Information Processing

in

Neural Networks

by

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As a background to a comprehensive discussion on recent work in neural modelling, the thesis provides a brief biological background description of some of the components of Natural Neural Systems. The review of the work of earlier neural modellers concentrates on the work of the last fifteen years, with the exception of a few earlier, classic, papers. The research work performed for this thesis employs an Experimental System evolved to test the ability of a digital, discrete-time model of a neural net to process patterns of signals, provided as input. The aim of the Experiments was to find the type of networks that can perform useful pulse processing functions. The Experimental work is divided into two sections, the first analysing non-adaptive nets and the second analysing networks which use Hebb-type algorithms to alter the strength of interconnections between cells.

The first section describes and displays activity of many neural nets. Different inputs are applied to the net and the effects noted. The study is extended by employing Spectral Analysis techniques. The effect of many parameters on frequency of firing of the net are examined including, for example, the decay rates used in the cells and the frequency of the input signal.

The second section simulates adaptive nets and examined the relationship between input signals and the final activity of the adapted net. It also employs Spectral Analysis and a specially defined form of display, the Cell Firing Histogram which provides information on how the circuits are being altered by the algorithm. A simple mechanism, for recognising signal patterns, is proposed that employs several of the properties discovered using the Cell Firing Histogram.

Key words: digital, neural, net, model, adaptive.

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CONTENTS

CHAPTER I

Introduction

This chapter seeks to provide a biological background to the models constructed. It is not meant to be a definitive thesis on the subject as the total volume of material available would make a treatise in itself. The chapter should provide a sample of the numerous theories proposed for the mechanisms of brain function. These theories provided inspiration for the many models to be described in the next chapter.

The first section describes some of these general theories and the observations which prompted them, the second section deals in more detail with the neuron and impulse transmission.

Preliminary remarks

Comparative neuroanatomy indicated that the mantle of cells that covers almost all of the brains of higher mammals, the cerebral cortex, should shed some clue as to the mechanism behind intellectual behaviour. Staining of cells in slices of brain tissue (eg Lorenté de Nó. 1943) and their subsequent transfer to drawings indicated how complex the interconnections could be, although only a fraction of the cell bodies and their fibres were shown up by this method. Various layers could be made out, defined by the different types and density of cells within them. The relative thicknesses of these layers varied from region to region over the brain. Lorenté de Nó suggested the idea of linked chains of neurons providing reverberatory circuits. Scholl (1956) produced a detailed analysis of the cortex and a quantitative description of the cell population. For example he gave the thickness of the cortex as varying between 1600μ and 2800μ (μ= micron), and agreed with the estimate from previous workers of 9×10^9 neurons in the human brain. The density of cells showed no correllation with intelligence as, for example, the mouse was ten times more densely populated than Man. Scholl went on to indicate that the probability of two cells interacting varied exponentially with the distance apart. He was the first to propose investigations "based on the concept of probability and discussed in a statistical language".

Another eminent worker in the field of neuropsychology was Lashley (1953). In an enormous number of cruel and crude experiments on live animals he showed that their ability to perform and learn tasks, after part of their brain had been removed, was impaired such that the rate of formation of some habits was related to the extent of the injury. Unlike a digital computer then, the memory involved is presumably distributed throughout the brain and not located in a specific place. Lashley suggested that "the nervous unit of organisation in behaviour is not the reflex arc, but the mechanism, whatever be its nature, by which a reaction to a ratio of excitations is brought about". These experiments have been queried in their direct relevance to the human brain, but the principle of slow degradation of function is supported in the evidence from human brain damage, with the important exception of the speech area. This "new" functional development in the brain may be equivalent to a highly complex task requiring the correct retention of many "subtasks". Lashley found that complex tasks were the first lost. He went on to suggest that "the dendrites and cell body may be locally modified in such a manner that the cell responds differentially, at least in the timing of its firing, according to the pattern of combination of axon feet through which excitation is received".

These and other theories led to controversy over the nature of interconnections between cells. The lack of recognition of particular circuits in the stained slides and the inability to locate specific functions tended to suggest that the interconnections need only be specified "statistically", that is every fibre junction did not need to be positioned exactly. The vast problem of coding any such specific information in a deoxyribonucleic acid (DNA) molecule also appears to preclude such a method. The lack of repeatability of experiments involving intra-cortical stimulation of both animal subjects and humans during surgery, where the function elicited varied between stimulations, also supports the arguments against a "hard-wired" model.

In more recent studies however, specific circuits have been located in the cerebellum, described by Calvert (1972) and Hubert and Wiesel (1961) demonstrated the existence of columns of behaviourally complex cells in the visual cortex of cat. These cells were 'tuned' to a particular orientation of the object in the field of view. These findings and the sensitivity of the speech area to damage tend to suggest the existence of specialised circuits within the brain.

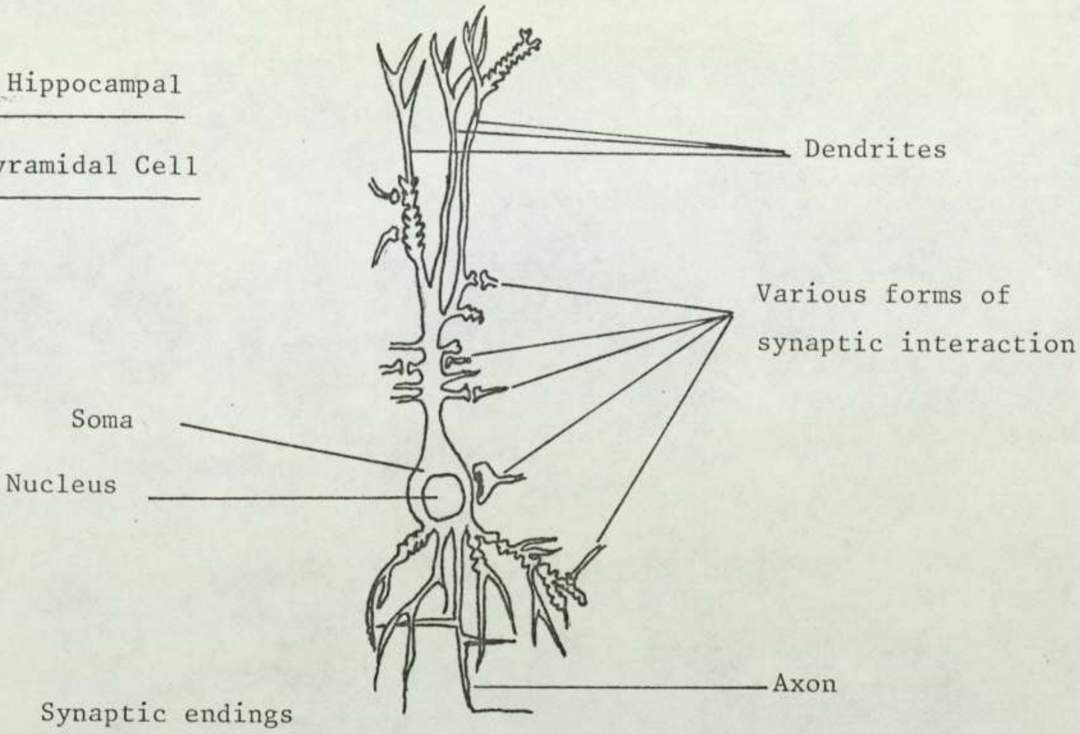
The attempts to investigate brain function and the theoretical models tend to reflect the progress of this controversy. Adaption to stimulus was sought at the single cell level by Eccles (1953) and via the gross electrode electroencephalogram (E. E. G.) readings. The signal to noise ratio of E. E. G. 's was so low that repetitive stimulation and averaging techniques of analysis were employed to improve this. Adaption was demonstrated at both levels for instance by the fatiguing of a cell and the 'anticipation' of a repetitive signal in an evoked response (for example see John (1967)). At which level memory can be said to be represented is also discussed by John.

The unit or organisation within the brain has been postulated to be of various sizes and shapes. Current ideas favour a compromise between the two points of view, typified by the work of Harth et al (see Chapter 2) where cell assemblies are defined specifically "in the large" and randomly "in the small". The mechanism for learning is generally considered to involve synaptic facilitation, that is the effectiveness a synapse has in firing a neuron, but the nature of this facilitation is still undecided. (eg Hebb 1949, Milner 1957, Brindley 1969, Marr 1970).

The code that neural signals employ is totally unknown but often assumed to be related to frequency of firing. That threshold devices (as neurons are) would seem to be suited to analysing patterns of incoming pulses in both space (spatio-) and time (temporal) is one of the reasons for the experimental approach of this thesis.

The Neuron

The neuron (see Fig. 1) is a specialized cell, of variable shape and size, found in the nervous system. Like other cells, each nerve cell has a nucleus and surrounding cytoplasm. Its outer surfaces consist of numerous fine branches called dendrites, which receive pulses from other cells and generally one long output fibre, the axon. Near the end of the axon it divides into branches which terminate in junction points termed synapses that come into close proximity with other dendrites and cell bodies. The cell membrane separates, in its resting state, two solutions of different ionic concentrations of Sodium, Potassium and Chlorine. The diagram (Fig. 2a) shows the relative concentrations and the resulting potential difference across the membrane. Normally K^+ and Cl^- ions pass relatively freely across this membrane (see Fig. 2b) but by a combination of a metabolic pump that forces Na^+ ions out of the cell and K^+ ions into it and the membrane's impermeability to Na^+ ions coming into the cell, the different concentrations are maintained. This situation can be temporarily reversed by the action of synapses contiguous to the cell body or the cell's dendritic surface by altering the cell membrane's permeability to Na^+ ions in the vicinity of the synapse. This causes local depolarisation of the cell, which



A Hippocampal Pyramidal Cell

Synaptic endings on neurons

Figure 1a

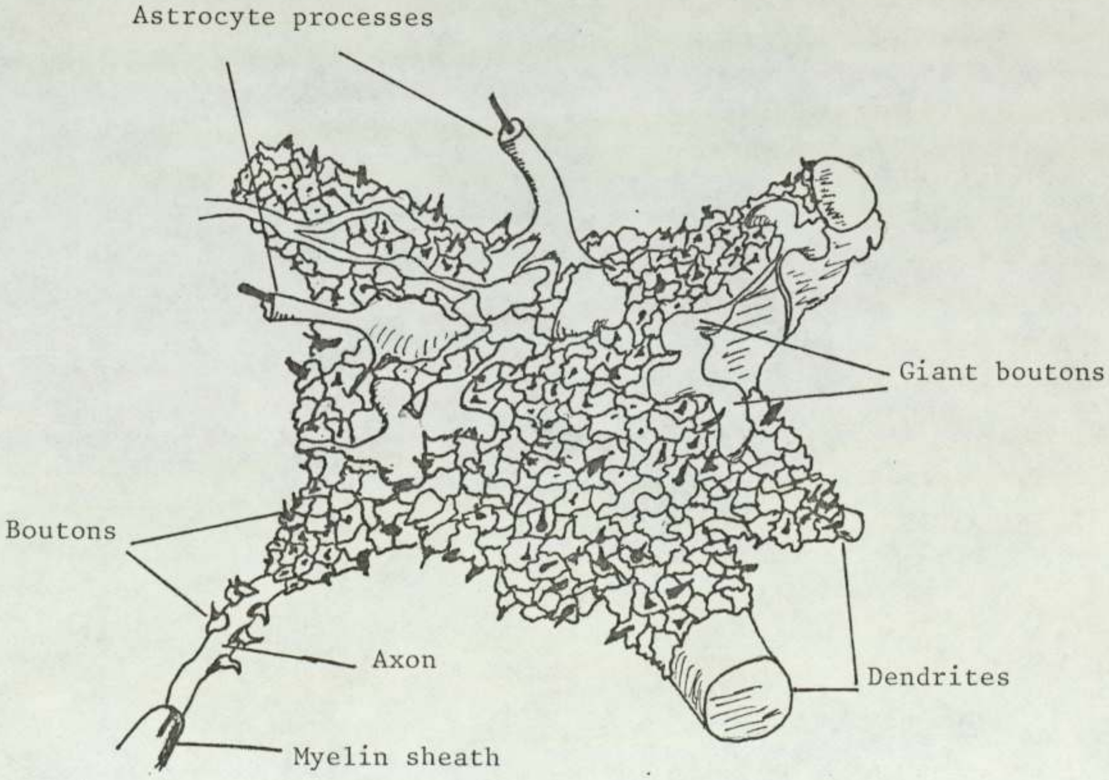


Figure 1b

Highly packed surface of a motorneuron

Conditions across the membrane of a Cat motoneuron

AQUEOUS EXTERIOR Ionic Composition mM		SURFACE MEMBRANE Lipoid - protein Equilibrium Potentials mV			AQUEOUS INTERIOR Ionic Composition mM
K^+	5.5	+	90	-	150
Na^+	150	-	60	+	15
Cl^-	125	+	70	-	9

Figure 2a

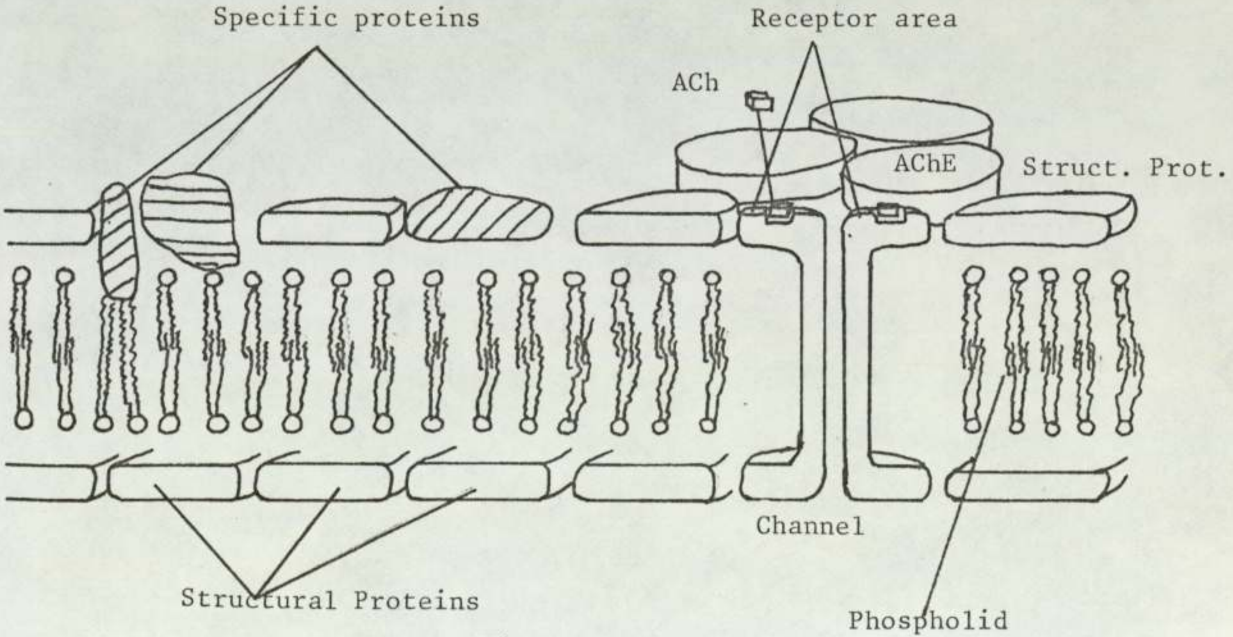


Figure 2b

Macromolecular organisation of surface membrane. The basic structure is a bimolecular leaflet of phospholid molecules that is stabilised by structural proteins. A transmembrane channel is also shown.

on reaching a threshold value, results in a spike being generated and passed down the axon. The spike is very sharp as the sudden influx of Na^+ ions causes even greater permeability through the channels of Fig. 2b and an explosive change occurs. This rapid change in the potential across the cell reaches an equilibrium value and the inward flux of Na^+ ions slows down and also a compensatory outward flux of K^+ ions curtails this imbalance to the extent of a final slight hyperpolarisation. This behaviour gave rise to the term 'all-or-none' spike discharge. Following a spike discharge the status quo is restored by the metabolic pumps mentioned earlier and possibly the interaction with specialized supportive glia cells which occur in even greater number than neurons. Further functions of the glia have been suggested by Galambos (1961). Firing rates of neurons vary between types but are surprisingly high, for example motor neurons: 200 spikes per second and certain Renshaw inter-neuron cells: 1600 spikes per second. Fig. 3 shows various types of cell and some aspects of the structural design of the cerebral cortex (from Colonnier M. L. 1966). The recovery time of a neuron (the absolute refractory period during which it cannot re-fire) is generally around half a millisecond.

The Synapse

The synapse (see Fig. 4a) does not make contact with the dendrite or cell body (termed the post-synaptic membrane) but is separated by a small gap, the synaptic cleft, of uniform size 20 millimicrons. It is into this gap that the synapse, on stimulation by a pulse from its parent cell, releases a certain quantum of transmitter substance held within small vesicles in the synapse body. This transmitter substance acetycholine (ACh) either reaches the postsynaptic membrane and opens the Na^+ channels of Fig. 2b or is turned into acetic acid and choline by an enzyme acetycholinerase (AChE), which resides on the post synaptic membrane surface. The acetic acid and

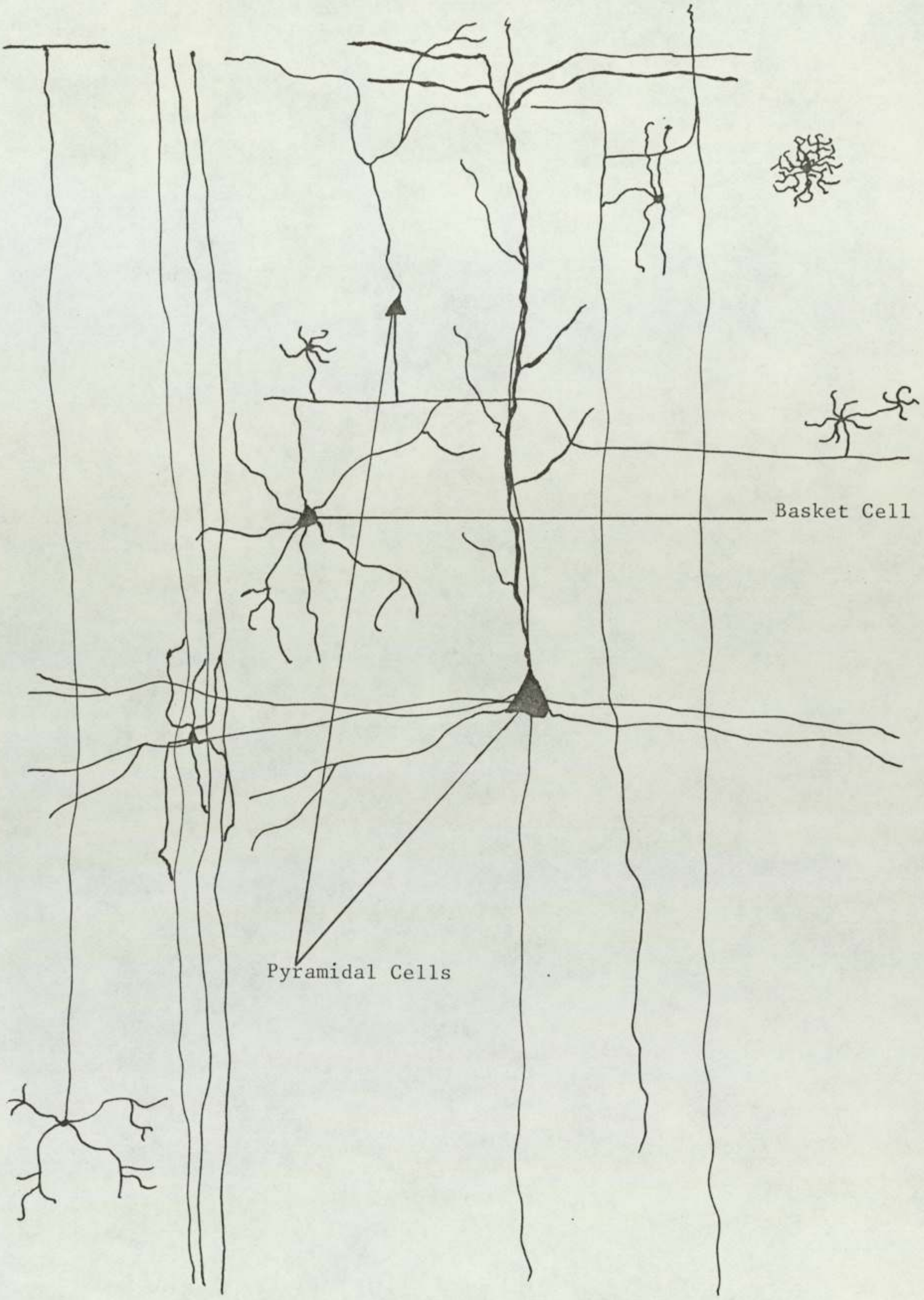


Figure 3

Freehand drawing summarising some of the types of neurons and aspects of the structural design of the cortex.
(from M.I.Colonnier , 1966 and Cajal ,1952)

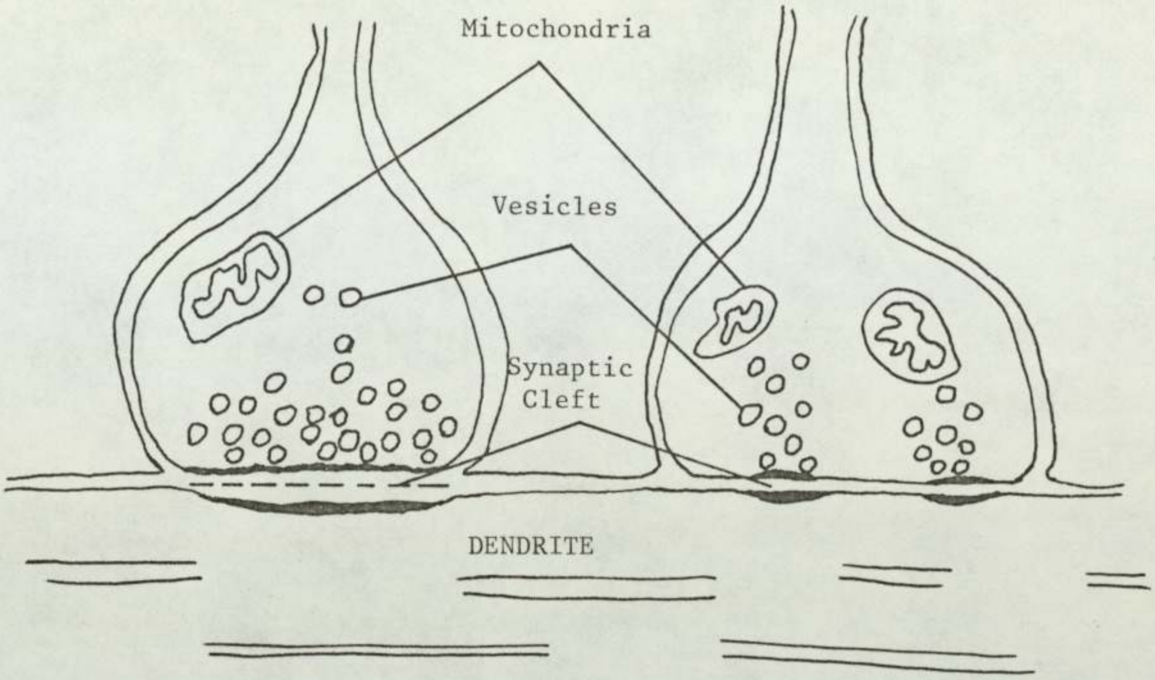


Figure 4a Synapse knobs

These release transmitter substances ,held in the vesicles, into the synaptic cleft. The Mitochondria supply energy to the cell. (from Eccles ,1965)

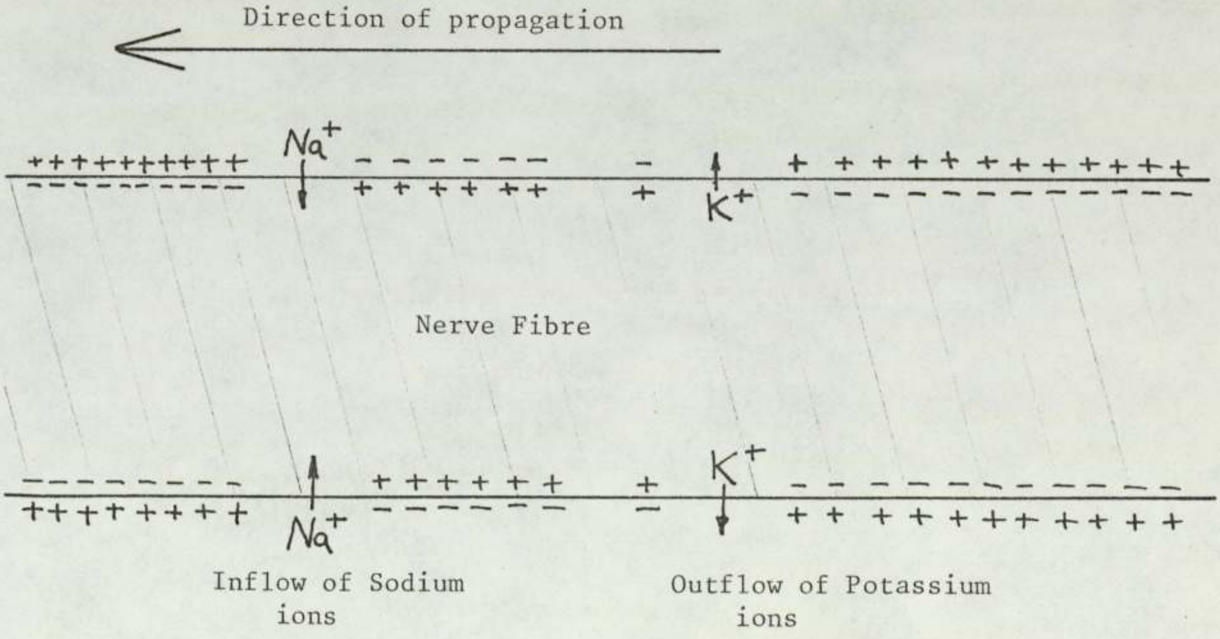


Figure 5a Cable properties of a nerve fibre

(from Eccles, 1953)

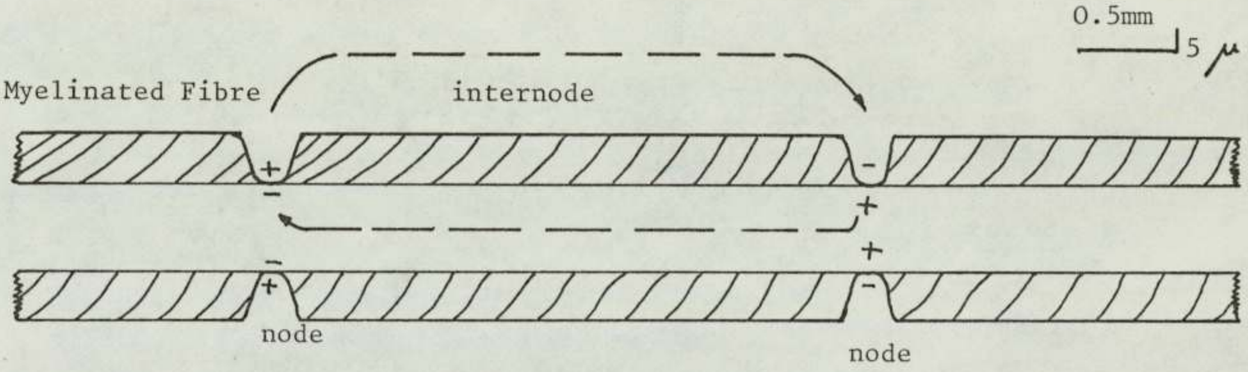
choline can penetrate the presynaptic membrane into the synapse and be reformed into ACh held in quanta in vesicles. The cycle represents a sophisticated control system in itself, the quantity of AChE and the recombining acetycholine transferase determining a synapse's effectiveness and state of fatigue.

