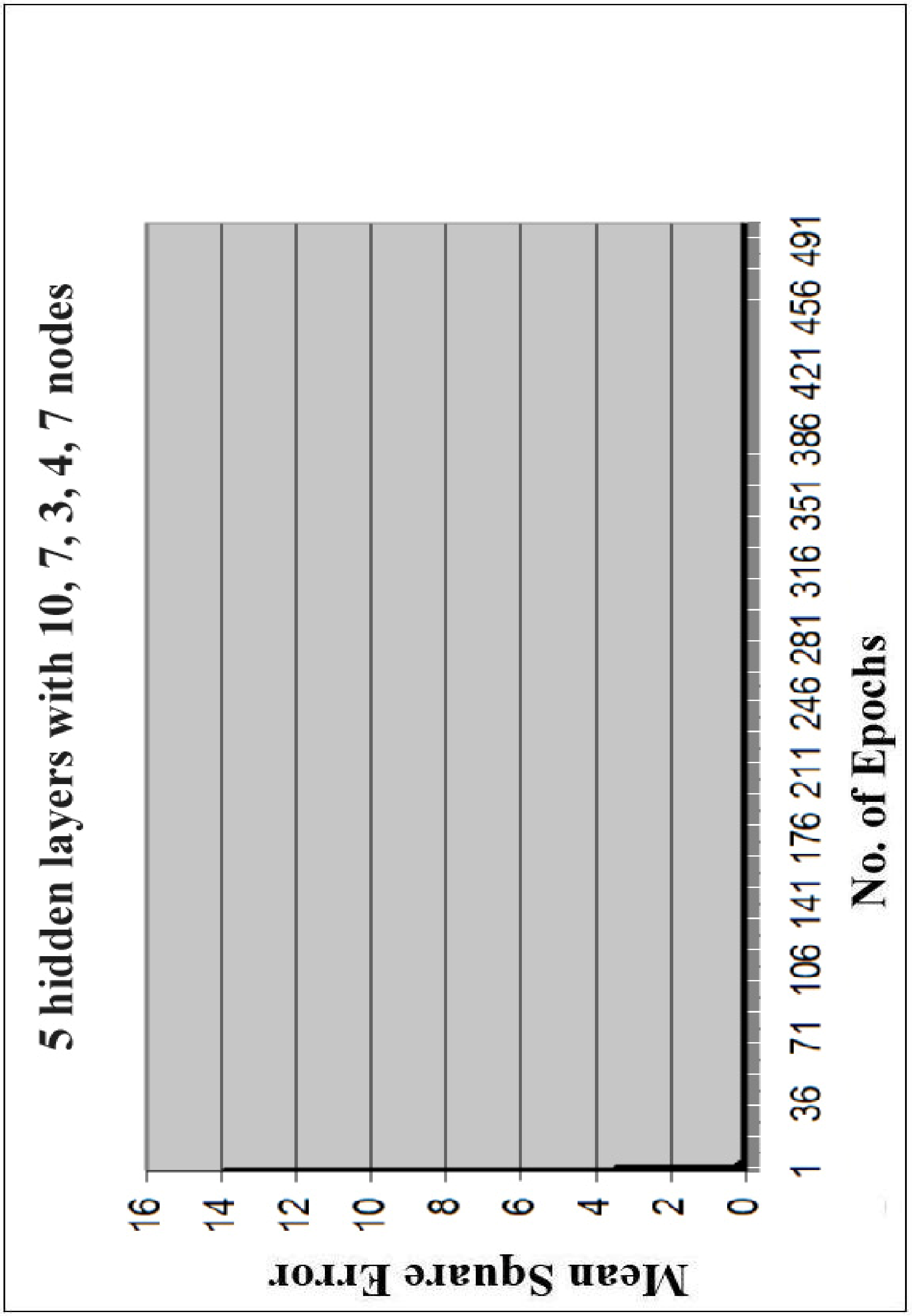

5 hidden layers with 10, 7, 3, 4, 7 nodes
Mean Square Error
16
14
12
10
8
6
4
2
0
1
36
71
106
141
176
211
246
281
316
351
386
421
456
491
No. of Epochs