This relatively simple direct action of synapse to dendrite has been queried by, for example, Shepherd (1972) who suggests direct interaction is possible between synapses layered on top of each other and between dendrites without the intermediate synapse. Also synapses of an inhibitory nature containing a different type of vesicle have the opposite effect of the excitatory ones described.

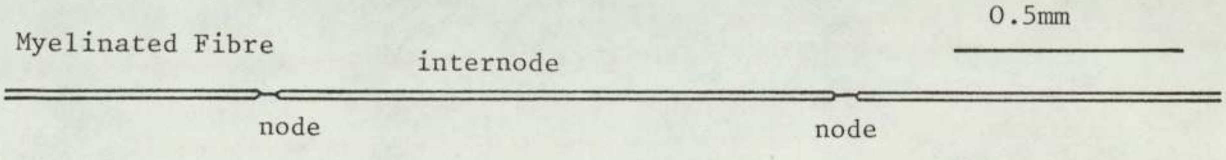
Conduction of the Nerve Impulse

The nerve fibre has a very low conductance but by employing the same mechanism of opening the Na^+ gates, this time by local depolarisation alone, the pulse can be regenerated in a manner analogous to the voltage boosters employed in long distance electrical cables. The diagram (Fig. 5a) illustrates how the cable effect of the fibre only has to transmit the depolarisation a minute distance ahead and the process then repeats itself. The outflow of K^+ ions in the wake of this impulse restores the resting potential. The very small change in ionic concentration implied can be rectified by the metabolic pump mechanism over a longer time interval. This method due to the ionic exchange involved is relatively slow (5 - 20 metres/second for a crab axon) but can be overcome for certain fibres by myelination. This is the coating of the fibre in a thick insulation that is interrupted at intervals. Only at these intervals (see Fig. 5b) can a current flow take place and the impulse hops from node to node without any interaction from the fibre in between. The hopping of the impulse, called saltatory transmission, and the enormous reduction in the electrical capacity between the axis cylinder and its surround, make the system very efficient and speeds of, for example, 100 metres per second have been recorded.

This brief resumé can be complemented with reference to Eccles 1965, 1973; Katz 1966; Ramón y Cajal 1952; Colonnier M. L. 1966.



Diagrammatic representation of current flow



Real Scale

Figure 5b

Myelination

CHAPTER II

Review of Neural Net Research

Introduction

This chapter is mainly concerned with work of a fairly recent nature, an approach made necessary by the volume of material available, although mention is made of some early classical papers. The reader who is interested in all the earlier work on brain modelling, including neural net simulations, should consult Harmon (1966).

The first paper that could be described to be dealing with neural nets was that of McCulloch and Pitts(1943). This paper analysed the behaviour of simple logical elements arranged in networks. The elements themselves had constant thresholds (ie. no refractory periods) and the connections between them were fixed. The authors suggested that despite learning variations any network subsequently formed could be replaced by an equivalent net and the laws of mathematical logic would still apply to analyse them. This implied a strict determinism which prompted biologists to point out the vast simplications that such an approach was making.

In a theoretical discussion on neural networks that appeared in a paper by Cragg and Temperly (1953) the analogy was suggested of a magnetic field affecting an array of small compasses. As the field changed in strength so the movement of the needles would reflect 'domains of equal excitation' spreading over the array. They predicted that there would occur during growth, a critical stage when the interconnections were of such a density that this 'cooperative behaviour' would begin. The sudden change observed in the form of young children's E E.G.'s as they reach a certain age could be explained by this and the movement of the domains hypothesised could be reflected in the detection of changes of potential over a global rather than local area. The study is interesting as a tool for imagining large scale networks of elements, but it does not allow for the individual differences in interconnection between elements which are currently believed to have a significant effect.

Another theoretical suggestion came from A. M. Uttley in 1954 in which he argued that due to the dense interconnections between neurons a classification system would automatically be set up. This would arise when neural firing was considered as indicators of every possible combination of active input fibres and with suitable delays involved, the networks could recognise all temporal patterns of these combinations as well. He constructed a small machine to demonstrate this. In a real network, however, I believe the unusual event would be swamped by the activity of its constituent sub-events and with some spontaneous firing as well the delicate wiring analogy would not function correctly.

In the same year, the first of the contributions of Farley and Clark (1954) appeared. This was the first to employ a digital computer to simulate a network. The elements employed were designed after the McCulloch and Pitts neuron, but refractory periods were added. When an element fired it simultaneously excited other elements in the net by means of a connection matrix originally created by selection from a specific probability distribution. The elements had thresholds associated with them which decayed exponentially. The excitation also decayed exponentially. The operation of the net was simulated by calculating the activity at discrete moments in time. The purpose of the work was to see if such a system was capable of self-organisation in that it would adapt to produce a desired response. The performance is reminiscent of linear classifiers such as the Perceptron where the task is inherent in the manner of modification of the individual synapse values and therefore could not be considered a random net.

A classic study by Rochester (1956) used digital simulations of neural nets to test the psychological theories of Hebb (1949) and Milner (1957). In a similar discrete time simulation to Farley and Clark's they modelled a net of 64 elements. They included a fatigue characteristic in their elements which reduced the firing rates of frequently firing cells. At first they felt that a model of short term memory was being displayed by a succession of net states which were typical of the input signal. However, they found that the slightest change in firing patterns, for a different signal, soon produced vastly different behaviour in the net. They modified their net to accommodate 512 neurons but, due to the restrictions of their machine's capacity, had to deal with the frequency of firing of elements rather than using the detailed knowledge of the individual states. This study suggested that, with adaption, cell assemblies did form near the input site, but there was little exchange of "information" between them and they remained separate entities. They finally proposed to introduce, on the suggestion of Milner, inhibitory connections and that these were subject to a greater decay of their impulses, which would allow activity to swap in dominance between one assembly and another in the manner of a flip-flop. The study serves to illustrate how difficult it is to guess the global properties of a network of elements whose individual behaviour is nevertheless well defined.

R. L. Beurle (1956) discussed the properties of a network or medium of excitatory cells. He suggested that due to their refractory properties waves of activity would spread across the medium. The propagation of the activity would be dependent on the values of the cell's thresholds and density of connections and could either die out or saturate the medium. For critical values waveforms could pass along the net. By a form of feed-forward mechanism a facilitatory response at the wavefront could support this spread by providing subthreshold excitation there. Similarly a damping mechanism due to prefiring at the wavefront could control the threshold levels within the critical limits. He postulated that when a wave did attenuate to a single cell it could effectively trigger a selective motor response and thereby act as a classification mechanism, selecting between patterns of active cells. He extended these suggestions, together with a conditioned reflex mode of action 'inherent in the nature of the medium' to propose a mechanism capable of regenerating sequences of waveforms previously experienced. An additional requirement was the need for a "discriminator of satisfactory situation". By trial and error initially and subsequent recall of events using this mechanism, an organism could "discover the most probable results of a contemplated action". This paper, twenty years later, is a most persuasive and interesting work. It marked the beginning of a series of papers, by many authors, that attempted to extract mechanisms by treating a net mathematically, without simulation. The only criticism can be from experience of simulating models and seeing the well-ordered waveforms so crucial to these proposals, broken up by internal and spontaneous firing. The use of the attenuated signals firing only one element would be very hard to extract in the background of the noise usually present.

In the first in a series of papers by either himself or related groups, Caianiello (1961) published a paper on a proposed theory of thought processes, based on a series of equations which described the activity of a neural net and its adaption. He considered networks of elements at discrete intervals τ , the synaptic delay, which combined the speed of propagation between neurons with the delay at the synapse. He described the net's behaviour by two sets of equations, Neuronic and Mnemonic equations, which represent the activity of the net and its adaption characteristics respectively. He justified splitting the two processes by an Adiabatic Learning Hypothesis which states that the changes to the network's structure is a much longer process than the firing sequence of the elements and can therefore be considered independently. This is an artificial simplification of the ideal situation where the coefficients of the Neuronic Equations would be taken as slow functions of time. Further approximations were that pulses arriving at a synapse are extinguished even if they do not contribute to a firing of the post-synaptic cell and the threshold of a cell is constant. However, included within this formulation was the ability for a pulse to have a delayed effect on the post-synaptic cell, but in his analysis this was considered to be of negligible effect. Also he suggested the possibility of interaction between cells and axons in a more direct fashion than via a synapse. The Mnemonic Equations determined that the coupling co-efficient between cells increased in value only if that pathway was active in the time instant before the post-synaptic cell fired. The coefficient could not exceed a maximum value and decays slowly at values below this. Caianiello tried to relate his equations directly to psychological phenomena such as thought-processes, punishment and reward, learning and generalisation. He argued that the small changes induced by the Mnemonic Equations, the possibility of external activity control by threshold manipulation and random connections would all contribute to a stable system. He also argued that the net would exhibit Self-Organisation by 'convergence in time to a more efficient operation'. Much of this paper was hypothesis with no actual simulation, presumably as a groundwork for later work, but he did suggest the consideration of network activity (size N) as trajectories within an N-dimensional configuration space such that a reverberation would be represented by a closed polygon. This description was subsequently used by many authors. In 1971 a paper appeared (Burattini and Liesis 1971) that extended this idea. They simulated elements similar to Caianiello's but included temporal summation of signals which decayed exponentially with time and had absolute refractory periods of length $T > \tau$. Rather than rely solely on the activity level alone for analysis they introduced variables which gave some indication of the similarity between any two states of the net. This was extended to produce a measure of the similarity between any two particular reverberations within the net. The mean and standard deviation of all possible values of this last coefficient were also calculated and plotted. These methods of analysis showed how the net approached reverberatory states and that the overall activity was acutely sensitive to changes in the elements' threshold values which apart from the absolute refractory period were kept constant during an experiment. An attempt was made to demonstrate adaption to an input signal using these measures despite the absence of the type of adaption implied by the Mnemonic Equations. The most recent papers of Caianiello (1975, 1976) attempt to extend the model to consider more latent responses between cells by allowing the effects of inter-cell communication to be calculated from a wider range of previous time increments. By considering couplets of neurons the authors attempt to demonstrate that Caianiello's original approximation of considering only the activity one time instant in the past was a fair one.

An example of a different approach was the work of Taylor (1964) where the emphasis lay in specifying exactly the connections between elements according to features extracted from observations of cortical organisation. He suggested a Perceptron-like model which involved feedback to produce a maximum amplitude filter of the output and 'pleasure and pain' teaching terminals. In his computer simulation various inputs were applied to the model and the connection weights between input fibres and threshold elements were modified when the outputs were correct and those elements were active, in a trial and error fashion. The model showed successive improvement until all patterns were recognised correctly. Some sets of patterns were unable to be separated in a similar way to the linear separation problems of Perceptron work. The paper serves as an illustration of the approach of testing by computer simulation a particular biological theory on cortical organisation and producing inferences from the results.

In 1964 (Perkel 1964, 1976) D. H. Perkel published a paper describing a new method of simulating neural networks. His intention was to provide a model that could be used as a direct comparison to a biological experiment by writing analysis programs that would be able to use the data from either source. To overcome the usual problems of discrete simulation and thereby "avoid the conditional probability problems" that he suggested these entailed, he designed an 'interesting event' type of simulation. Employing initially the simulation language SIMSCRIPT his net functioned by building up 'epoch lists' of future events such as the predicted arrival of a pulse at a cell or the end of a cell's refractory period. By examining these lists and finding the next 'interesting time' specified, the simulation proceeded in time jumps from event to event. At each of these points the network state was altered as appropriate for the incident and further additions were made to the epoch lists. When a cell fired the firing interval was recorded in the same format as the biological experiments produced. He used this method to investigate the possibilities of detecting functional interaction between cells as indicated by cross-correlation techniques. He applied this analysis to a known model and could therefore illustrate what the correlations would imply when used on real systems. A second investigation examined the role of spontaneously firing cells in networks functioning as pacemakers, and the results were confirmed by comparison with intracellular recordings from a sea-slug (Aplysia californica). The simulation had considerable flexibility in that all parameters such as refractory periods, conduction time along a fibre and decay constants could be drawn from different statistical distributions. The synapses and cells were considered as wells of transmitter substances which would be depleted on use and consequently the cells would exhibit fatigue effects. The spontaneous firing of a cell was modelled by allowing the threshold of a cell to decay quicker than its membrane potential and hence an independent re-firing of the cell would take place without external inputs from other cells. Perkel suggested various shortcomings of his model, for example the restriction of summation at a cell to the axon hillock and instantaneous post-synaptic potentials rather than graded responses as observed in the physiology. These 'shortcomings' have never been modelled by anyone else. Gerstein (1972) used Perkel's model to test a method of analysing the temporal relationships between spike trains of individual neurons. He presented a joint peristumulus time (PST) scatter diagram which was formed from the various intervals between stimulating either two or three cells and their subsequent firing. By defining the connections between neurons and displaying the resulting scatter diagrams he was able to illustrate how this technique could indicate the underlying connectivity between cells. For three cells a stereoscopic pair of 3-D graphs was produced. The method appeared to fall down when interneurons were involved rather than direct interaction. Wood (1973) used a similar method to model a small net of two or three neurons that might be the controlling mechanism of a locust's wing.

A form of network involving different basic elements was proposed by Aleksander (1967, 1968, 1970, 1974). His units were Stored Logic Adaptive Microcircuits of 8 bits (SLAM-8s). These were adaptive logic circuits which were capable of performing all the logic functions between its sets of N input terminals and M output terminals, $2^{M^{(2^N)}}$ of them. They had "teach-terminals" built in to specify which functions were required. The purpose of this unit was to overcome the limitations of linear separability with Perceptrons. Networks of SLAM-8s incorporating feedback and random connections between input and units were applied to pattern recognition tasks such as recognising spectra. The SLAM-8s were produced in microcircuit form and in one machine combined in a set of 12. This study remains one of the few that actually does anything and serves to illustrate that by rigorously sticking to certain details of the neuron, interesting machines may be overlooked.

One of the most promising approaches was introduced in 1967 by Harth (Harth and Edgar 1967, Harth et al 1970). The basic idea in these papers was to consider neural nets on both a microscopic and macroscopic level. In the earlier paper, the connectivity matrix was defined differently in certain areas to allow a general mode of connection to be specified between groups of neurons, whilst retaining randomness on the local level. This approach reflected the current uncertainty as to the degree of randomness of interconnection in real neural systems. Their model employed a neuron which had a fixed threshold and fired on receiving excitation, sufficient to exceed this threshold, from those elements which fired in the previous time instant. The quantity of excitation that passed from one neuron to another was defined in the connectivity matrix. This matrix was modified to simulate synaptic reinforcement by a scheme based on the coincidence of pre- and post-synaptic firing. Such a net was shown to have certain association abilities, such as the classical conditioned reflex, by examining the changes made to the connectivity matrix after an experiment. In the second paper the emphasis was shifted from the adaptive behaviour to consider the activity levels in more detail. They reproduced graphs of activity curves and defined various modes in a similar manner to Smith and Davidson (1962). They included computer simulation runs of actual nets as an indication of the deviations from the statistically predicted behaviour and these deviations were found to be quite small. They also included activity level graphs of netlets (their term for those groups of elements with similar interconnectivity) which received steady input in preparation for the study of large nets of netlets interacting with each other. This particular approach yielded a hysteresis effect. This was found by plotting the steady state values of activity of a netlet against the strength of the afferent input. It was found that the steady-state activity had two main levels and the netlet would be in either of these two regions depending on whether the input was increasing or decreasing.

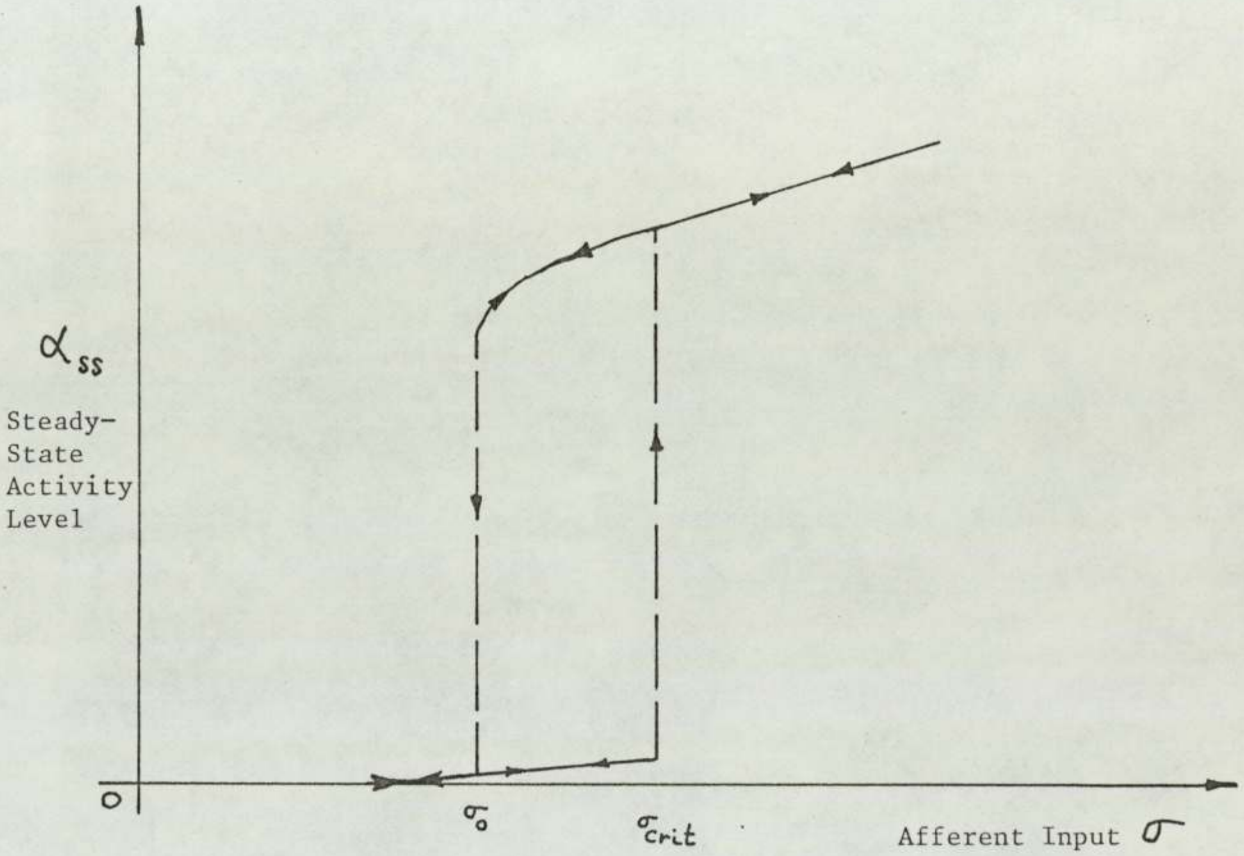


Figure 1

Hysteresis loop generated by slow changes in σ, the fraction of afferent fibres. Irreversible changes are shown as dotted lines.

This was suggested as being analogous to the Barkhausen effect in ferromagnetism which is the basis of some computer core memories. Some experiments were also performed on pairs of netlets interacting and it was demonstrated that either higher or no activity results in both nets to the same degree in a very short time (15 time units). One of the authors, Anninos (1970), of the companion paper to this last paper, had dealt with the mathematical analysis and derivation of the equations used.

He subsequently extended the idea of the hysteresis phenomenon as a memory mechanism by investigating the settings of the parameters that destroyed the hysteresis loop (Anninos 1972). He based his paper on the assumption that the adding of inhibition to the net as an input was equivalent to the noisy effect of different inputs being presented to the net. He showed that the hysteresis loop disappeared with increasing inhibitory input and suggested this was a model for forgetting. In his next paper Anninos (1972a) investigated the cycling phenomena, in the graph of firing levels, he noted in the computer simulated models. These are distinct from the statistical models which dealt solely with activity levels as he now felt ".. that not only the total number of neurons firing at any moment was significant but also which particular elements were firing". These models, like Harth's first paper, dealt with the microstates of a netlet employing a state vector indicating the firing patterns at one instant. Anninos examined the cycling of his models under various conditions of parameter settings. As with all simulations of this type there is a limit to the number of states any one net can be in and as the activity of an element depends only on that in the previous instant, the nets soon achieved cyclic behaviour of small period. He related the period of cycling to the level of inhibition. As the level of inhibition increased the time taken to the onset of cycling increased, almost exponentially as the net approached a ratio of 1 excitatory to 1 inhibitory element. He concluded also that "the period of oscillation is a sensitive function of the magnitude of the external input" but ".... on the other hand the statistical parameters of the net play an important role in establishing the cycling activity....". He also noted that the exact original microstructure of the net was unimportant between nets whose global parameters were the same. In other words the "seed" to the pseudo-random number routine he used to generate a netlet's connectivity matrix did not affect the cyclic activity. Anninos criticized Andersen's (Andersen 1966) work as he could only see "... rhythms in the autocorrelation function graphs and the cycles in the raw data were not visible on inspection". He later (Anninos 1972b) concentrated on what he defined as the latencies of response of a net, the delay before cyclic activity, and tried to demonstrate a similarity between these and evoked responses noted in averaging analysis of the E. E. G. The statistical model was called the "neuron gas model". By considering only the activity level, any coherence effect of the connection weights, which were 'frozen' to take one value each throughout the experiment, was ignored as the calculations effectively re-randomised the connections at each time instant. Wong (1973) provided further evidence for the validity of this approach by considering K-order netlets. He defined these as netlets whose behaviour was determined by activity in K previous time instants. He proposed a formalism and a description of the resultant activity in a K-dimensional activity graph analogous to the '1-dimensional' version of the previous workers. He demonstrated this with a three-dimensional graph which displayed a recursion surface to show the stability of a second order netlet. Wong also suggested employing the method of a Δ-phase plane to describe second order nets in the manner taken in classical mechanics to describe a coordinate-momentum pair. He showed his computer simulations of K-order nets were approximated by the neuron gas model and that such a system could now cater for synaptic delays, summation times, absolute and relative refractory periods.

An example of an approach which committed itself to one aspect of neural networks in an attempt to reduce the data involved to manageable proportions was the work of Amari S. (1970, 1971, 1972, 1974). He argued that the fact there was considerable redundancy in the brain, shown, amongst other things, by its recovery from damage, suggested the microstate of a network was not the most important parameter, for, if it was, the behaviour of each individual element would be critical to its correct functioning. He suggested that the activity level would be a convenient and useful parameter to study. This enabled the description of the network to be made in statistical terms, ignoring the actual behaviour of individual elements. Amari proposed defining neural nets as groups of Random Threshold Element Networks (RATEN) and analysing their activity levels and subsequently their effect on each other, when interconnected. His analysis of the stability of RATEN's suggested three modes:-

1. Monostable: only one stable activity level.
2. Monostable-bistable: either one or two levels.
3. Monostable-astable: either one level or oscillatory.

The effective weight (W) was defined as a function of the total weight vector for the RATEN and proved to be one of the factors which determined which of the three modes a RATEN exhibited. A hysteresis effect was demonstrated for a RATEN and an attempt was made to analyse interconnected RATEN's. An oscillator and an association ability was claimed although not built. A second parameter, H, a function of the settings of threshold values, was also found to be a factor determining the mode of stability. Amari also suggested treating nets in terms of the dynamics of distance between microstates and provided a few theorems based on these.

An extension of this work was that of Yoshizawa (1974) who extended Amari's analysis to include refractory periods. He produced predictions on the regions of the H-W graph that produced stability which were different from Amari's. He also implemented a fatigue factor which he concluded was necessary for reverberations of long period to be produced.

Taylor (1972) and Martin (1973) published an account of various mathematical analyses of neural nets in continuous time with spontaneous firing in cells. The nets had various topological structures, line toroid or "doughnut" (no edges). He concluded that non-homogenous nets (non-random connections) and doughnut nets were beyond mathematical analysis. Oscillations or steady state activity was predicted for other forms. He suggested that in spatially homogeneous nets with spontaneous firings, any signal put into them would be lost in the noise of the net's activity. An attempt was made to relate the final "chaos state" to the input. He admitted that he could not conceive of a method to 'readout' from such a system but pointed out that a net of only 100 neurons had upwards of 10^{30} final states and therefore capable of considerable information storage and redundancy.

The same year produced various attempts at network simulation, some involving learning techniques, an example being that of J. A. Anderson (Anderson 1972). Using matrix algebra methods he analysed a system with synaptic modification proportional to the product (obtained from the dot product of the state vectors) of post and pre-synaptic activity. By defining a measure of the memory of a net as the ratio of the output due to the signal input to the output due to noise, he concluded that an interactive memory works better as it gets larger and more richly connected.

Wilson (Wilson & Cowan 1972) treated nets as subpopulations of inhibitory and excitatory cells interacting. They employed a coarse quantisation of time as they considered that there is no information carrying capacity in fixed high frequency responses. They predicted multiple hysteresis effects and limit cycle activity which disappeared if the input was too high or low.

Kuijpers (Kuijpers and Smith 1972) provided an interesting example of treating a net as a self-organising system. They proposed that nets could be taught to recognise patterns by producing a particular reverberation for each one. Their nets were similar to Caianiello's and their elements consequently had only two states which considerably reduces the number of possible reverberations. They considered in particular two-state reverberations and employed the method to separate 80 patterns into four classes using a 36 element net. More than four classes were less successful.

Sedykh (1972) simulated a neuron medium in a continuous mode and suggested that learning was not a modification of synaptic weights to produce a specific response but an orientation effect on the direction of propagation of the wave through the net, for example to a motor area . The number of interconnections between cells was proportional to the distance separating them and he employed spectral analysis techniques in the analysis.

A network which employed synaptic adaption was described by Von der Malsburg (1973). The effect each cell had on its neighbours was defined by one number which represented the total effect of all possible synaptic connections between the cells concerned. Various other assumptions were made to simplify the analysis, such as linear summation of excitation or inhibition at a cell, and its subsequent linear decay, and the size of the post synaptic potential being the total input minus the threshold value. This replaces the all-or-none output of fixed size by an output with no intrinsic upper limitation, as is imposed by an absolute refractory period, for example. The interconnections were defined depending on the nature of pre- and post synaptic cells. All types of interconnection were dependent on distance with the probability of connection from inhibitory to excitatory decaying more slowly than the other cases. The cells were arranged in two hexagonal layers, the inhibitory cells being in the lower layer. The activity of the net was described by a series of non-linear differential equations, each equation defining the change in a cell's excitatory state (i. e. the output) with time. These are similar to Martin (1973). As there are no mathematical ways to solve these equations, approximation methods were programmed on a computer. One of the techniques was to consider only steady state solutions. The net programmed had four modes of connections. The connections between Excitatory (E) cells and Inhibitory (I) cells were defined by three constant weights and the variable connections between a 19 element retina and each of the E cells (i. e. 19 x 169 fibres) were held in a matrix. The experiments proceeded by finding, sometimes by trial and error methods, the steady state solutions for various weight settings of the net and after this performing synaptic adaption on the retinal matrix. The method of adaption was to increase a particular fibre stength if there was a coincidence of activity in that fibre and the cortical cell it affects, by an amount proportional to both the fibre signal and cell signal. All other fibres impinging on that cell have their weights re-normalised to ensure a constant total weight value to a particular cell. This prevents instability. A set of nine stimuli was applied to the retina and the synaptic manipulations performed after each presentation. As more learning steps were performed the E cells tended to fire in clusters. By drawing a diagram indicating for each E cell the median of the orientations of the stimuli it responded to for various steps of learning, it was demonstrated that areas of cells responded to similar orientations. They concluded that "organization of orientation specific units is brought about by a learning strategy rather than genetic determination". They also indicated generalisation abilities and resistance to noisy input by calculations of entropy values at successive learning stages.

A Neuronal Circuit Modelling Program (NCMP) was described by Knox (1973, 1974). It was capable of simulating up to ten neurons, forty axons, ten interneurons, ten relay neurons and a pulse generator and a random stimulator arranged in a way specified by the "user". The user could also specify which type of output was required from a set designed to produce the same form of output as biological experiments. The simulation was quoted as having a two-to-one ratio of time course to a real system for a single neuron simulation. The activity of the elements was calculated using the compartment model approach of Rall (1964). This system was employed in an investigation of the information produced by a cross-correlation function between cells.

Wigström (1974) produced a mathematical model of a network with learning on the same basis of coincidence of pre-synaptic and post-synaptic firing. He noted that the largest initial component grew at the expense of the others and postulated a 'domination principle' to explain the lack of confusion in thought processes.

Macgregor (1974) produced rhythmic oscillations in a net of 100 identical neurons and related this to the refractory period of his elements. He concluded that tightly connected nets could be used for spreading activity and loosely connected nets for following periodic input as tightly connected nets fired in clusters and "... fired at their own internally determined rhythmic period and did not faithfully follow applied periodic input".

Another synaptic modification method was proposed by Fukushima (1975). Employing Brindley synapses, as defined by Marr (1970), he modified their weights if there was a coincidence between post and pre-synaptic firing and if the post-synaptic cell was firing more than its neighbours. He suggested this would enhance individuality between synapses and prevent them growing to the same value. A multi-layered Perceptron type model was built along these lines but required preprocessing for successful pattern recognition.

Two approaches employing information theory in the analysis were those of Tsukada (1975) and Uttley (1976). Tsukada's work involved simulating the excitatory post synaptic potentials (EPSP) of a single cell and calculating I, the mutual information per symbol pair for various sizes of EPSP. He found two maxima, one for small values of EPSP and one for large. Related sequences of input gave different values from unrelated sequences. Uttley criticized Von der Malsburg's (1973) method of synaptic weight normalisation saying it would fail to work for small fluctuations from normalisation, as might be expected in a noisy system, and eventually the output would bear no relation to the input. By examining the form of typical learning curves of psychology, which indicated that adaption should be a two-phase process of gradual reinforcement followed by gradual non-reinforcement, he derived a synaptic modification algorithm which included a third component to the normal two, which was a fixed inhibitory synapse. This maintained the stability of the total synaptic weight as after a period of time, when the inhibitory signal was absent, the conduction strength of a fibre would decay back to its original value. The exact form he postulated as an example of this approach was that the synaptic conductivity of a pathway i, γi, should be a function of the log of the mutual information calculated between the output signal and the signal on the fibre. A mechanism, called an informon, was proposed that performed the desired manipulations of γ for a particular set of fibres. A hierarchical arrangement of 210 informons with 8400 simultaneously variable pathways was shown to be completely stable and capable of recognising handprinted numerals, with the help of a feature extracting preprocessor.

CHAPTER III

The Experimental System

Introduction

Chapter 2 gave an indication of the variety of approaches to neural modelling that have been attempted in the past. These attempts can be broadly classified as either based on probability theory or not. The 'statistical nets' of the former category, reduced the vast complexities involved by sacrificing the knowledge of exactly when each element fired, describing the network activity by activity level only. This meant they could study nets of a non-trivial size and they were often used in conjunction with physiological experiments. However they consistently failed to produce any clue as to the method of signal processing in the brain other than demonstrating types of conditioned reflex behaviour on a gross level rather than the single unit level of the 'hard-wired theory' school. The 'non-statistical' nets were often dismissed by biologists as irrelevant to their studies and many workers abandoned any idea of biological comparison, pursuing the search for interesting machines (e. g. Perceptron, Adaline, Slam-8's). These computing machines are described by Harmon (1967).

Whilst the computing power available has increased explosively since the early researches were carried out, it is felt that there is unlikely to be any major contribution from digitally simulating neural nets in order to test biological theories on the functioning of the brain. The current trend in physiology of identifying more areas of the cortex with typical patterns of connectivity tends to throw considerable doubt on the statistical description as a helpful model. Also, until the advanced development of, for example, parallel processing machines or array processors, the task of simulating these circuits is intractable.

The approach of this thesis is therefore to simulate, at a low level, the action of small networks of neurons with a view to finding machines capable of processing information encoded in terms of pulses. No relevance to natural systems is claimed and attempts are made only to abstract those features from biological systems that appear promising for such an aim.

To save space and reduce ambiguity, a policy is now adopted whereby terms such as neuron and synapse will refer only to the models thereof. When the biological equivalent is meant this will be explicitly described.

Description of the Experimental System

The simulation is a digital, discrete time approach, each neuron's state, at any time instant, being calculated from its state in the previous time instant. The state of each neuron is held in a disk file, the Neuron Information File (NIF). The interconnections are defined by a connection algorithm and the effect each synapse has on a cell, the synaptic weight, is recorded in another disk file, the Connection List. A great many parameters define each net and the system as a whole is designed to test the effect specified signals have on it. To achieve this an "Experiment" is performed which consists of four stages, Net Generation, Signal Definition, Net Evaluation and Further Analysis (optional).

Generation of the Net (Stage 1)

In this phase a neural net is interactively defined. The options on the parameters possible in the latest version of the System are listed below. These are described using Capital Letters to help explain the shorthand employed on Experimental listings and source code.

Net Size: three dimensional, those used were 5 x 5 x 5 and 10 x 10 x 5.

Threshold Range: this is the value used to generate the thresholds for each cell. It can either represent the upper limit of a rectangular distribution of values that the thresholds are selected from or the actual value the threshold takes. The actual mode used in generating is defined by the Threshold Type. The Threshold Seed is the number used by the pseudo-random number generator to start producing the threshold values in the first mode described. It has no meaning in the second mode.

Threshold Decay Range, Type and Seed: the threshold decay is the percentage reduction of the threshold value over 1 simulated time unit. The values generated are produced in a similar manner to the previous parameter group, as are the next three groups.

Excitation Decay Range, Type and Seed; this is the percentage decay of a cell's subthreshold stimuli over 1 time unit. (When a cell fires, all stimuli received the previous unit are extinguished.)

The Connection Range, Type and Seed and maximum Number of Connections: the maximum number of connections defines how many synapses originate from a cell. Also, the Connection Range defines the value of the weights of each synapse. The actual number of connections decided for each cell is a preliminary step in the algorithm for generating weight values.
The Inhibitory to Excitatory cell Ratio: this is used in the weight generating algorithm to decide the ratio of cells with excitatory synapses to those with inhibitory ones. All synapses from the same cell are the same type.

The number defining which connection algorithm to employ and the seed it uses;

The maximum value for a synapse in an adaptive net;

The values defining how to designate the elements which can refire spontaneously.

The length of the simulation.

The latest system allows multiple experiments to be performed in one run and the last parameters define the networks involved.

Signal Definition (Stage 2)

This phase is achieved with an interactive program which enables the following parameters to be specified:

The number of signal inputs:

The centre positions: the first slice of the three dimensional net is defined as the input slice and the co-ordinates of the input site specify the position within this slice that the signal will be applied to.

The signal type: this defines the signal generation algorithm employed. (These will be described later).

The signal spread and radius of spread: instead of applying the signal to a single element it can be spread, in various ways (to be described) to surrounding cells in the input slice, within a given radius.

For early experiments on adaption, (see Chapter 4) output elements in the final slice can also be defined and the techniques of matching input and output signals are specified.

The number and identity of those elements whose individual history is to be traced throughout the run and subsequently displayed.

The maximum lag for the Spectral Analysis routines (see Appendix A).

The interval between the trailing edge and the next leading edge of a periodic input signal (that is, the length of the 'off' state).

The length of the 'on' state.

The delay of the signal: this is the length of time from the start of the simulation that the signal begins.

The learning factor: this is the percentage by which the synapse weight is changed in the Hebb-type adaption algorithm, described later under "Support Routines".

The value of any constant signals employed.

Net Evaluation (Stage 3)

At this stage the defined net is run. Various 'in flight' analyses are possible, such as a display of the cells firing on the line printer, a dump of the Neuron Information File (NIF) and a display of those connection weights changed in the previous time instant. These are all controlled by control panel switches (See Fig. 1). The run may also be terminated from the switches. A description of the main routine appears in the Program Description. At the end of the run, graphs of the totals over the whole net of the remanent excitation, threshold levels and number of cells firing are displayed. In later runs this data could be analysed employing Spectral Analysis, when Autocorrelation and Power Density Functions are displayed. For certain individual elements, specified in the second phase, the raw data alone is displayed. During the run the raw data is written to disk where it can be accessed at the end of the run, as described, or during the fourth stage of the experiment.

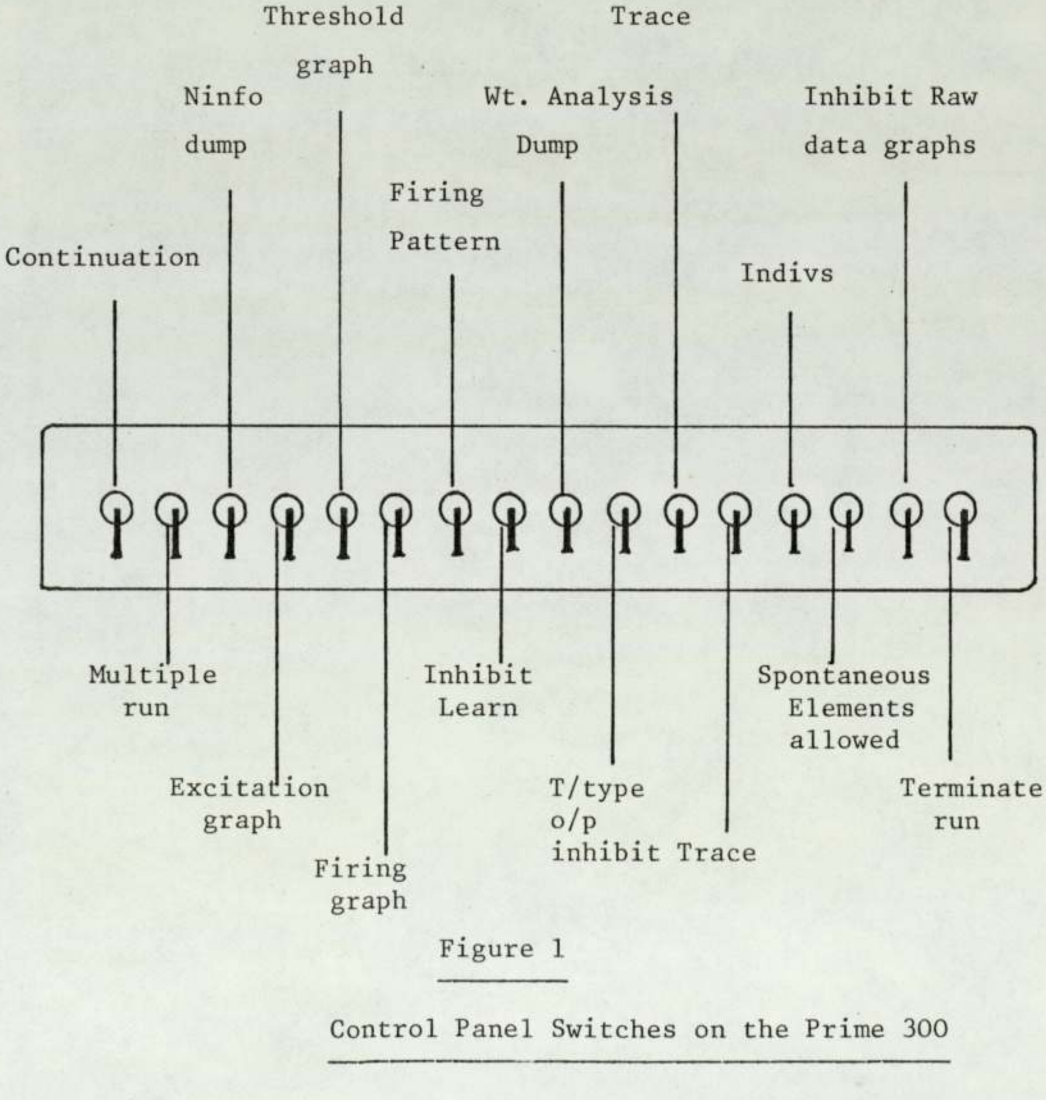


Figure 1

Control Panel Switches on the Prime 300

Further Analysis (Stage 4)

The final phase may be repeated to perform Spectral Analysis on specified subsets of the original data. It is also at this stage that a list of the major connections can be printed out and the special form of analysis for the adaptive nets of Chapter 5, the Cell Firing Histogram, can be calculated.

The Computer System Description

Figures 2-5 are system flowcharts for the latest system. It is capable of running up to twenty experiments unattended, writing the results to disk. A run of twenty nets takes 30 hours. The fourth stage for each experiment was performed subsequently. This mode of working was adopted fairly late in the thesis to overcome the unreliability of the hardware used.

The information input in Stage 1 of the experiment is stored in a Parameter File (IP), one block (e. g. a disk sector on Prime 300) per net. This file is subsequently updated in Stage 2 so that it contains all the information necessary to generate and run the network concerned. These files are archived to a separate area of disk and can be recalled at will to provide the basis of a new network or enable a re-run to take place. In the Multiple Run mode the generation program produces the NIF and connection weight file for each net and stores them in the areas referred to as the SU files (e. g. SU2, SU3, etc.).

The first net to be run does not need to be stored in this way and is held in the corresponding disk files used in the actual running. Subsequent runs copy the initial settings from the SU files before starting. The SPON file is the list of neurons having spontaneous firing characteristics.