Fig. 8.19

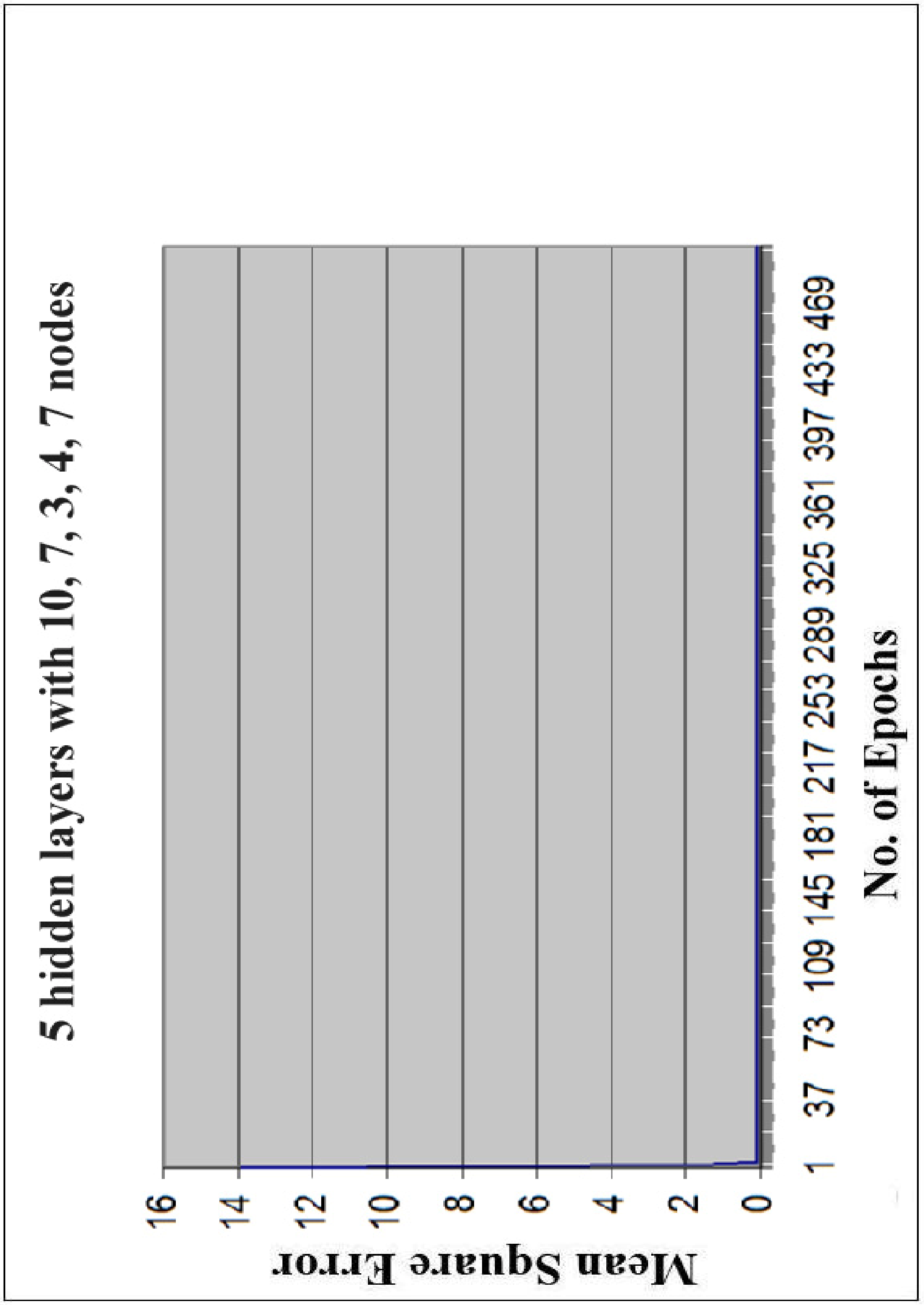

5 hidden layers with 10, 7, 3, 4, 7 nodes
Mean Square Error
16
14
12
10
8
6
4
2
0
1
37
73
109
145
181
217
253
289
325
361
397
433
469
No. of Epochs