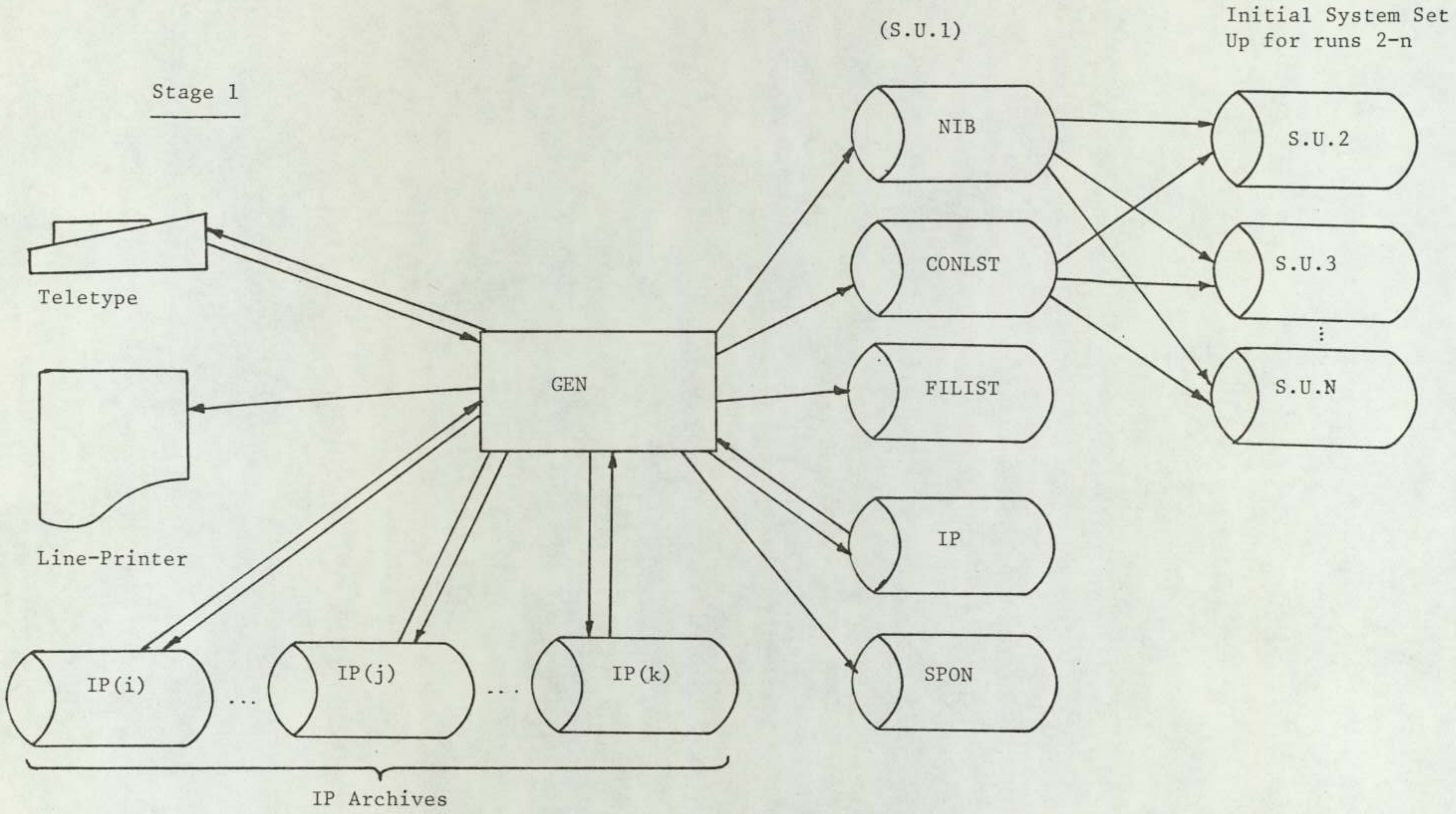


Figure 2 Generation of the nets

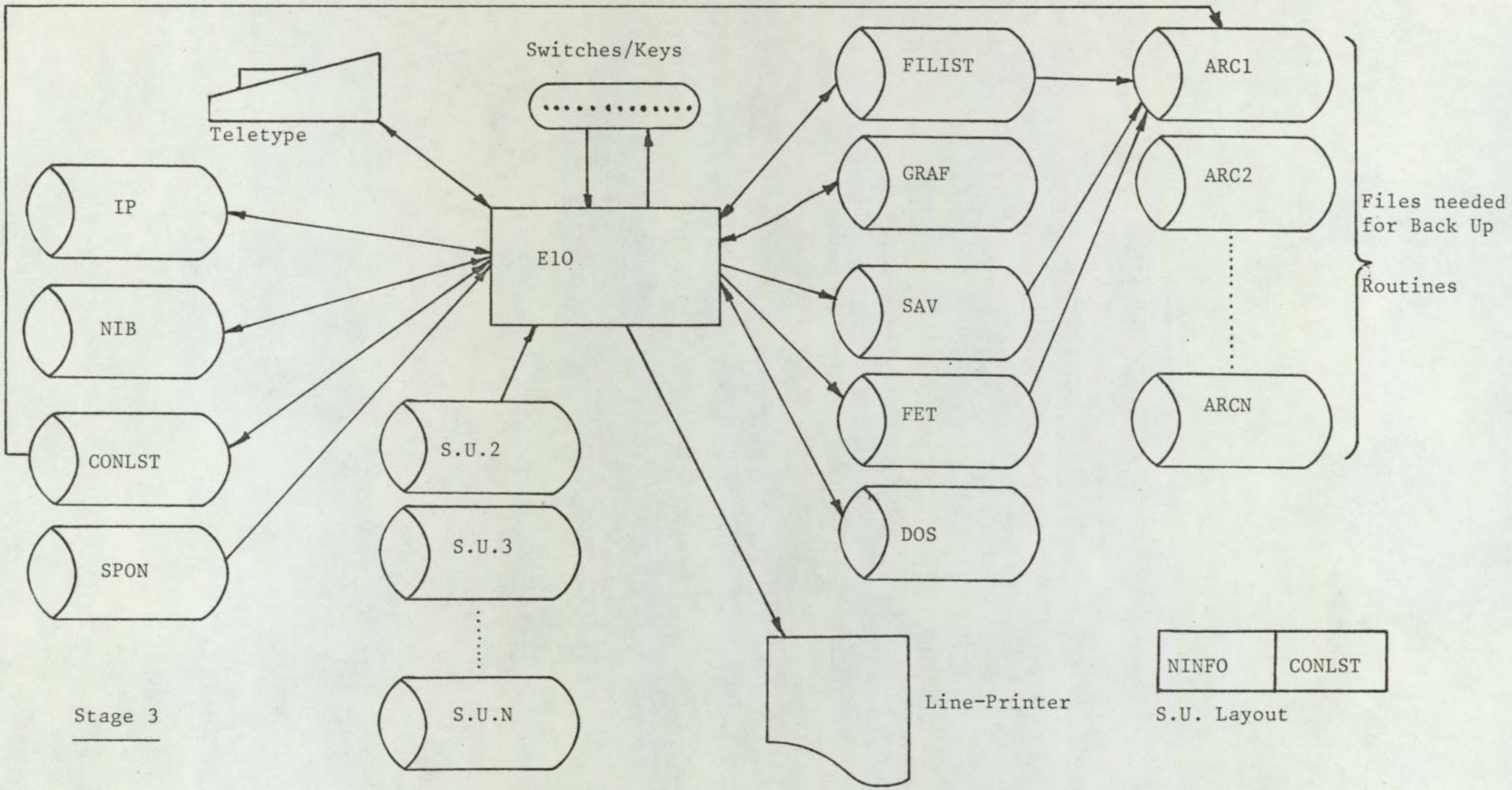


Figure 3 Running the Experiments

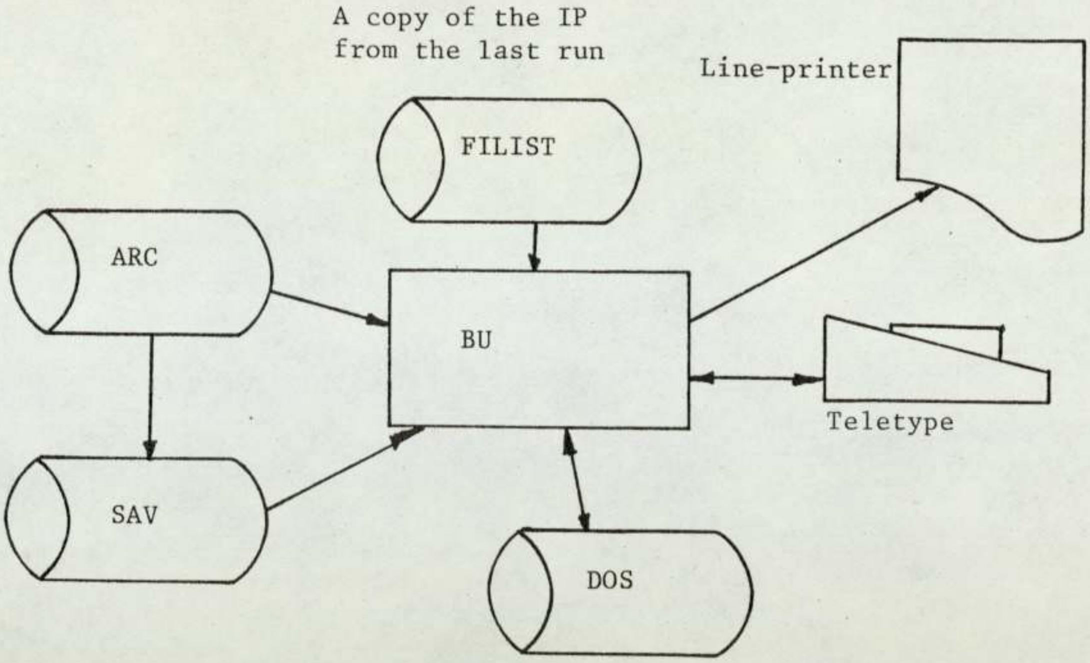


Figure 4 Stage 4 part 1

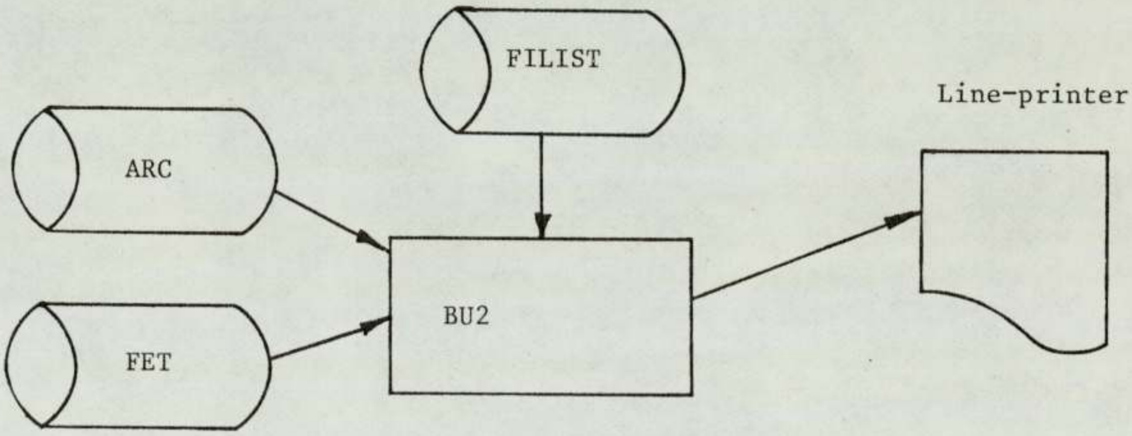


Figure 5 Stage 4 part 2

ARC File layout

FILIST	SAV	FET	CONLST

Experiment layout

Old IP's	NINFO	CONLST	FILIST	SPON	IP	GRAF	SAV	FET

DOS	ARC1	S.U.2	ARC2	S.U.3	ARC3	etc...		ARCN

The FILIST file is used in the first stage to hold a table that accesses this file. In Stage 3 however, this file holds the number of the cells which fired in the previous time instant.

Stage 3 runs all the nets and produces an Archive File (ARC1, ARC2, ...) for each net that holds all the information the Analysis routines require in later stages. The file GRAF is used as an intermediate storage to generate the line-printer graphs. The FET file holds a record of the firing patterns at each time slice. The running of the net can be controlled by the sense switches which can, for instance, enable the printing of the line-printer graphs (see Fig 1). Stage 4 currently consists of two sub-phases, the first being the selective use of the graph plotting and Spectral Analysis routines, to analyse specific subsets of the raw data. The second, in a similar mode of use, employs the cell firing histogram for the final experiments of Chapter 5.

This System represents the current situation. The Multi-Run capability was produced for the later experiments of Chapter 5. There are approximately 80 FORTRAN and 20 Assembly code routines making up the four Stages. On the Prime 300 the Stage 3 routines occupy 32K and a run of 1000 time units takes, typically, 90 minutes.

Program Description

Main Simulation Subroutine

To describe in great detail every routine would take vast space and contribute little to the understanding of the simulation techniques. However, a brief mention of some routines, particularly the main subroutine, NET, should explain the basic ideas employed. A listing of this routine and the main program is held in Appendix B. A flowchart of the main routine is in Fig. 6. The following description should be read in conjunction with this diagram.

Figure 6

Net Subroutine

AFFECT STAGE

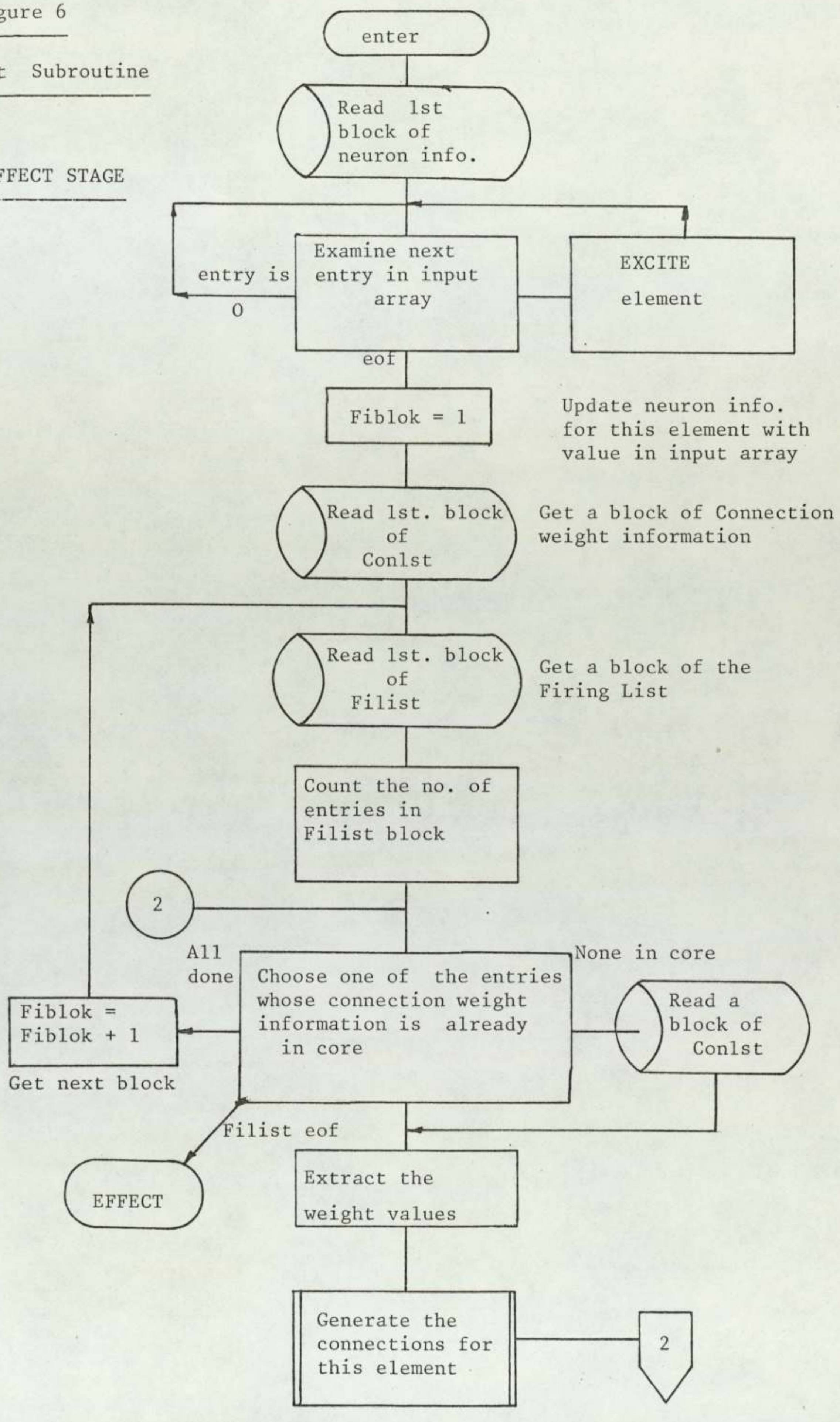
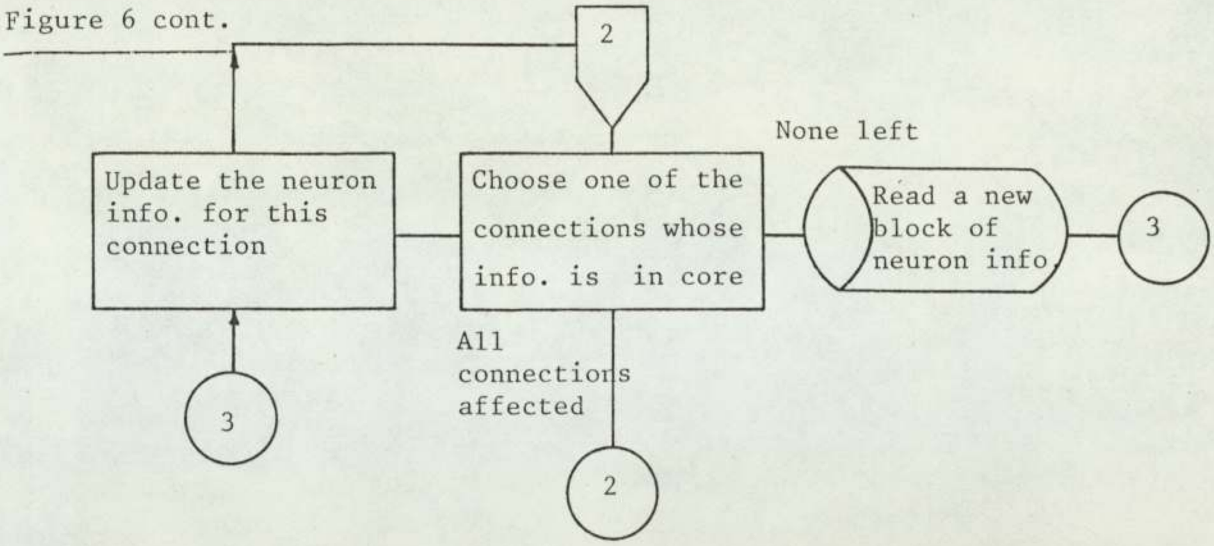


Figure 6 cont.



Effect Stage

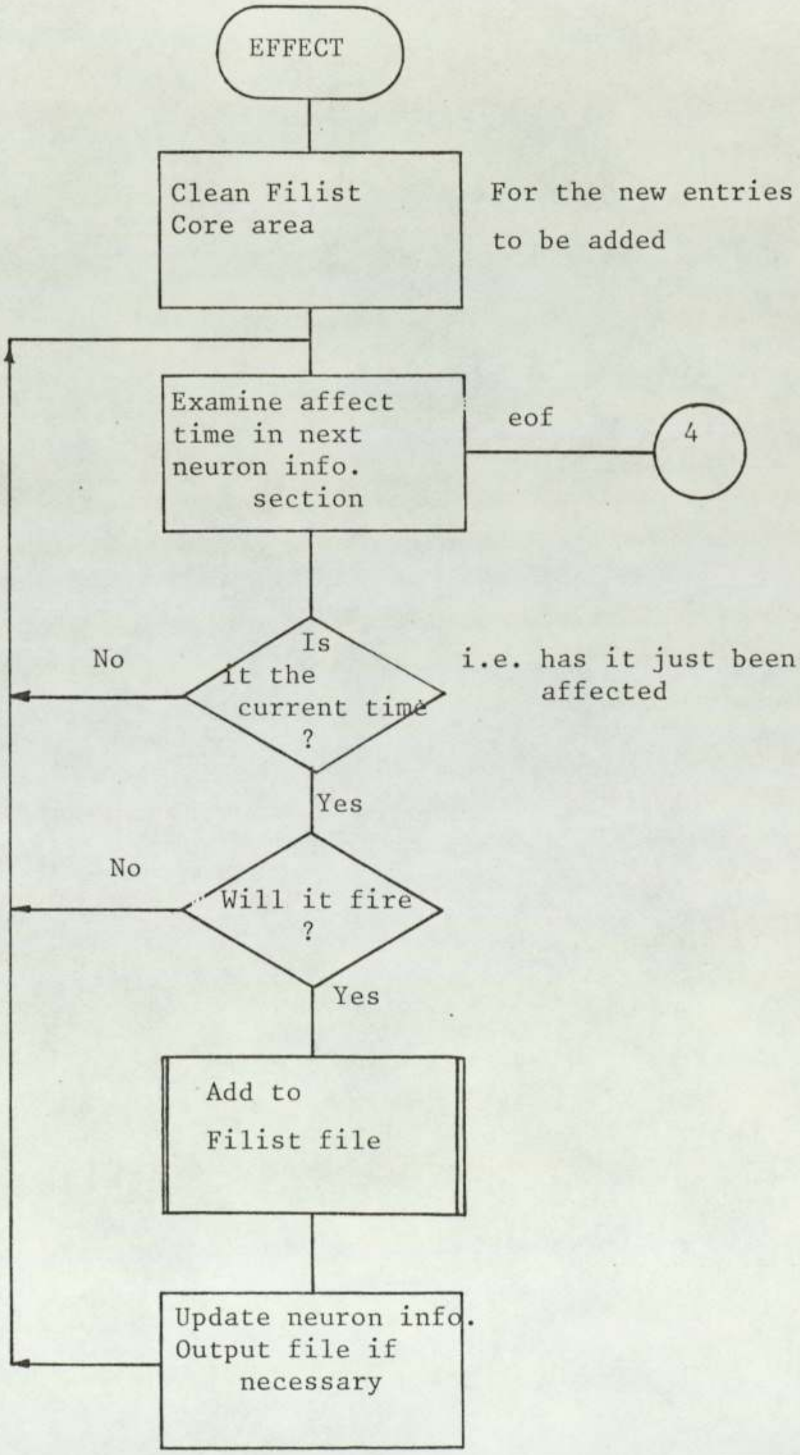
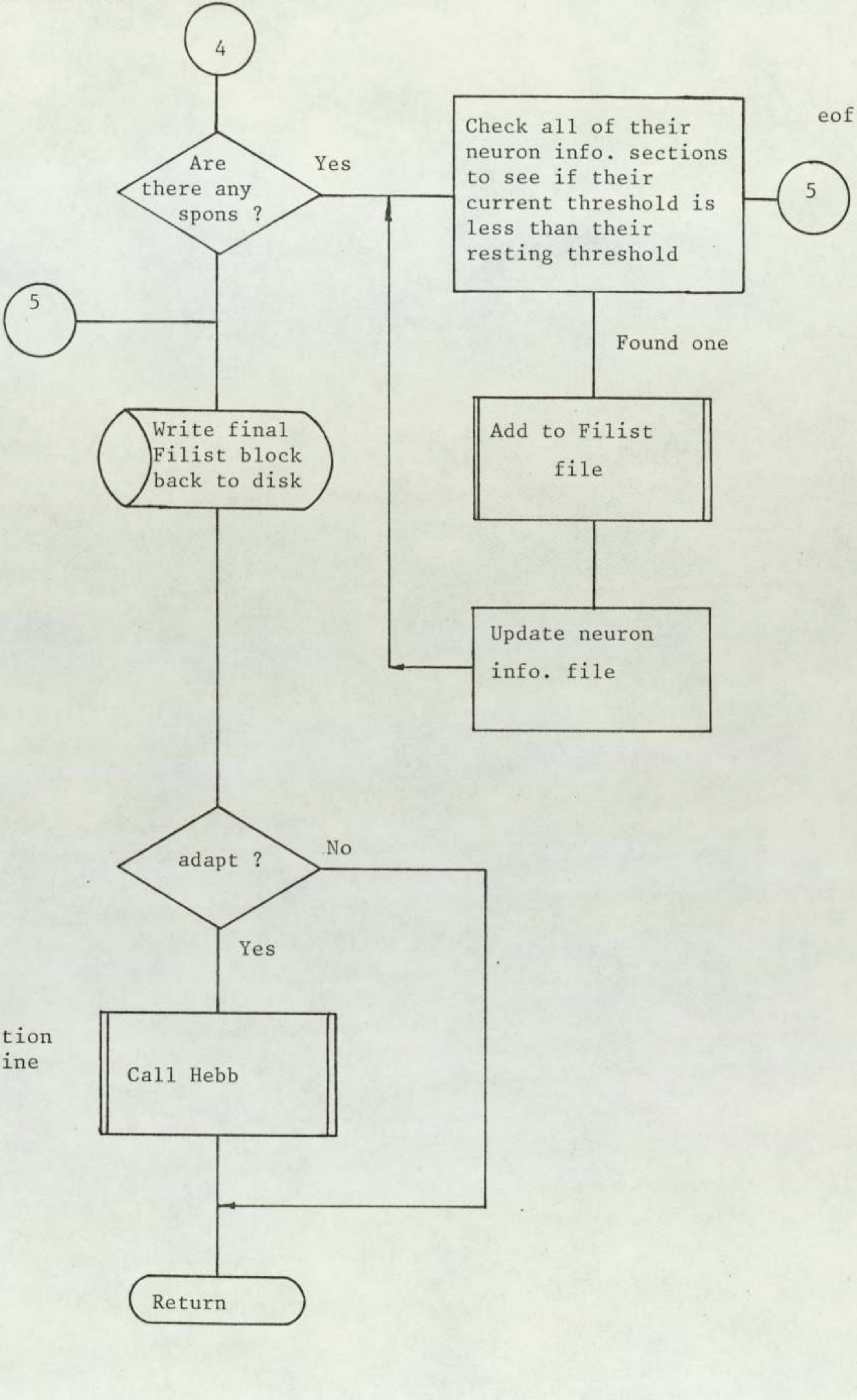
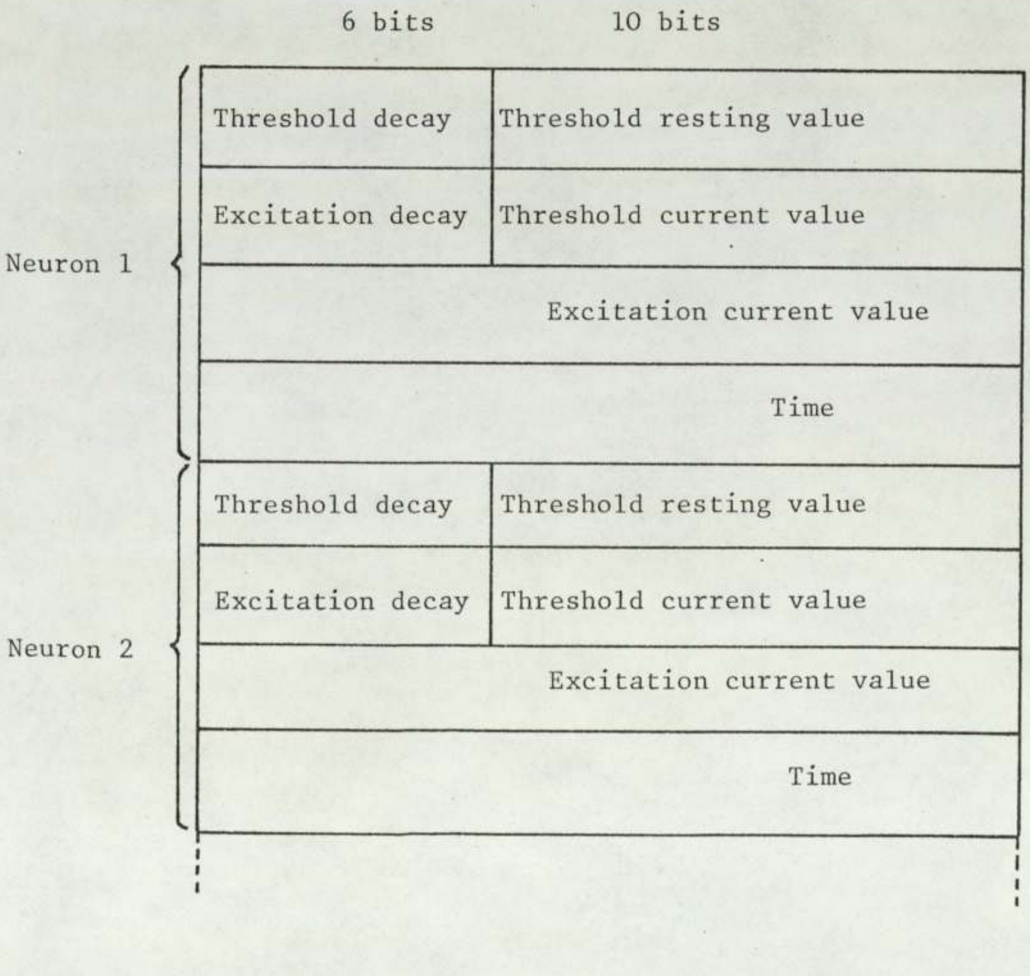


Figure 6 cont.



The basic routine that performs one time slice of neural activity is the subroutine NET. There are two stages in the calculation of the activity flow, the Affect Stage and the Effect Stage. The Affect stage updates the neuron information file (NIF) (See Fig. 7) by changing the excitation levels of those cells connected to the elements which fired in the previous time instant, as defined by the Firing List File. The effect stage then checks affected elements only to see if they will now fire by comparing their excitation level with the current value of their threshold. The result is a new Firing List file, held on disk. The routine then returns to the controlling program (E11, see Appendix B) which will continue to call it for the rest of the simulation.

Figure 7 Neuron Information File



The technique employed throughout the routine attempts to minimize all disk transfers. At the program design stage, by roughly simulating the simulation, optimum buffer sizes and file design were laid down. The routine uses all the information in a particular disk record when it is in core, before accessing the next block.

In the Affect Stage the input to the net is received in an intermediate buffer which corresponds to the first slice or array of the three dimensional net. The main routine will have previously called a particular signal generation routine which supplies the signal value into this array. This information is used to update the relevant sections in the NIF. The Firing List file is now used in conjunction with the Connection weight file (see Fig. 8) to decide which elements are affected and by how much.

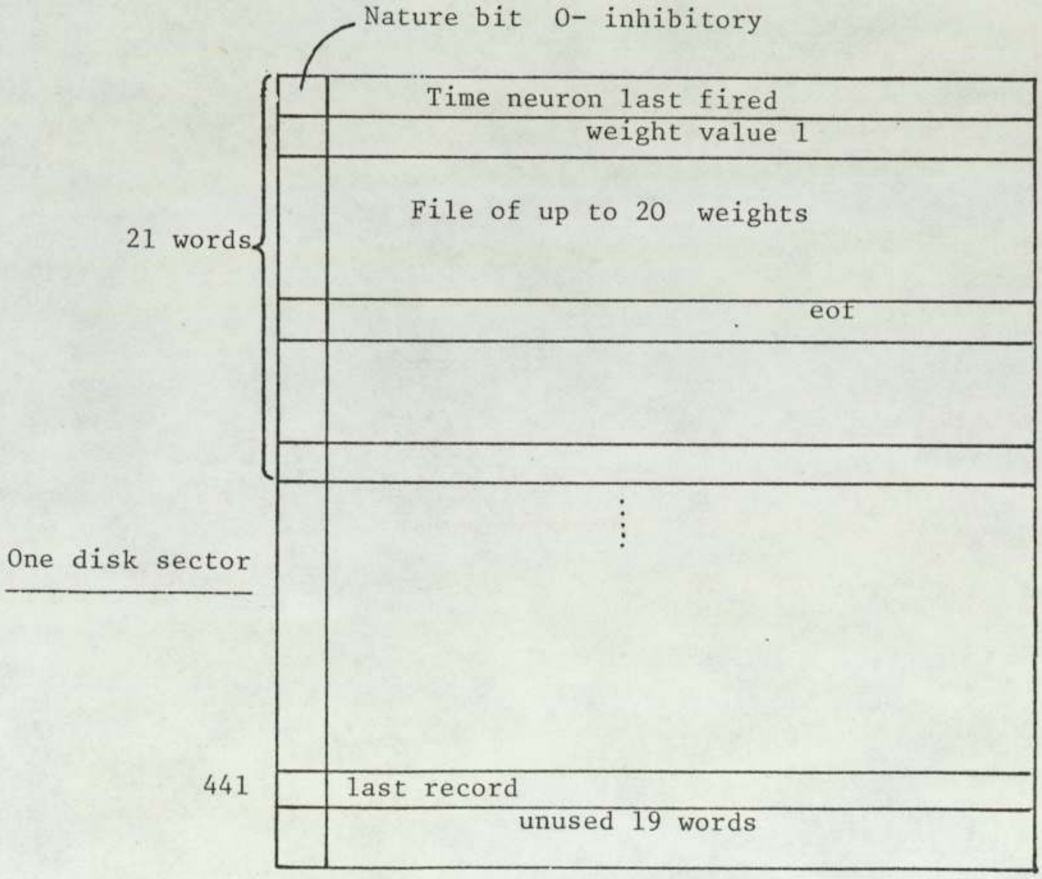


Figure 8 Connection weight file

The actual connections are determined each iteration by a modified pseudo-random number generating routine.

The Effect Stage, as well as compliling a new Firing List File from the changes already made to the NIF, examines the spontaneous elements to see if their thresholds have decayed to the resting threshold and therefore refire as well. As an element fires, its threshold is set to a maximum and its excitation extinguished.

By only examining those elements affected in the first stage, considerable reductions in accesses to the NIF are achieved in the Effect Stage and make longer simulations of larger nets possible.

Support Routines

The routines are described in approximately the order they are used in the Experiments. They are briefly described if the techniques employed are felt to be useful to subsequent researchers or important to the understanding of the simulation as a whole. There are many routines which are straightforward and are only mentioned to aid those examining the source listings. Before the simulations began many programs were written to help design the Experimental System. These are mentioned first. Finally the Assembly Language routines are described and a mention is made of the routines written for other machines.

Preliminary Routines

Several random number generating routines were examined that produce integers from a rectangular distribution over the possible range allowed on the Prime 300 (0-32767). These were tested by plotting histograms derived from the streams of numbers generated. They were also tested for speed using interrupt timer programs. The routine chosen is called RAN2A and can be defined by the algorithm RAND → (RAND$_*$237) mod. 32749. This takes approximately 64μsecs. As the basic simulation was being designed, calculations using buffer sizes and disk access speeds were performed to try and find the highest speed of simulation. The results suggested a good method would be to read and write the NIF in cylinder mode, that is 16 sectors at a time and the other main files in sector mode. Although the additional routines and disk files added later involved far greater overheads than the original calculations allowed for, the efficient design of the actual network simulation meant it was practically possible to add on complicated analysis procedures and still have a reasonable experimental time. Many routines were written to debug the program as no facilities except a Trace and Patch routine were supplied with the computer. The assigning of almost all variables in the simulation to a small part of the Blank Common Area meant a dump of the corresponding section of core provided a post-mortem dump in the event of a crash. Using these routines, comparisons with hand simulation could take place. A hand simulation of three time units of the original simple net of 5 x 5 x 5 elements took over eight hours to complete, even with the help of a pocket calculator. A Multiple Run of 30 hours on the Prime 300 would therefore take at least 20 man years to hand check.

Generation Support Routines

The main generation program, GEN, takes the information typed in at the terminal, under control of sense switches for each group, and updates the IP file. It finally writes a list of the new parameters onto the line-printer. The routines which generate the first three parameters of the cell are all similar, as described earlier, either producing the same value for each cell or selecting from a distribution. The routines that give a single value, that of the range parameter setting, are TGEN9, TDGEN9 and EDGEN9 for thresholds, threshold decays and excitation decays respectively. The routines which select from a distribution all work the same way in that they call the random number routine RAN2A, with the given seed (this value is altered in the process) and the number produced is converted from the range 0-32767 to 1 to the range previously provided. These routines are TGEN1, TDGEN1, EDGEN1. The synaptic weight values are generated (GEN9) in a slightly more complicated way. The connection weight seed is given as the parameter in the first call of RAN2A. The result is used, in conjunction with the parameters describing the inhibitory to excitatory ratio, to determine what type the current cell is. Next, the number of synapses each cell has is calculated by a further call to RAN2A and a range conversion performed to satisfy the parameter NCON (The maximum connections per cell). This step is omitted in GEN9C which generates only the maximum number of connections for each cell. Then, using the parameter CONRAN, that specifies the upper value for the weights, further calls to RAN2A produce the initial synaptic values. (These are only changed in the Hebb-type experiments of Chapter 5). The spontaneous cell generator GSPON1 produces a list of those cells with the characteristic of refiring when their threshold decays to the resting value. This routine also employs SORT, which produces an ordered list for writing to the disk file SPON.

It was decided as a policy throughout the simulation to provide separate routines to interface with the assembly level routines to ease any transfer to different computers. The routines employed in this way are INTH, INTD, INED, RESET and PUTEON.

Evaluation Support Routines

The Learning and Servo mechanisms employed in the early experiments of Chapter 4 will be described first as they were used relatively briefly. The Adaption algorithm, HEBB, did not appear until Chapter 5.

The original Learning mechanism was implemented within the Evaluation Routine itself. The basic idea was to reward high firing rates within a specified output area. In the subroutine NET, an area in core was set to represent the pattern of firing within the output area in the current time slice. Subroutine MATCHS subsequently examined this area and produced a score of the total of the elements not firing. The Learning algorithm used this value to determine the strength of the reward, a low value producing the maximum reward. This value was entered in a table (LEARN) of maximum size 50, the newest entry replacing the oldest, the algorithm being entered every time slice. The effective size of the table could be specified as a parameter, the Learning Range. Any reward not applied before this limit was lost. The learning value was used within the subroutine NET, in the Affect Stage, when calculating the weight values for each synapse. Before putting the weights, which were held on disk, into an array (IWT), they were altered by the percentage value (generally between 10 and -10) held in the Learning Table. The value used was the entry corresponding to the time the 'father' cell last fired. These new weight values would be written back to disk at a later stage.

The Servo was a number between -50 and +50. The actual score calculated every time unit depended on the level of activity of the net,being high for low activity and vice-versa. In the early versions of the Evaluation Routine this score was entered in a table (ISERVO) which had a fixed effective length of 50. The Servo was applied in two routines EXCITE and UPDATE. EXCITE takes the afferent input to the net and changes the excitation levels of the elements that each input corresponds to. It initially extracts the excitation level of the cell receiving the input from the NIF and decays its value using the Excitation Decay rate. It then uses the

Servo value as a percentage and alters the decayed excitation by this amount. In other words it amplifies the excitation that is present at the current time. This value is then added to the value of the afferent input and the NIF is updated. The routine UPDATE does the same thing but takes its afferent excitation input from other cells. The aims were to reward particular connections with the Learning Schema and thereby reinforce pathways that raised the firing level of the output area and, using the Servo mechanism, to globally control the level of firing.

The afferent input to the net is provided by two sets of routines, the signal generators and the signal spreaders. As described earlier, certain elements are designated input elements and the signal is applied to these. It is also applied to certain of its neighbours, determined by the signal spreader routine. The signal generators GN1S1G to GN8S1G provide a level of excitation for a given simulation time. GN1S1G provides a constant signal, the value being that set in Stage 2 (the constant signal value). GN2S1G provides a pattern changing every 50 time units (50, 0, 20, 0) and GN3S1G provides a sinewave. The remainder are for use with the split run type of experiment, described in Chapter 4, where for example an on/off signal is provided for the first 500 time units and a constant signal thereafter. GN5S1G, GN6SIG and GN8SIG also employ a delay before the signal train starts and a variable 'on' signal length. In all the periodic signals, the period, delay and length of the 'on' signal have been defined in Stage 2.

Whatever the signal is, it is spread around the input centre with the radius defined as a parameter. The method of spreading is to excite six additional points, in the input slice, on the main axes and diagonals through the input centre. Two typical patterns are shown in Figures 9 and 10, the latter having two adjacent input centres.

```
O   O   O   O   O   O   O   O   O   O
O   O   O   O   O   O   O   O   O   O
O   O   O   O   O   O   O   O   O   O
O   O   O   *   *   *   O   O   O   O
O   O   O   *   *   *   O   O   O   O
O   O   O   *   *   *   O   O   O   O
O   O   O   O   O   O   O   O   O   O
O   O   O   O   O   O   O   O   O   O
O   O   O   O   O   O   O   O   O   O
O   O   O   O   O   O   O   O   O   O
```

Figure 9   *- receiving input stimulation

```
*   O   O   O   *   O   O   O   *   *
*   *   O   O   *   O   O   *   *   O
O   *   *   O   *   O   *   *   O   O
O   O   *   *   *   *   *   O   O   O
*   *   *   *   *   *   *   *   *   *
*   *   *   *   *   *   *   *   *   *
O   O   *   *   *   *   *   O   O   O
O   *   *   O   *   O   *   *   O   O
*   *   O   O   *   O   O   *   *   O
*   O   O   O   *   O   O   O   *   *
```

Figure 10 -taken from Experiment F12

The routines GEN, GEN1 and GENC define two methods of interconnection of cells, Random and Local Bias. GEN generates random connections by calling RAN2A and reducing the range to be from 1 to the total number of cells in the net. The Local Bias method is more complicated. It involves the setting up of a table, by calling GENC in the Evaluation Routine (E11) before starting the net. This table sets out all possible displacements from a cell situated at the centre of a 2 x 2 x 2 cube to every possible connection on the surface of the cube. The distances between the cell and its connections is therefore 1 or $\sqrt{2}$. GEN1 chooses between the two subsets so defined, with a proportional bias to the shorter distance. The routine then selects within the selected subset and obtains a three dimensional displacement to be added to the original cell's own co-ordinates. GEN1 then checks that the proposed connection lies within the net and, if so, enters the value in the connection array. Various modifications to this were later added at this stage to enable toroidal or semi-toroidal nets to be simulated. Both routines ensure the same unique set of connections are generated every time, for a particular cell, by multiplying the connection seed by the cell number before the first call of RAN2A.

During the running of the program the internal state of each cell can be printed out on the line-printer, using NINLP, and a diagram of the net indicating the firing cells can be printed out using PATTRN. Also the synaptic weights that were changed in the previous time slice can be displayed, using WTDUMP, to give an indication of the changes taking place in adaptive nets. These three options are controlled from the sense switches (see Figure 1). Various routines are used to store and retrieve data in the disk files of Figure 5: GRAFIN, INDIV, GRIND, ADFIL, SAVTIM, TRANSF, ARCHIV, NIBSEK, THEXL, FILEV. The routines providing all decay functions are DCAYTH, DCAYEX, DECAY 1 and DECAY 2 which employ the rounding routine ROUND. QFIR examines the NIF data in the Effect Stage of the simulation to see if a cell is going to fire. Similarly SPNFIR examines any unfired cells nominated as spontaneous to see if their special conditions for firing are satisfied.

The final major routine used within the actual simulation is the adaptive algorithm HEBB, employed in the experiments of Chapter 5.

The purpose behind the design is discussed in Chapter 5. The idea is to modify the synaptic weights, as with the previous algorithm, but dependent on conditions local to each fibre rather than the global conditions used before. The value of a synaptic weight is increased if there was a coincidence of pre and post-synaptic activity. In other words the condition is satisfied if a particular fibre was active and the next time slice the receiving cell fired. If this condition was not satisfied the weight value decays. Various forms of this idea were implemented but in all cases the routine determines whether the reinforcement condition was satisfied by first examining, as the last operation of the Effect Stage, the Connection Weight List file. In the Affect Stage, if a certain element had fired in the previous time instant and its connections were therefore active, the weight information used to update the NIF file would have been accessed. Each element's Connection Weight List contains a record of the last time used (see Fig. 8) and this is updated, if used, in the Affect Stage. The routine HEBB therefore accesses this variable and can tell which elements had been on the Firing List the previous instant. If the subsequent afferent connections from these previously firing elements are on the current Firing List then the reinforcement condition is satisfied. This is determined with the aid of FILMAT. The actual altering of the weights is performed within HEBB. Several parameters can be specified in Stage 2 of the Experiment which define, for instance, the reward as a percentage and the maximum synapse weight allowed.

After the run is finished a routine RESUL2 is called which, dependent on sense switch settings (see Fig. 1), displays graphs of the data produced and calls the Spectral Analysis routines. All these Analysis routines employ a suite of programs for displaying graphs on the line-printer. There are five versions of these routines that produce either graphs that occupy a single sheet of line-printer paper or spread over several. A variety of scales are used, integer, real and logarithmic in certain combinations. A version that produces several data sets on one graph is employed to display the Cell Firing Histogram (to be described). RESUL2 can also call a routine called AFPROF which produces the Affect Profile for the run. This is a histogram of times since cells last fired and gives an indication of how many cells are affected each time slice.

The two back-up programs, BU and BU2 call a different form of RESUL2 and the Cell Firing Histogram routine FEATUR, respectively. BU provides the facility for accessing subsets of the raw data and does so by either listing and plotting graphs or calling the Spectral Analysis routine SPEC3. Finally it can call LINK, a routine that lists the major connections left in the net after an Adaptive Run of Chapter 5. The options are once again controlled by the sense switches. The routine SPEC3 takes the raw data, normalises it (displaying the mean and standard deviation) and produces autocorrelation data, raw power density data and smoothed power density data. These data are listed and also plotted on the line-printer. As this program was coded from a textbook, and not basically my own work , it is only briefly discussed, together with some underlying mathematics, in Appendix A.

BU2 also analyses subsets of data, but this time the data written onto disk by the routine FEATUR during the running of the program. This is a coded form, in eight words per time unit, of the firing pattern of a 5 x 5 x 5 net. This was used in Chapter 5 to analyse, in more detail, patterns of cell firings. BU2 uses the routine F1 to extract the data from disk and unpack it and then produces a series of histograms that show the number of times each cell had fired at various stages of the run. All the histograms are displayed on one graph to show changing rates of cell firing. The reasons for doing this form of analysis appear in Chapter 5.

The Assembly Language routines written for the Prime are basically to provide the bit manipulation facilities FORTRAN does not supply. However, it also became clear that the Prime Disk File System provided only serial access mode and therefore new disk drivers had to be written to implement random access file organisation. These routines were written and tested using the interrupt routines written to test the speed of the pseudo-random number generators. The random number routine RAN2A was also written in Assembler.

When the CDC 7600 at Manchester and the 1904S at Aston (see next section) were used all the above Assembly routines had to be changed. The system was originally designed with the idea of localising any such changes in a group of routines, such as these, to maintain the portability that might be vital if one machine irretrievably broke down.

Machines Used

All of the experiments reported in Chapters 4 and 5 were performed on the Prime 300 mini computer. The System was tried on the CDC 7600 at Manchester and the ICL 1904S at the Computer Centre at Aston, but both were impractical. The ICL 1904 S was incapable of running a set of more than two networks in the Multi-Run mode without being interrupted by operators or hardware failure, and had a turn-round of 24 hours. The CDC 7600 had an even longer turn-round and the workload from other Aston users made access difficult. The CDC machine did provide a solution to an intractable error on the Prime when the equivalent code failed even to compile.

Approximately 200 experiments were carried out on the Prime 300 in dedicated user mode over a period of approximately 16 months. The machine became extremely unreliable in the last six months having an up time of approximately one day in five. A great deal of that time was wasted tracking intermittent errors which invalidated much of the work. This meant all the runs of Chapter 5 had to be run twice and compared.

CHAPTER IV

Network Activity

Introduction

This Chapter is divided into two main sections. The first section deals with preliminary experiments which attempt to find interesting areas that can be investigated, in greater depth, in the attempt to locate machines capable of signal processing. This section is described in detail, not because of the relative importance of the results but to indicate both the type of data produced in these simulations and the most basic properties of the nets modelled. The second section of experiments, employing spectral analysis techniques, presents the important results, but only describing in detail the facets of the experiment that supply evidence for an observed property.

All the parameters defining each experiment are listed in Table 1, which can be found at the end of the chapter. The first section describes experiment groups A, B and D and the second section uses the results of groups D, E and F.

The cell numbering of the networks used is from 1 to the total number of cells used, with the dimensions varying quickest in the order column, row, slice.

Group A Experiments

Net Number 1 was generated with the parameters given in Figure 1. This is a reproduction of how they appear on an experiment listing.

NET NUMBER 1
SIZE: M=5 N=5 Z=5
THRESHOLD: RANGE=10 TYPE=1 SEED=4
THRESHOLD DECAY: RANGE=4 DISTN TYPE=1 SEED=2
EXCITATION DECAY: RANGE=4 DISTN TYPE=1 SEED=11
SYNAPSE WEIGHTS: RANGE=125 DISTN TYPE=1 SEED=65
MAX NO OF WTS = 5
IE RATIO I TO E: 1 TO 1
SPONTANEOUS NEURONS: NUMBER=5 DISTN TYPE=1 SEED=2

FIGURE 1

The details of signal input are found in Table 1 under Experiment A1. The purpose of this group was to find the type of activity certain parameter values produced. Five spontaneous elements were generated and the signal input area is illustrated in Fig. 2 by the square of four firing elements in the pattern of firing diagram. The input signal value was 50, the units being the same as those of the excitation and threshold data. The subsequent activity (see Fig. 2) was very low, dying out, for the first time, by time unit 6. The spontaneous elements had fired immediately as the initial net state was such that the resting and current threshold values were equal and therefore satisfied the special criterion for refiring. The simulation was run for 51 time units. Figs. 3-5 illustrate the three basic types of raw data that the simulation produces. As the activity is so low, the effect of the input on the excitation graph is clear, the high values being extinguished when there is a burst of firing. Normally, with nets of later experiments, this effect is not so noticeable as the remanent excitation values do not accumulate. Similarly with the threshold graph, the refractoriness of the net can be seen. Initially with a relatively high burst of firing the net becomes highly refractory, the total threshold value reaching a maximum. As this value is decayed (the threshold decays all being 4%) a few elements refire and the threshold graph shows a peak again. As the level of activity is so low,

```
                          TIME SLICE 2
 . * . . .     . . . . .     . . . . *     . . . . .     . . . . .
 . . . . .     . . . . .     . . . . .     . . . . .     . . . . .
 . . . . .     . . . . .     . . . . .     . . . . .     . . . . .
 . . . * *     . . . . .     . . . . .     . . . . .     . . . . .
 * . . * *     . . . . .     . . . . .     . . . . .     * . * . .
                          TIME SLICE 3
 . . . . .     . . * * .     . . . . .     * . . . .     . . . . .
 . * . . .     . . * . .     . . . . .     . . . . .     . . . . .
 . . . . .     . . . . .     * . . . .     * . . . .     . . . . .
 . . . . .     . . * . .     . . . . .     . . . * .     . . . . .
 . . . . .     . . . . .     * . . . .     . . * . .     . . . . .
                          TIME SLICE 4
 * . . . .     . . . . .     . . . . .     . . . . .     . . . . .
 . . . . .     . . . . .     . . . . .     . . * . *     . . . . .
 . . . . .     . . . . .     . . . . .     . . . . .     . . . . .
 . . . . .     . . . . *     . . . . .     . . . . .     . . . . .
 . . . . .     . . . . *     . . . . .     . . . . .     . . . * .
                          TIME SLICE 5
 . . . . .     . . . . .     . . . . .     . . . . .     . . . . .
 . . . . .     . . . . .     . . . . .     . . . . .     . . . . .
 . . . . .     . . * . .     . . . . .     . . . . *     . . . . .
 . * . . .     . . . . .     . . . . .     . . . . .     . . . . .
 . . . . .     . . . . .     . . . . .     . . . . .     . . . . .
```