Fig. 8.20

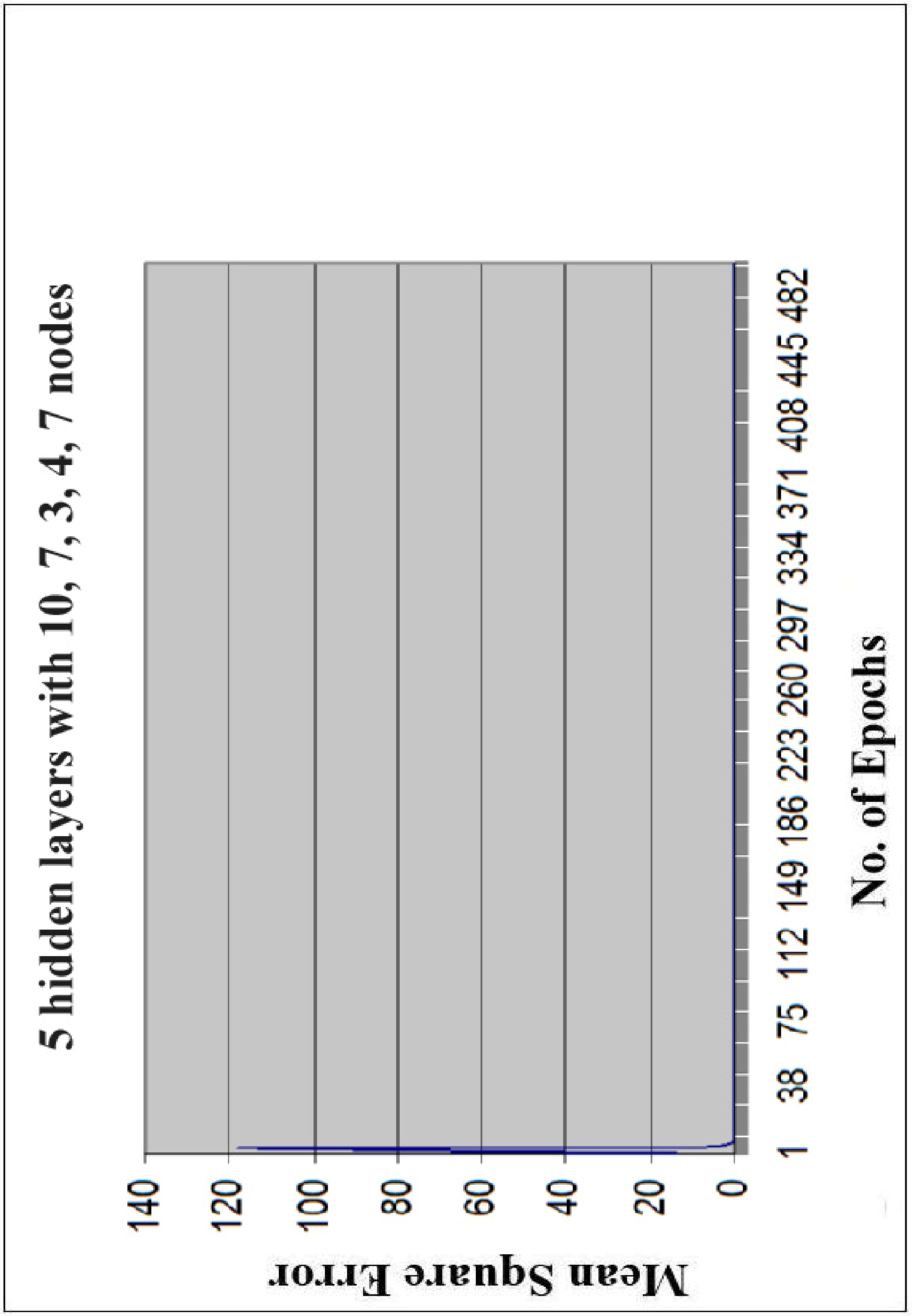

5 hidden layers with 10, 7, 3, 4, 7 nodes
Mean Square Error
140
120
100
80
60
40
20
0
1
38
75
112
149
186
223
260
297
334
371
408
445
482
No. of Epochs

Fig. 8.21

Chapter 9

CONCLUSION

CONCLUSION

From the above graphs we came to the conclusions regarding the parameters for obtaining the optimum structure for ANN.

- The optimum number of layers including the hidden layers.
- Structure for the number of neurons in each hidden layer.
- Optimum value for the learning rate.
- The difference between the batch& sequential mode.

The graphs are drawn between the number of iterations as the independent variable and the mean squared error as the dependent variable. From Fig 8.1 it can be seen that the mean square error starts at 1.6 and gradually reduces to 0.07 at the end of 500 epochs. Thus we can say that the weights of the ANN model has got trained, and will give the output of the function approximated for any input with an error up to 0.25

From Fig 8.1- Fig 8.12 it can be seen that the mean square error starts from around a reasonable value to a minimum of about 0.07 hence these are good examples of training. But our quest for a best trained ANN structure is not over.

From Fig 8.13- 8.15 show that for a structure like five hidden layers with 8, 6,4,3,1 neurons in each hidden layer have a poor quality of convergence. Here the term convergence means that the graph between the number of epochs versus the mean square error value must be smooth. But in the above said graphs the graph is not smooth, even the mean squared error value just before the 500th epoch is equal to the mean squared error value at the starting of the program. Therefore we conclude that the structures having a large number of hidden layers and having the neuron number in each hidden layer in descending order have a poor quality of convergence. This may be due to over fitting.

Contrary to the above said phenomenon the Figures 8.16- 8.21 show that for the structures like 4 hidden layers with 9,6,4,6 neurons in respective layers have a very good quality of convergence. The mean squared error starts at a very high value and at the end of 500th epoch reaches a very low value (as low as 0.07). Hence we can say that the structures having a medium number of hidden layers with a specific kind of neurons have good quality convergence. Here good convergence is because of the smoothness of the graphs which could not be observed in case of Figures 8.13- 8.15

The specific kind of structure of ANN, as we have mentioned above is that the minimum number of neurons are present in the middle hidden layer and it increases on both sides of this layer. For example if there are four hidden layers, the minimum number of neurons are present in either of the second or the third hidden layer (9, 6, 4, 6).

Thus we have found out the optimum structure for the ANN model for function approximation leaving the learning factor parameter untouched. The comparison for getting the optimal value of the learning rate is given by the graphs in each group. From the graphs it can be seen that there is no much difference between them as the learning rats is increased. Hence we choose an optimal value for the learning rate as 0.1.

Hence it can be seen that the Fig 8.17 represents the best structure for function approximation at the above said learning rate.

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