Figure 2 Initial activity of Experiment A1

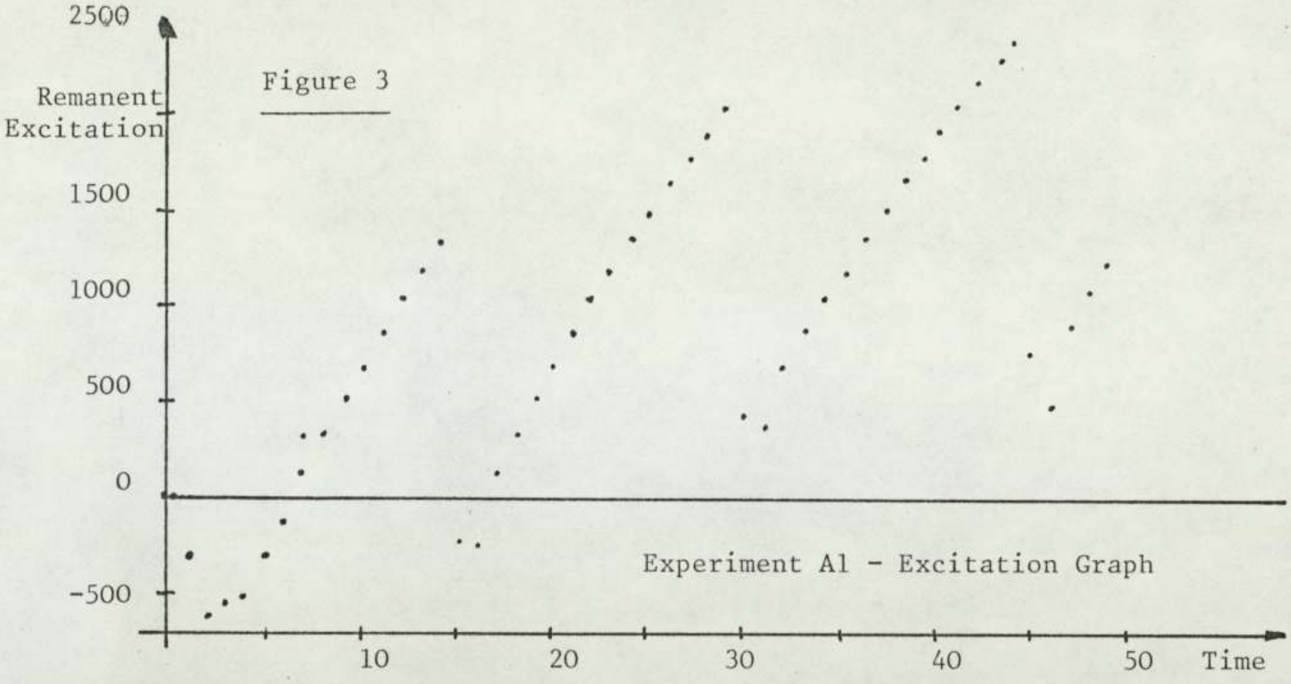


Figure 3

Experiment Al - Excitation Graph

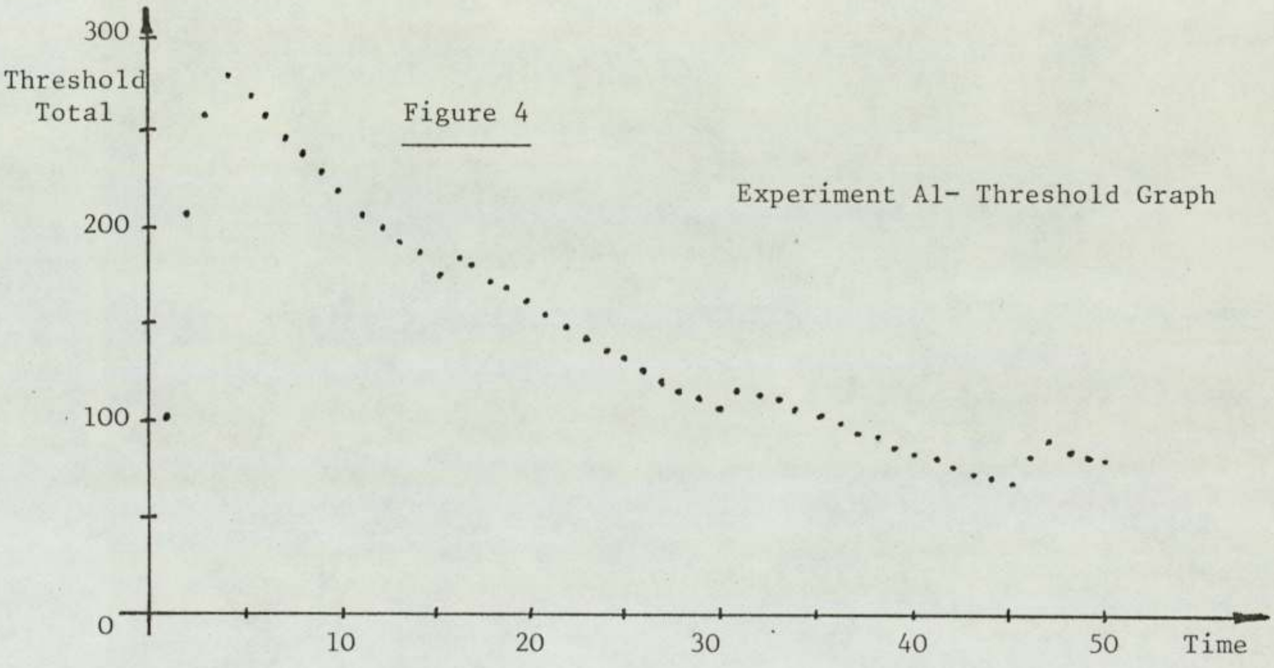


Figure 4

Experiment Al- Threshold Graph

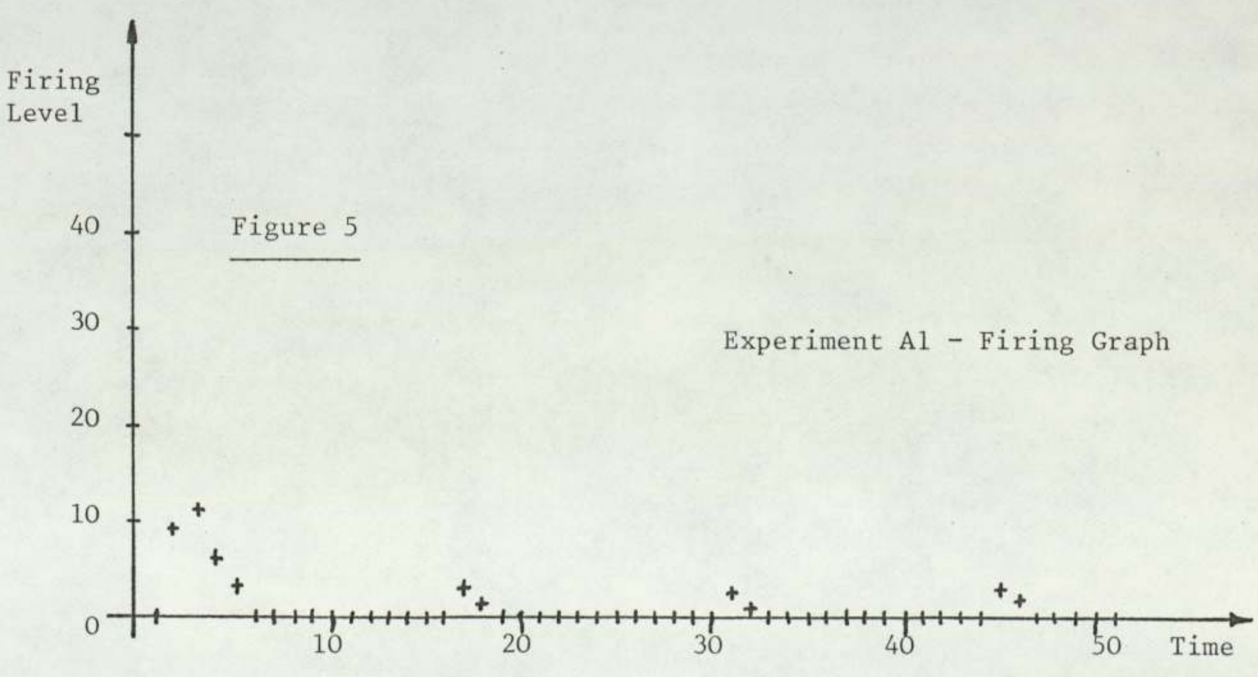


Figure 5

Experiment Al - Firing Graph

however, a general downward trend is observed until near the end of the experiment. The second experiment, A2, omitted any spontaneous elements (by sense switch control) and the activity was slightly lower. The third experiment, A3, made an attempt to increase these firing levels by changing the ratio of inhibitory to excitatory elements from 1:1 to 1:5. It also included spontaneous elements again. It had been noticeable in the previous two experiments, from the dumps of the Neuron Information File (NIF), that many elements had negative excitation totals which, even with a very low threshold, made it impossible for them to fire. The result of the changes was quite marked and the first four time units (or "time slices") of activity is displayed in Fig. 6 and the raw data graphs in Figs. 7-9. Activity is maintained until time unit 11, indicating that this is still a highly damped net. Experiment A4 omitted spontaneous elements and, as in Experiment A2, the difference was slight, the maximum firing level being slightly less as the five spontaneous elements were not present to fire in the first time slice.

Group B Experiments

The previous nets had decays that were too small for any maintained activity and so both excitation and threshold decays were increased from 4% to 20%. This group of experiments was to test the Servo and Learning Schemes (described in Chapter 3) and briefly examine their effect on the activity levels.

The first experiment, as it was a new net, was run with neither facility to provide a comparison with later runs. The effect of the increased decay is immediately obvious from the Excitation, Threshold and Firing data graphs (see Figs. 10-12). The activity only dies out immediately

```
                                   TIME SLICE 2

. * . . .        . . . . .        . . . . *        . . . . .        . . . . .
. . . . .        . . . . .        . . . . .        . . . . .        . . . . .
. . . . .        . . . . .        . . . . .        . . . . .        . . . . .
. . . * *        . . . . .        . . . . .        . . . . .        * . . . .
* . . * *        . . . . .        . . . . .        . . . . .        . . * . .
                                   TIME SLICE 3
. . * . .        . . . * .        . . . . .        * . . . .        . . . . .
. * . . .        . . * . .        . . . . .        * . . . .        . . . . .
. . . * *        . . . . .        * . . . .        * . . . .        . . . . .
* . . . .        . . * . *        . . . . .        . . . * .        . . . . .
. . . . .        . . * . .        * . . . .        . . . . .        * . . . .
                                   TIME SLICE 4
* . . * .        . . . . .        . . * . .        . . * . .        * . . . .
. . . . .        . . . . .        * . * . .        . . . . *        * . . . .
. . . . .        . . * . .        . . . . *        . . . . .        . . * * .
. . * . .        * . . * .        * . * . .        . * . . *        . * . . .
. . . . .        . * . . *        . . . * .        * * . . .        . . . . .
                                   TIME SLICE  5
. . . . *        . . * . .        * * . . .        . . . . *        . . . * .
. . . . .        . . . . *        . * . . .        . . . * .        . . . * *
. . * . .        . * . * *        . . * * .        . . . . .        . . . . .
. * . . .        . . . . .        . * . . *        * . . . .        . . . * .
. . . . .        * . . . .        . . . . .        . . . . .        . * . . .
```

Figure 6 - Initial activity of Experiment A3

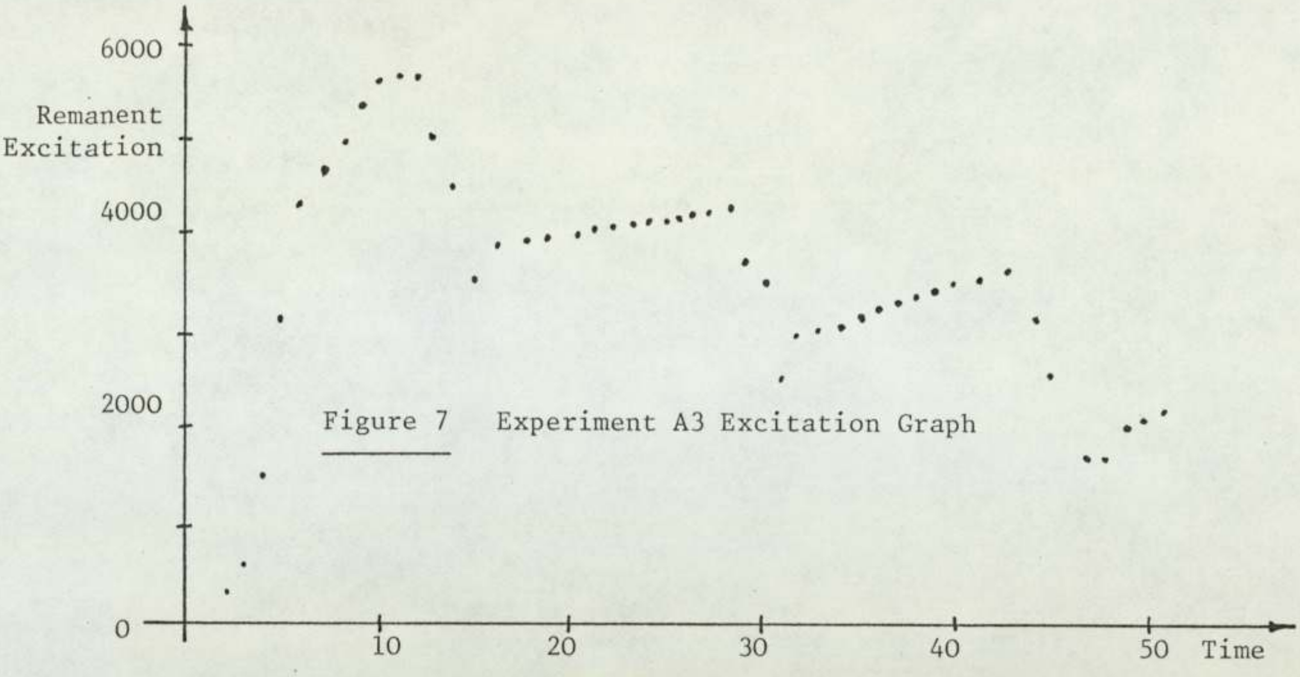


Figure 7 Experiment A3 Excitation Graph

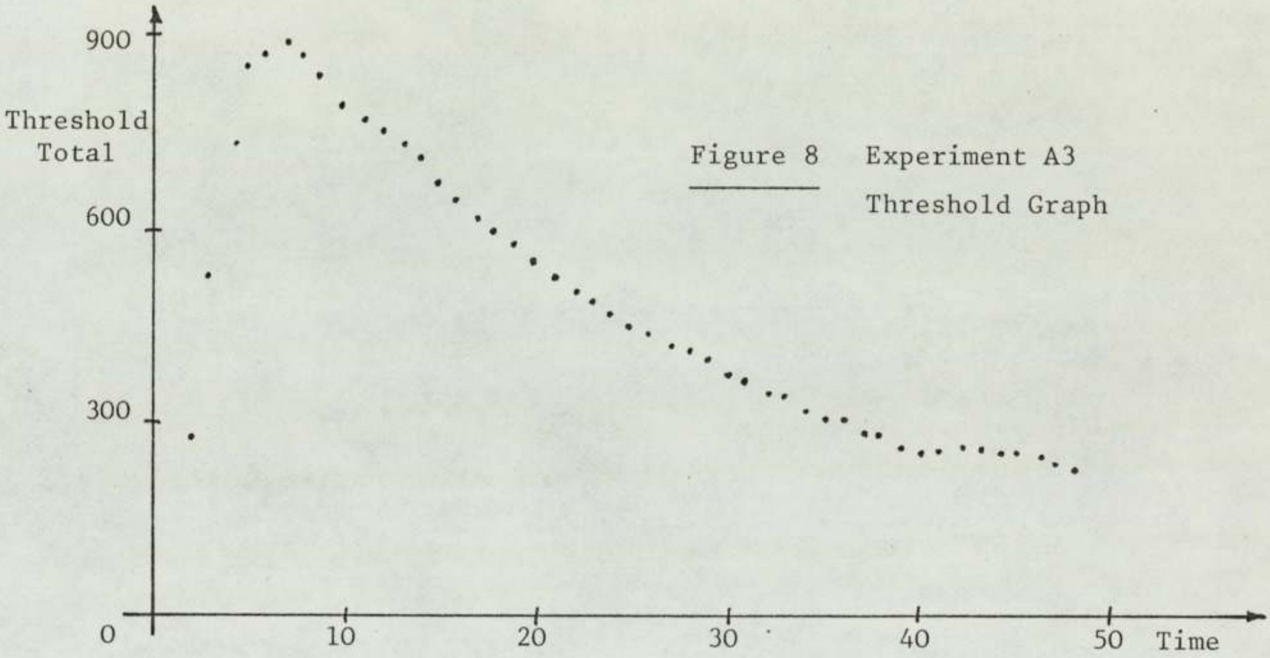


Figure 8 Experiment A3 Threshold Graph

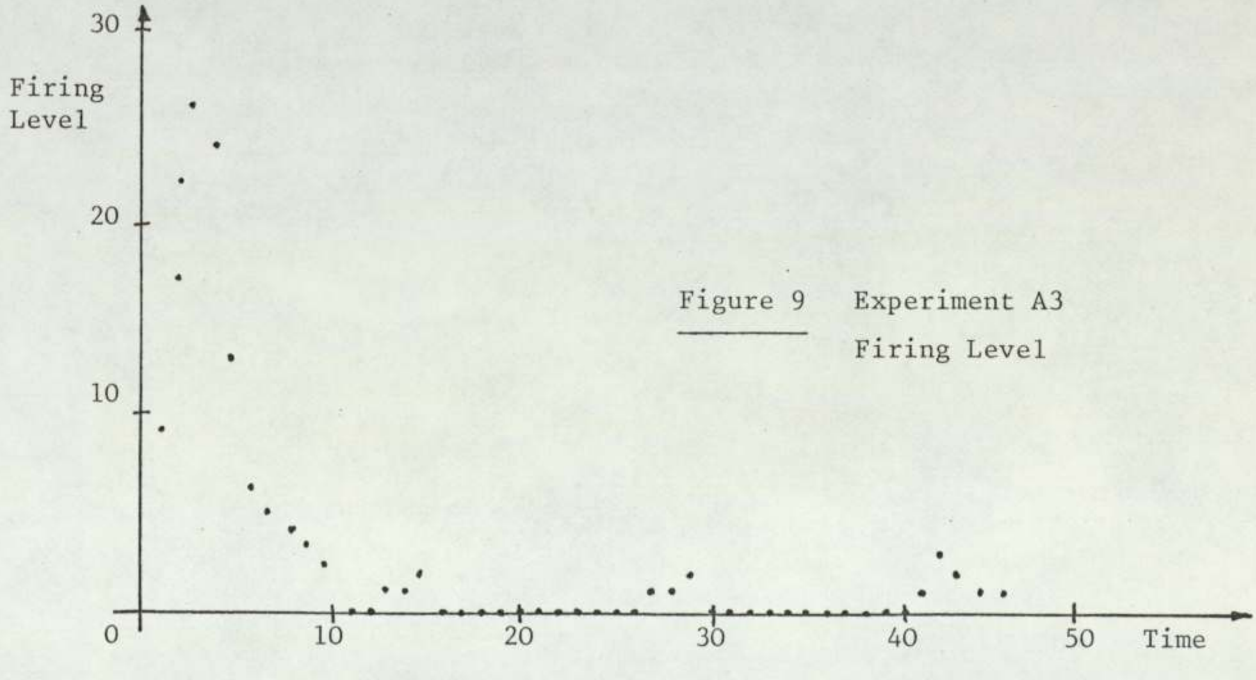


Figure 9 Experiment A3 Firing Level

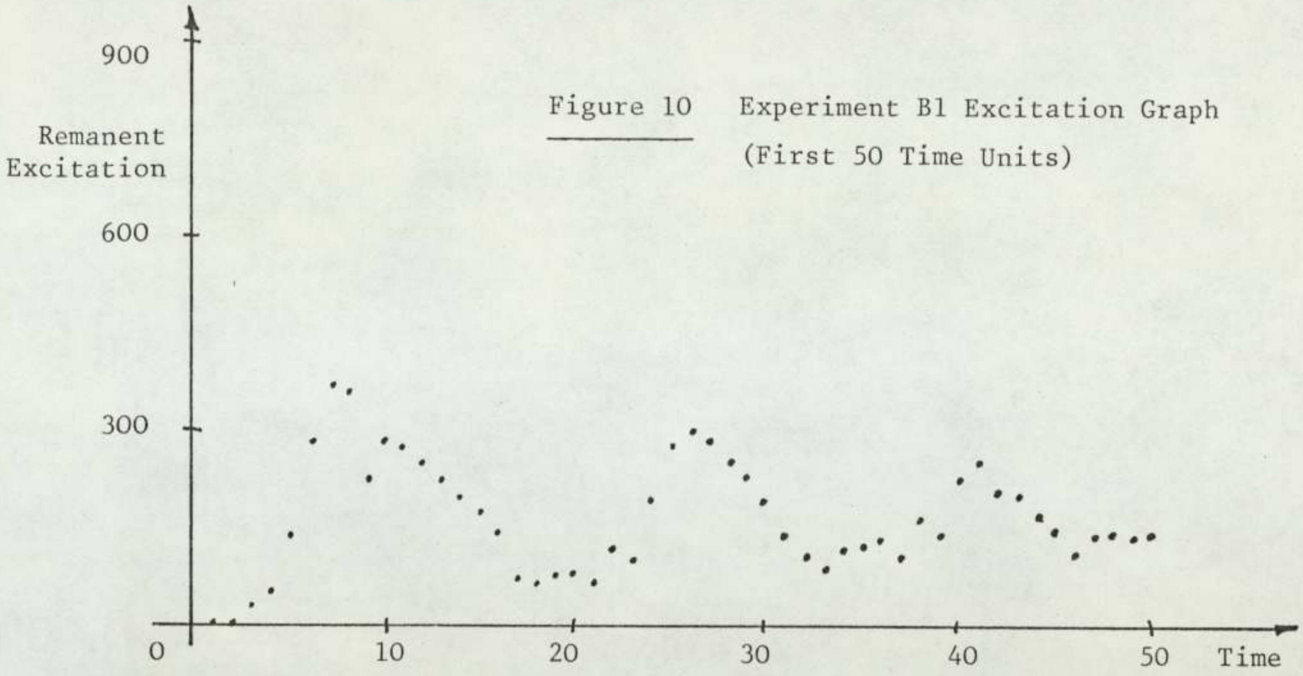


Figure 10 Experiment B1 Excitation Graph (First 50 Time Units)

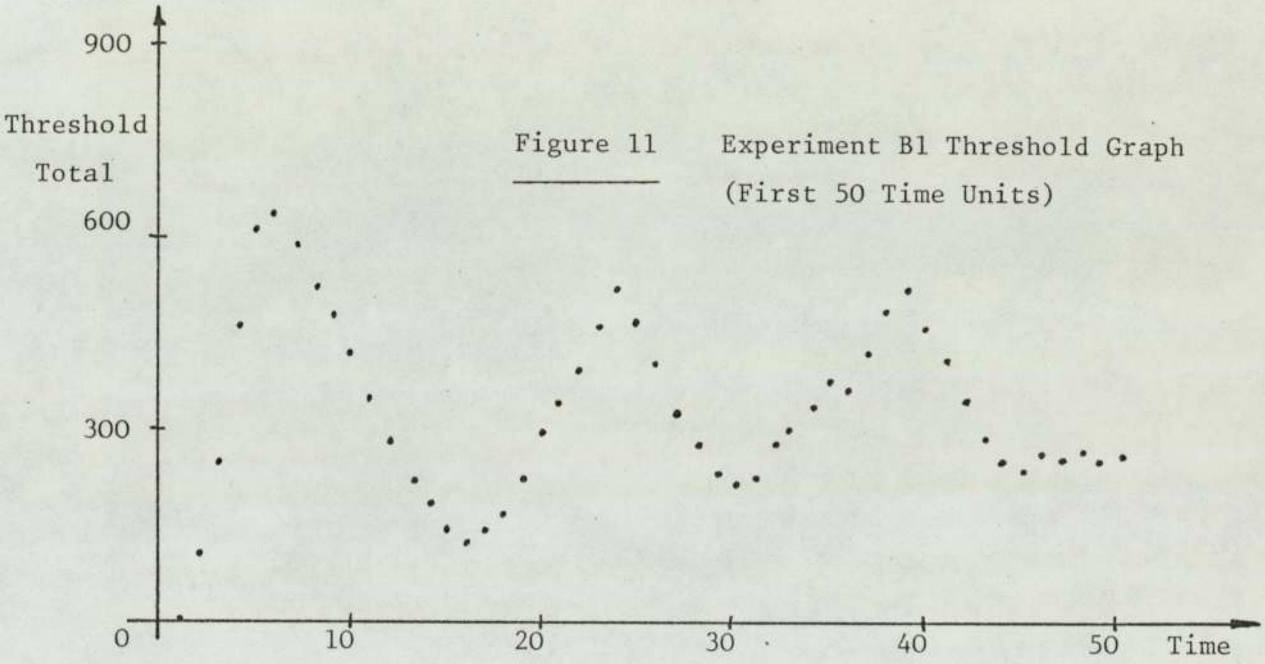


Figure 11 Experiment B1 Threshold Graph (First 50 Time Units)

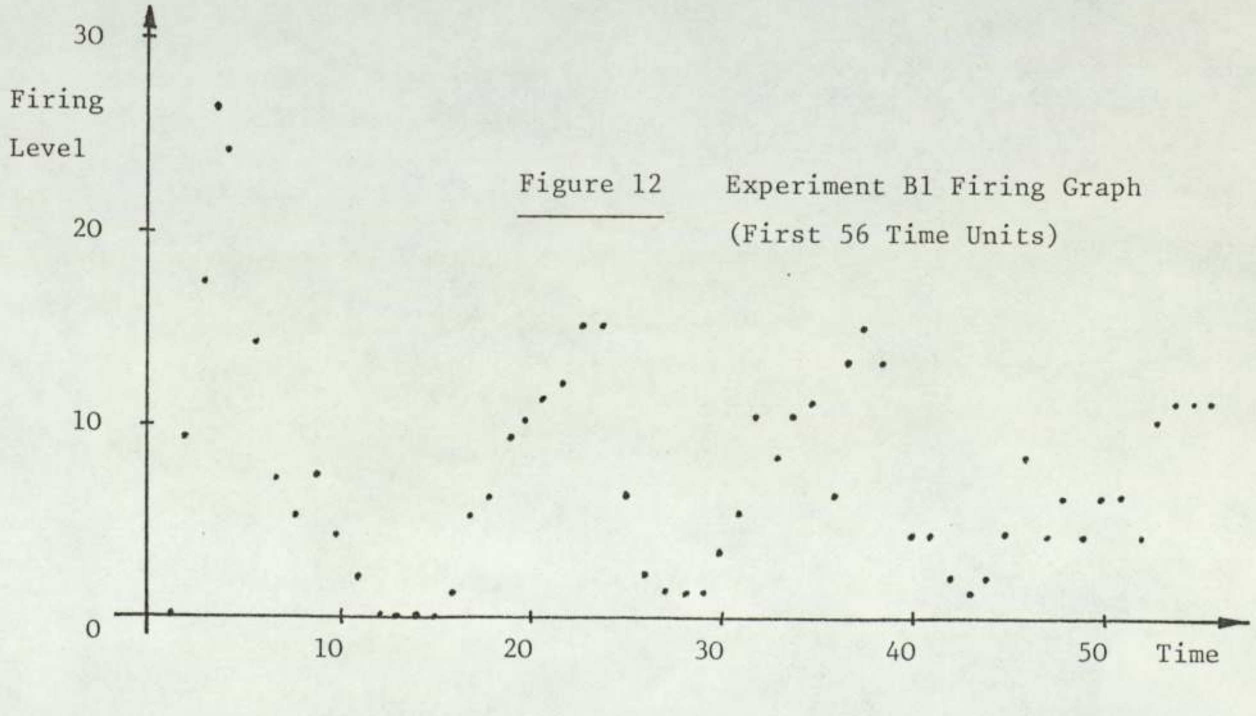


Figure 12 Experiment B1 Firing Graph (First 56 Time Units)

after the main peak of activity and a wavelike fluctuation around a mean level of 8 (elements firing per time unit) is noticeable. The threshold graph emphasizes the wavelike behaviour as the changes produced in the data displayed when an element fires are not as relatively large in the threshold graph as they are in the firing level diagrams. The threshold graph is reminiscent of the threshold graph produced by Farley (1960). The Excitation graph shows lower values and this is because the remanent excitation is extinguished with higher firing rates. Examination of the NIF during the run showed that, whilst most cells were different in state, there were groups of elements that had similar states and this may explain the tendency towards synchronized activity in the firing data. Experiment B2 introduced the early form of Global Learning, here termed Reward. As described in Chapter 3 the Reward is calculated to be directly proportional to the firing level of a specified output area. This area was defined as elements 119, 120, 124 and 125 only. (i. e. a square of 4 elements in the bottom right-hand corner of the final slice). The Reward was printed out on the experimental listing and never increased above zero. The possible Rewards were (-10, -5, 0, 5, 10). Despite the increased firing rates the refractory nature of the cells meant that the continued firing of the output area was unlikely. Consequently the synapse weights were generally reduced. The effect of this is not particularly noticeable until after time unit 50 (see Fig. 13) when the activity is different, but at a similar level.

The next experiment, B3, employed the servo mechanism described in Chapter 3. As the activity was always below half the number of elements in the net, which would correspond to the 'zero' value of the Servo, the Servo was always attempting to amplify the activity. The changes

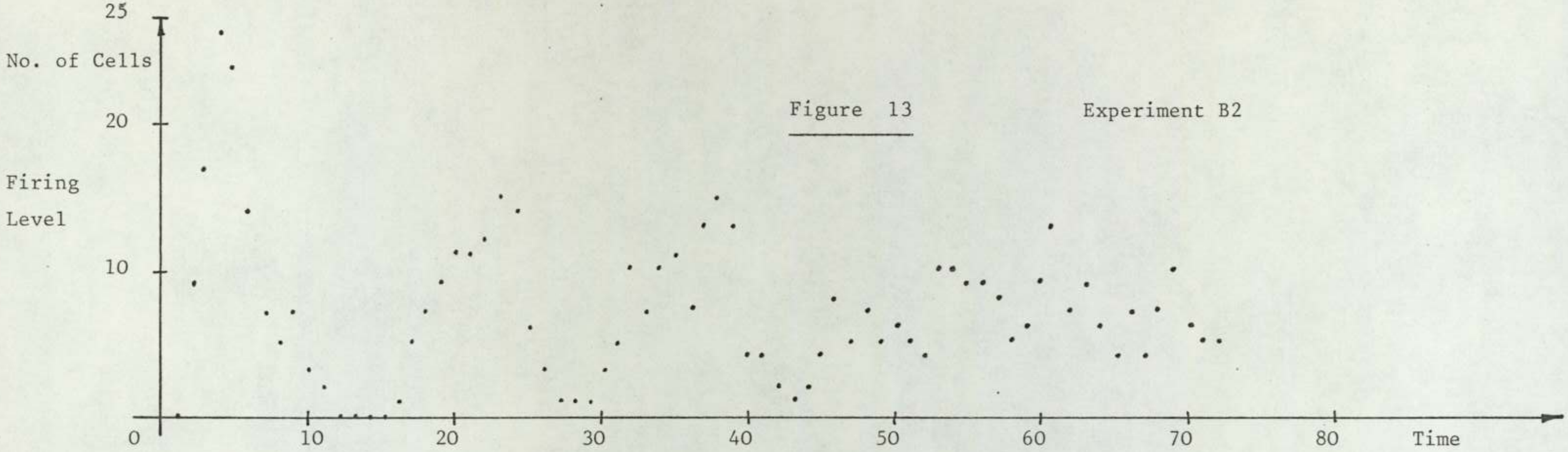


Figure 13 Experiment B2

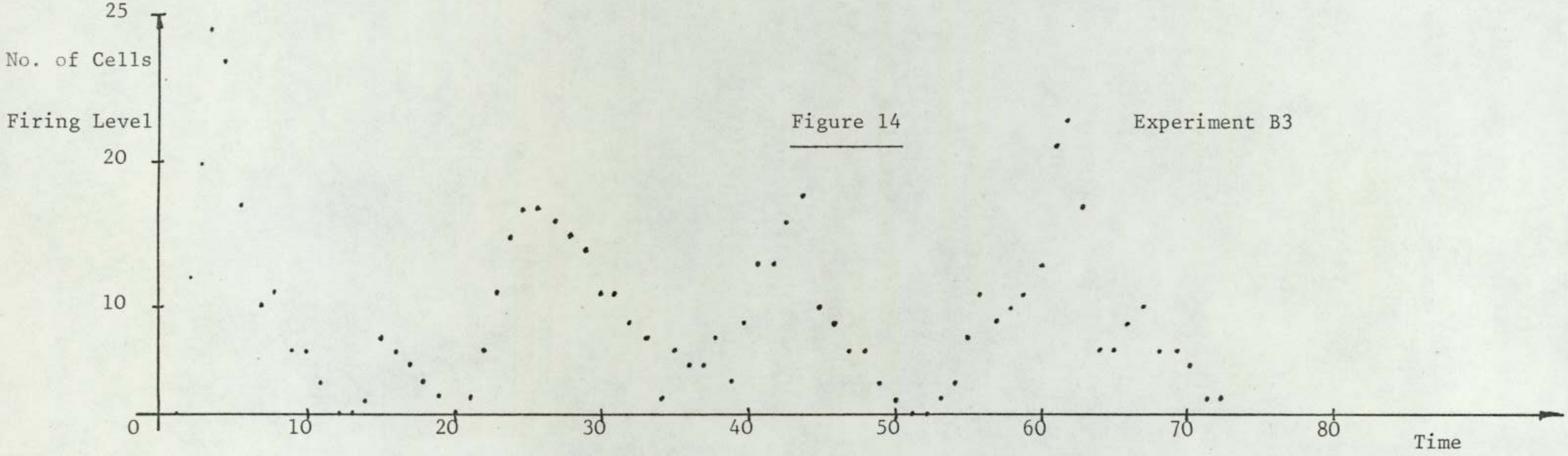


Figure 14 Experiment B3

caused by the servo are noticeable very soon (see Fig. 14) but there is only a slight suggestion of an increase in the mean level of activity, towards the end of the run. Experiment B4 employed both mechanisms and different activity again occurred but with similar general form as Experiment B3.

Conclusions

1. As previous authors have found (e.g. Farley (1955, 1960), Anninos (1967, 1972)) extremely complicated behaviour arises from these networks which can change with the slightest change in parameter values.

2. The data needs to be considered on a global level by for example graphical displays, that show overall patterns of behaviour.

Group D Experiments

The previous small group of experiments had very short simulation times and it was felt larger nets could be simulated without any difficulty. They could show if the lack of smooth waveforms in the firing data was a function of the small net size and low activity level. A net of 500 elements was therefore generated (10 x 10 x 5). Apart from the increase in size, the net was similar to those used in the Group B experiments as the individual cell parameters were the same (see Table 1). The input area was again a square of four elements in the bottom right-hand corner of the first slice and the output area was the corresponding square in the fifth slice. Experiment D1 was run twice, once for 69 time units and then, when the system was enhanced, for 200 time units. The Firing Level is displayed in Fig. 15. Both Reward and Servo functions were enabled. The firing was extinguished after the initial surge, as

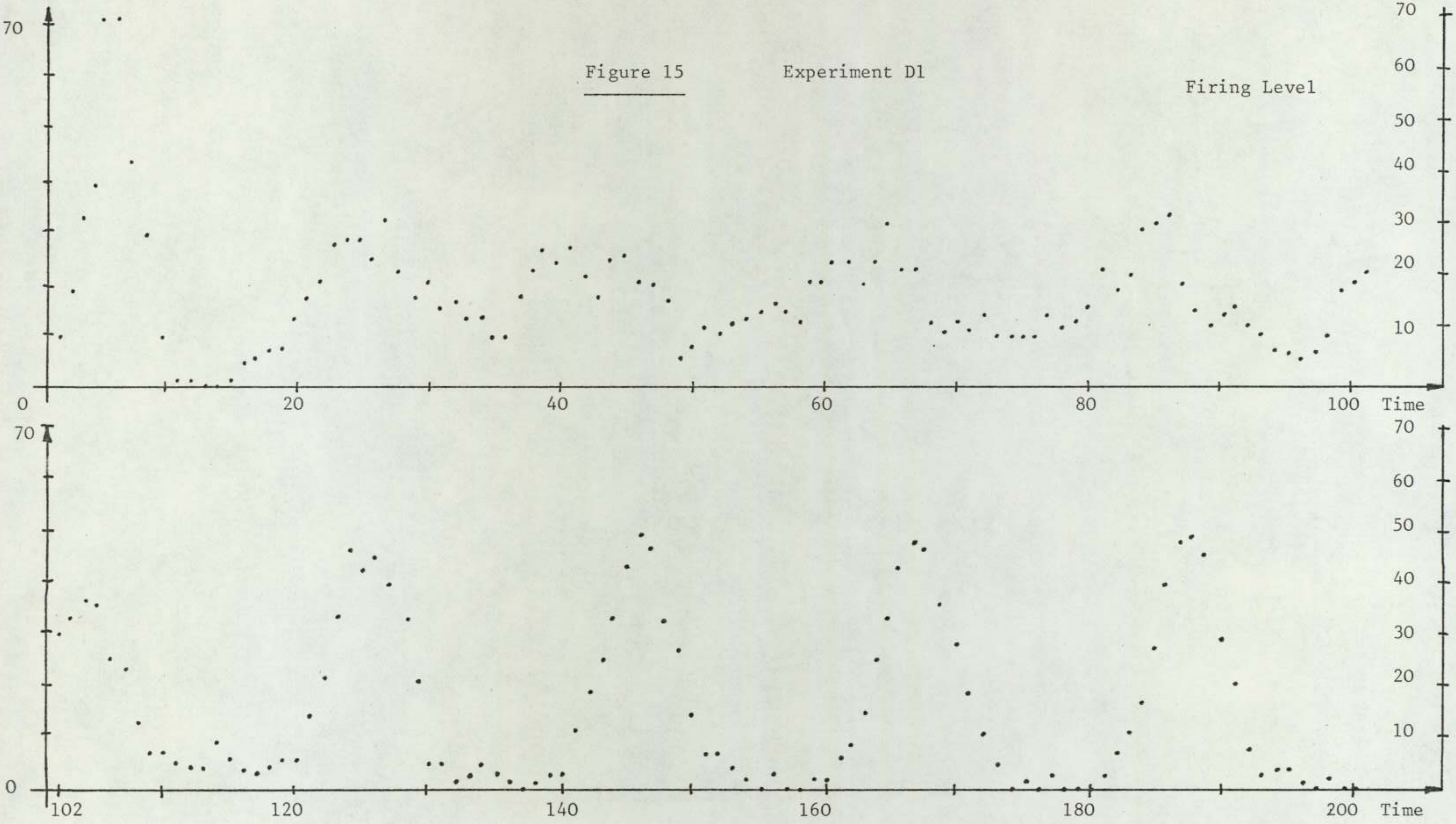


Figure 15 Experiment D1 Firing Level

with the previous experiments. However the activity also died out towards the end of the run. Either the spontaneous elements or the input restarts the net. The waveforms appear much smoother, particularly late in the run with a period of near 20, as in Group B. Also there appeared, by examining the NIF, many elements with similar states. One factor which is noticeable and is at variance with Anninos (1972) is the lack of cycling. Whereas later firing waves were similar in form, none duplicated another. The reason for this is that these nets, compared with those of Anninos, have far more possible states as each cell has many threshold and excitation levels. Throughout every subsequent experiment cycling does not occur with the exception of some experiments late in Chapter 5 whose interconnections have been drastically reduced by the learning algorithm HEBB, which made the net effectively much smaller. The mean level of firing was approximately 25 with a maximum of 71 (14.5% total). By examining the state of the NIF during the run it appeared 122 elements never fired, but the vast majority had fired 'recently'. This means either the non-firing cells had received no connection or were affected only by inhibitory synapses. In Experiment D2 the servo was omitted but only slight changes were noticeable in the graph of the firing data. The servo, therefore, could not have affected the level of firing in the previous run as it had failed to alter the mean level of activity from that of this experiment, despite its value being nearly always at the maximum. The experiment did illustrate that the waveforms, as they were similar to those in Experiment D1, do not depend on a particular sequence of firing elements and must therefore be a function of the net parameters themselves.

In Experiment D3 a new net was generated, with elements the same as those in Experiments D1 and D2 with the exception that the threshold decays were all made 50%. The increase in the threshold decay made the refractory periods much smaller and the waveforms of the firing activity changed considerably (see Fig. 16), having a period of 9 or 10. The remanent excitation data was very low and often only the inhibitory wells of excitation remained. These persist longer as they can only be extinguished by decay or receipt of excitatory pulses from other cells. If the cells never receive positive pulses the inhibition tends to accumulate despite the decays. These wells are the main reason many cells never fire (123 out of 500). There was an initial downward trend in the firing data which seemed to disappear towards the end of the run.

In Experiment D4 another new net was generated with the maximum number of connections emanating from one cell being raised from five to ten. As a consequence of the manner of determining individual weight values (see Chapter 3), this altered the synaptic values too. The excitation level graph was much higher due to the surplus of positive pulses now possible. The maximum firing level was now 198 and an initial decay was still evident. This was due to the fact that the learning algorithm was producing an overall decay of weight values as discussed before. The firing level of the output area was still on an average less than 50%. An interesting feature (see Fig. 17) was the dip in values of the excitation graph before its main peak as all the positive pulses were extinguished and only the inhibitory (negative) pulses remained to be counted. The massive number of cells firing subsequently produced a large spike of remanent excitation due to the net's refractory state.

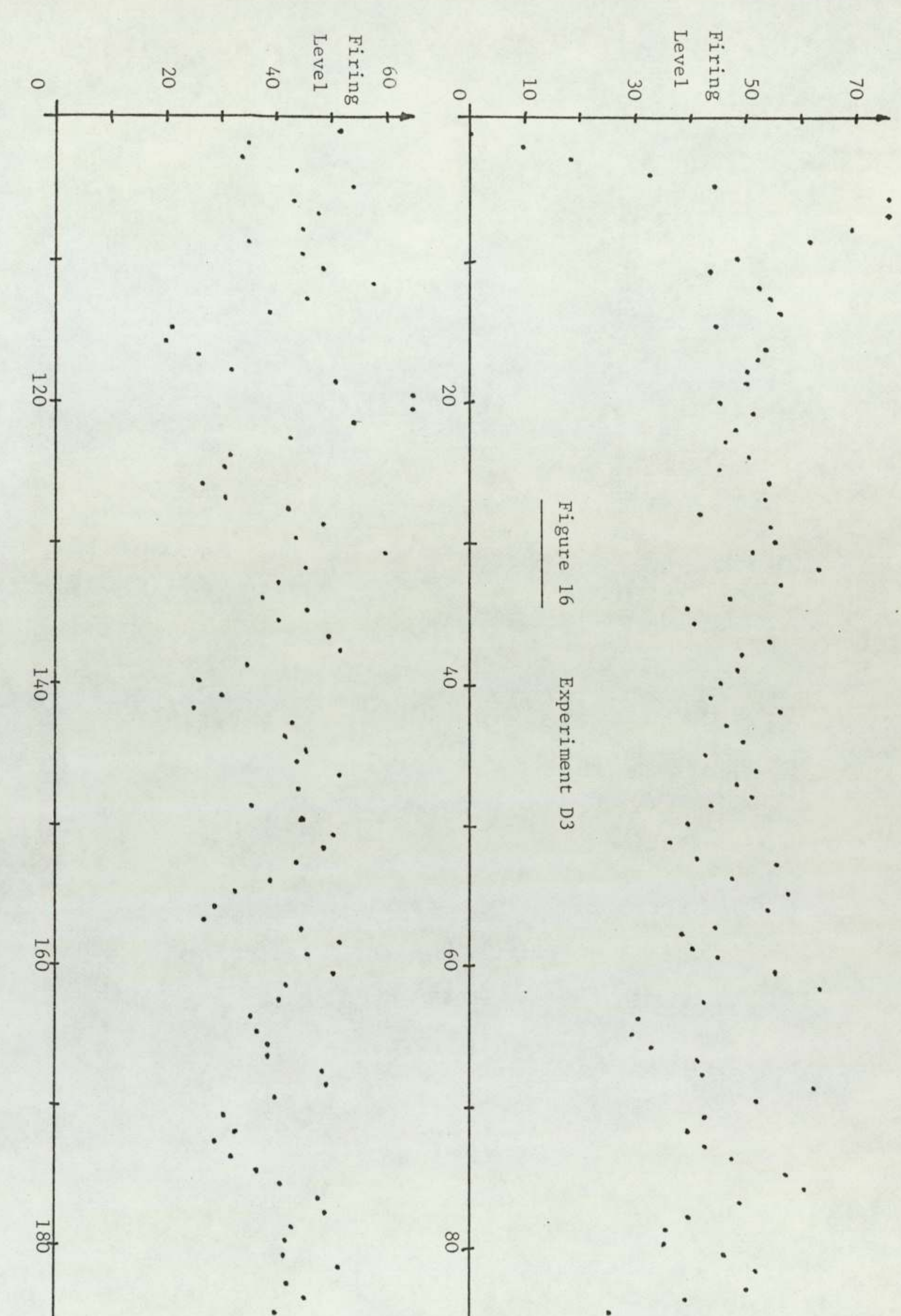


Figure 16 Experiment D3

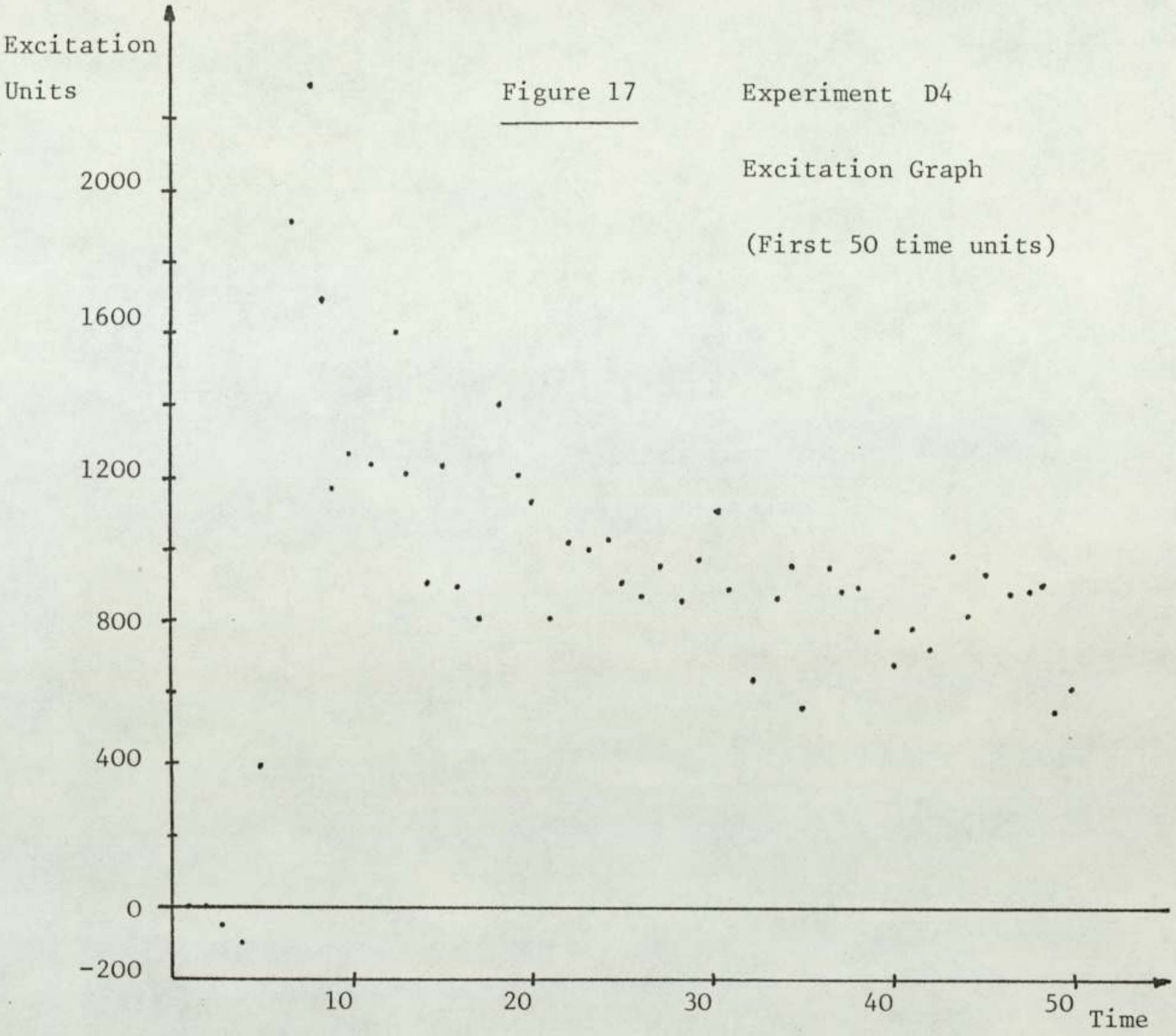
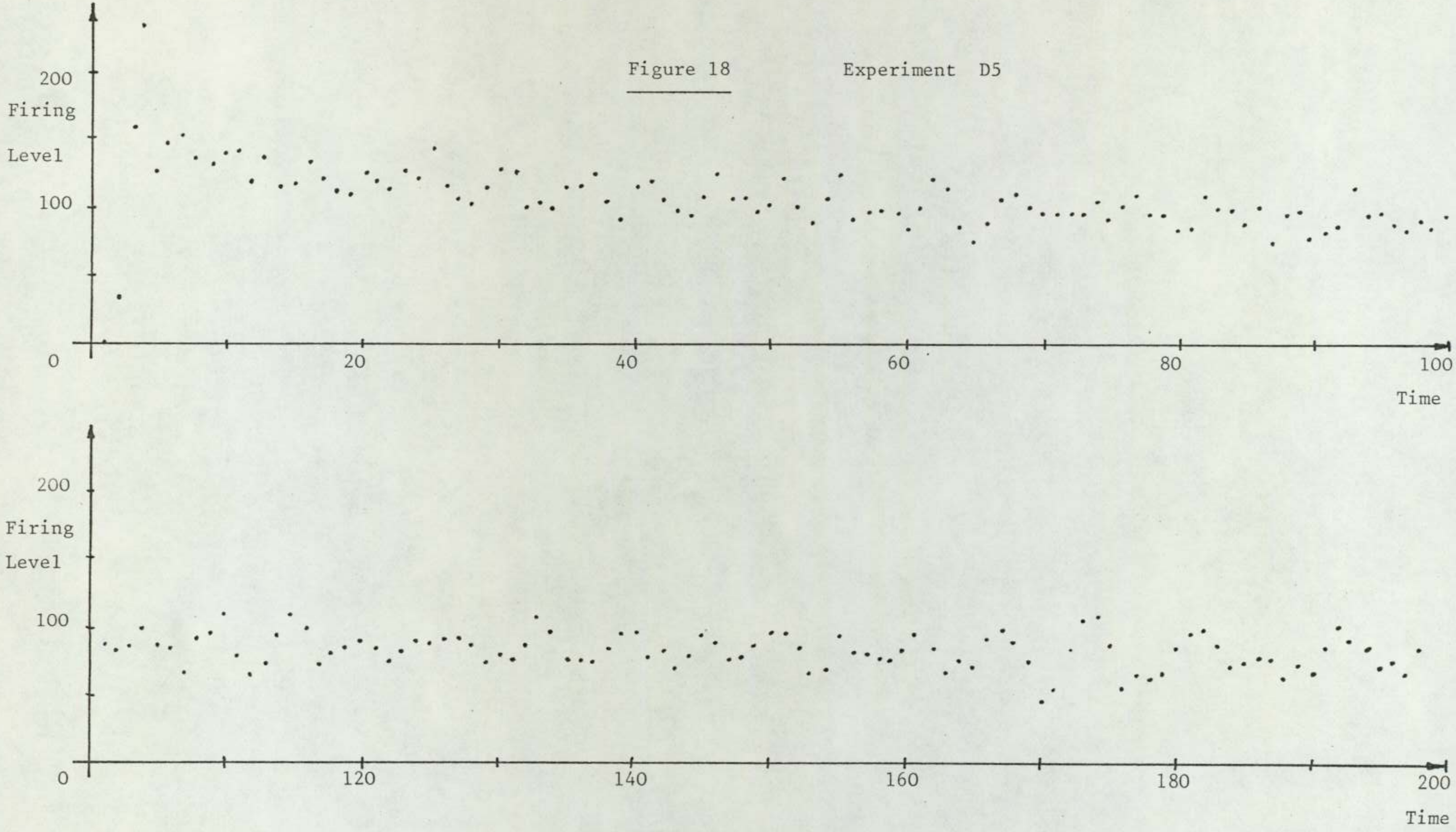


Figure 17 - Excitation graph showing initial dip in values.

All cells now fired at some stage in the run. The next experiment, D5, increased the number of possible connections from a cell to 15. Very little difference in overall activity was noted. (Fig. 18). This may be because the additional afferent excitation each cell receives is insufficient to cause it to refire earlier than before. A cell may be thought of as existing in one of several threshold states, each state being defined by the threshold level. If one assumes that the cells are firing at fairly regular intervals, as the cooperative argument of similar cell states would tend to imply, then a particular cell may fire at either one threshold state or the one 'next' to it. To be forced to fire at a higher rate, then, the cell must

Figure 18 Experiment D5



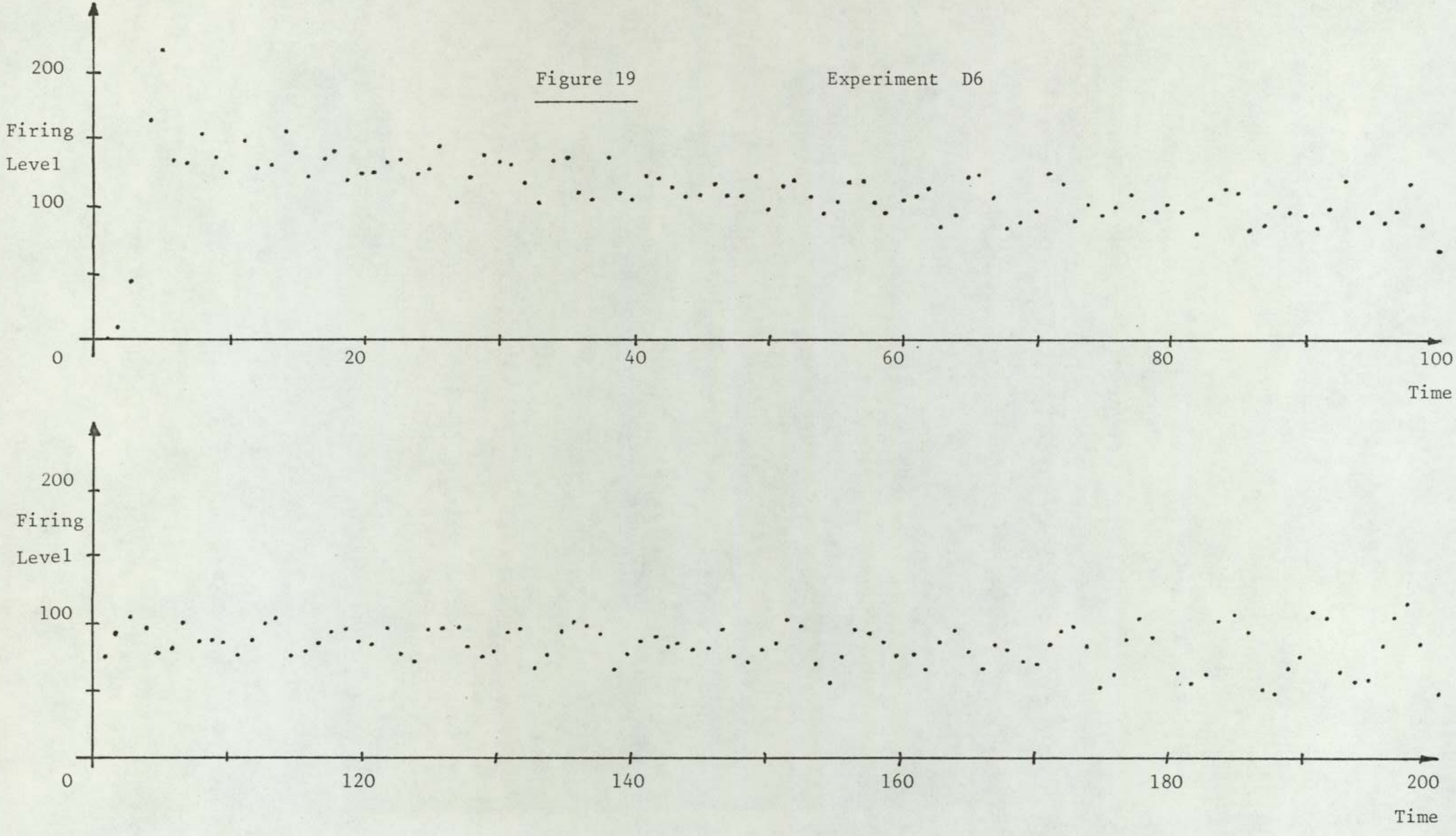
fire at a higher threshold state and therefore be receiving proportionately more excitation. As the decays involved are percentage decays, the steps involved imply that the required increase in excitation is also a percentage increase, which becomes very large with high firing rates.

Experiment D6 generated a similar net but with a different seed to the pseudo random generating algorithm producing the connections. Despite every connection now being changed the overall behaviour was similar (see Fig. 19). Whilst the Firing graph is different, the only noticeable change in general pattern occurred in the last 25 time units, when a series of oscillations of increasing amplitude appeared. It would appear, therefore, that the general pattern of firing is independent of which cell is connected to which. This agrees with similar findings of Anninos (1967). To try and isolate the cause of the gradual decay in activity the servo and learning were now inhibited in Experiment D7. The gradual decay disappeared and a highly stable form of activity resulted (see Fig. 20). This agrees with the argument proposed after Experiment D4. Experiment D8 repeated D7 but inhibited the servo mechanism and Experiment D9 omitted the learning mechanism. The Firing data is displayed in Figs. 21 and 22.

Intermediate Conclusions

1. From Figs. 20 to 22 it is clear that the servo (in its current design) is having a minimal effect. Subsequent experiments indicate that nets with regular or continuous input are stable anyway and so the use of the servo mechanism is abandoned. The results of Experiments D7-9 were later confirmed by Experiments D22-24, see Table 1.

Figure 19 Experiment D6



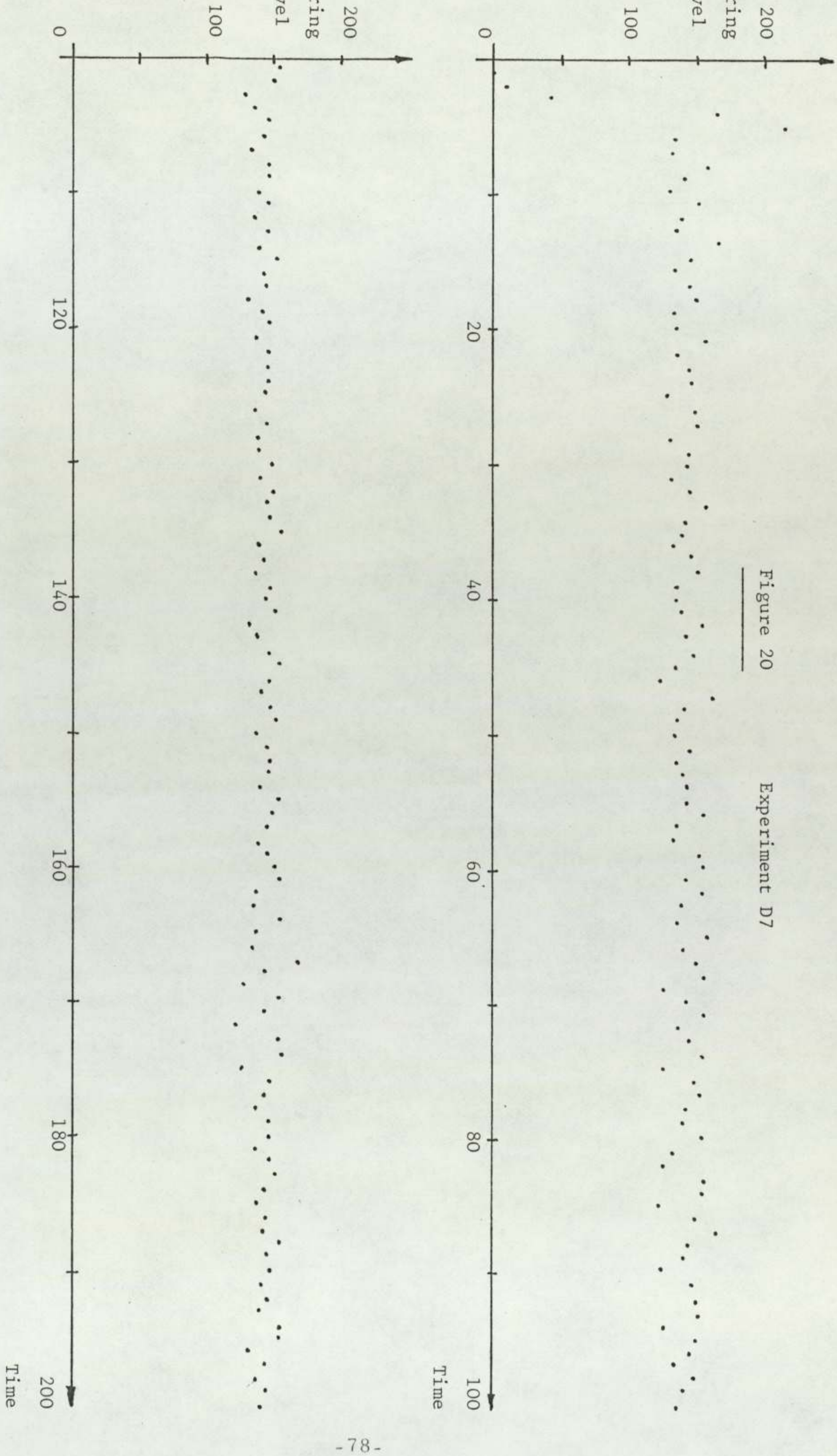


Figure 20

Experiment D7

Figure 21 Experiment D8

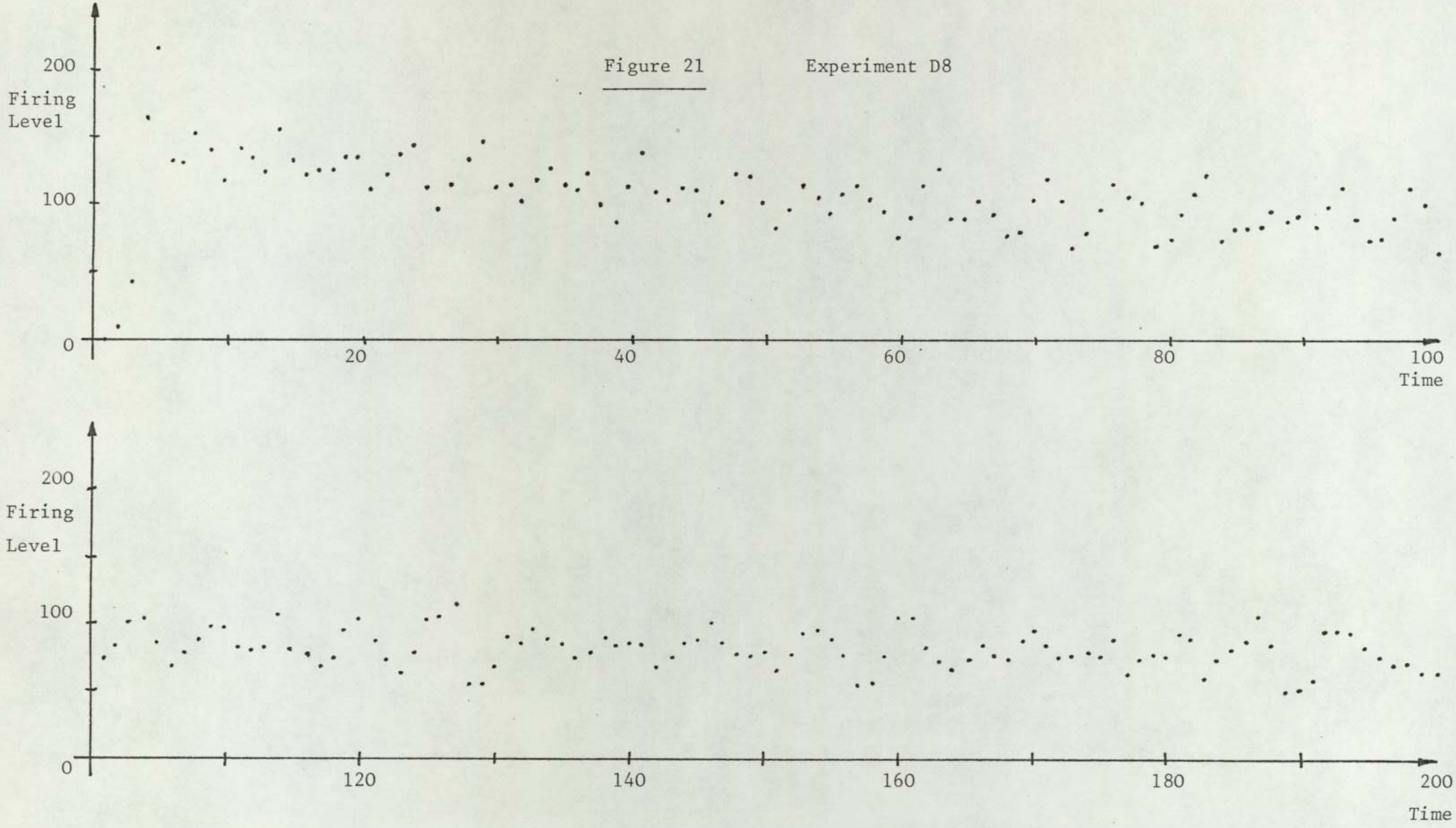
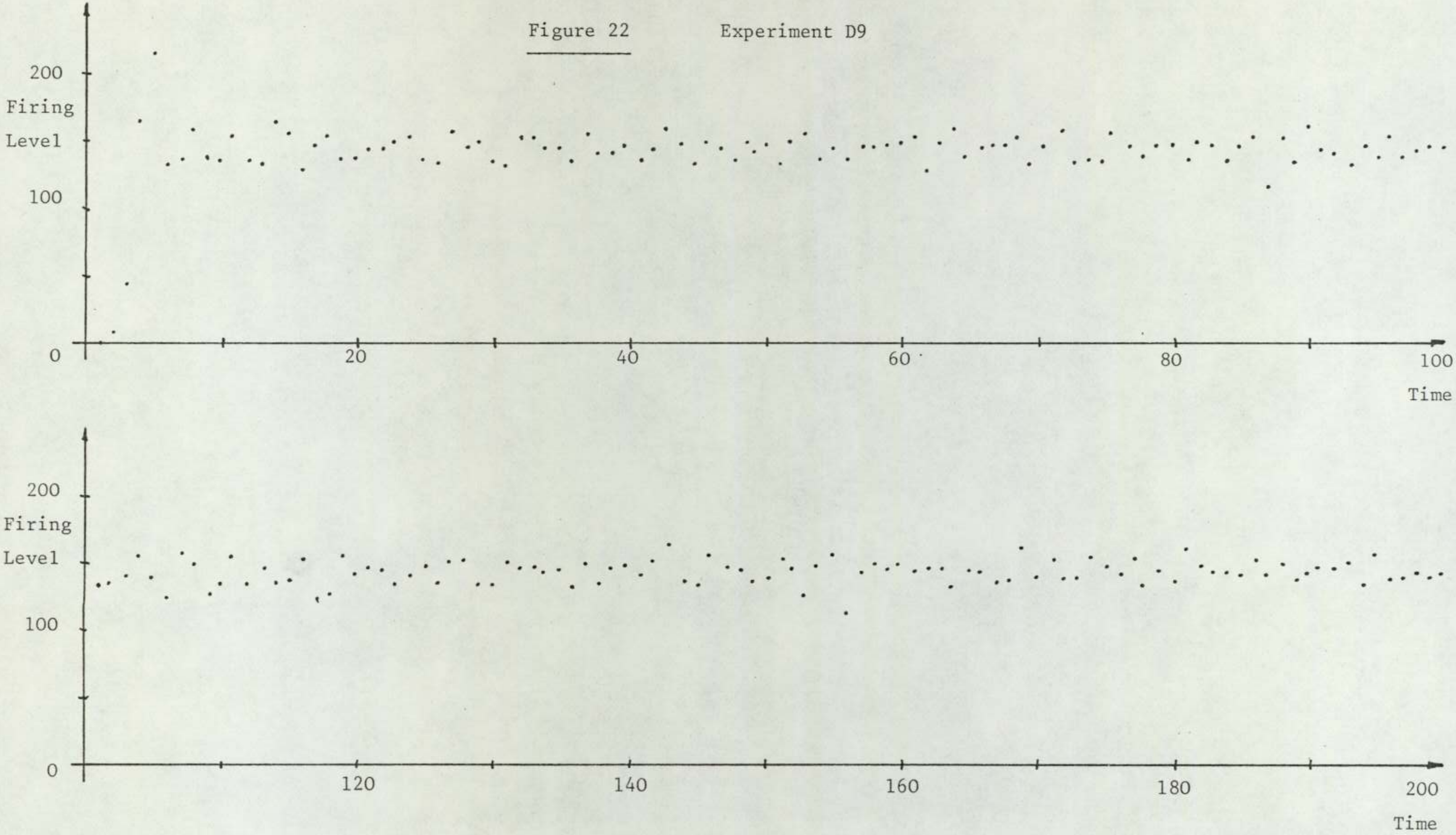


Figure 22 Experiment D9



2. The Reward Scheme is only reducing the level of activity because of the low probability that more than half the output area is firing at any one time.

3. The stability of the nets was a little surprising as previous workers (eg Accardi 1972; Allanson 1956; Amari 1972) emphasized the instability of nets. Their nets however did not receive constant or regular input and it is this and the spontaneous elements that restart the net or keep it going. Harth (1967), for example, dealt with nets receiving constant input but his elements had refractory periods of only 1 time unit and therefore a greater likelihood of firing. He considered his nets to be damped and as the nets considered here have longer refractory periods, these nets may be described as highly damped also.

The final set of experiments within this group examined the effects of inputs of certain patterns on the net as a whole and on individual elements within it. In order to classify signals it was considered that the net, of necessity, must exhibit changed behaviour when the input changes.

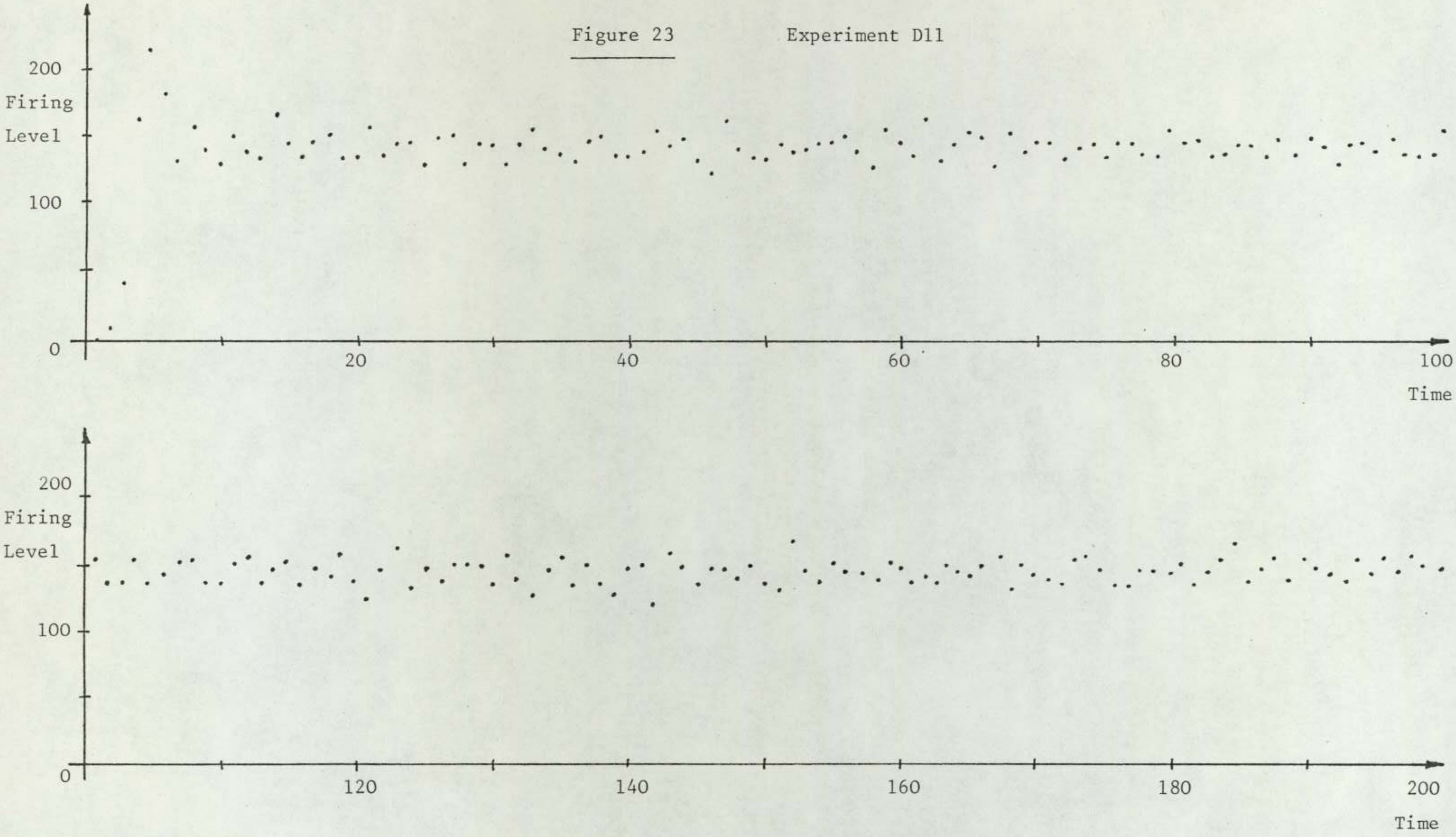
The first Experiment, Dll regenerated the net used in Experiment D7 and applied an input as follows:-

Time	Input
1-50	50
51-100	10
101-150	0
151-200	500

The Excitation level graph changed from that of D7 at time 51 but a brief increase was noted despite the lowering of the input signal. This apparent anomaly was probably caused by the non-firing of some inhibitory cells. Subsequently the activity is different but the general mode of the activity remained the same (see Fig 23). The only discernible difference was in the reduction in amplitude of the oscillations and so nothing in the general behaviour could signify the type of input being presented. In Experiment D12 the threshold decay was reduced to 30% to slow down the rate of firing and involve longer effective refractory periods. (An effective refractory period is the actual quiescent time of a cell for those cells that regularly fire before the threshold has decayed to the resting value.) This would mean the net had more possible 'microstates', to use the terminology of Anninos (1967). The total behaviour of the net was insensitive to the input signal changes, but examination of three individual cells showed one which displayed changes of activity when the input changed (see Fig. 24).

A net with denser interconnections (20 per cell) was generated and a new seed employed. Certain cells in this run, Experiment D13, did show sensitivity to the input but this was not visible on the global data. Experiments D14 and D15 used maximum synapse weights of 80 and 40 respectively and Experiment D16 dispensed with spontaneous elements, but again few effects of input signal changes were discernible. An additional input centre, with a radius of spread of two, was added which increased the total number of input cells to 13 in Experiment D17. At the three points in the simulation at which the input signal changes, different modes of activity were noticeable (see Fig. 25). The individual cells examined at the same points did not show any corresponding changes. In Experiment D18 two different input centres were used involving 6 elements. The Firing level data showed less changes in the amplitude

Figure 23 Experiment D11



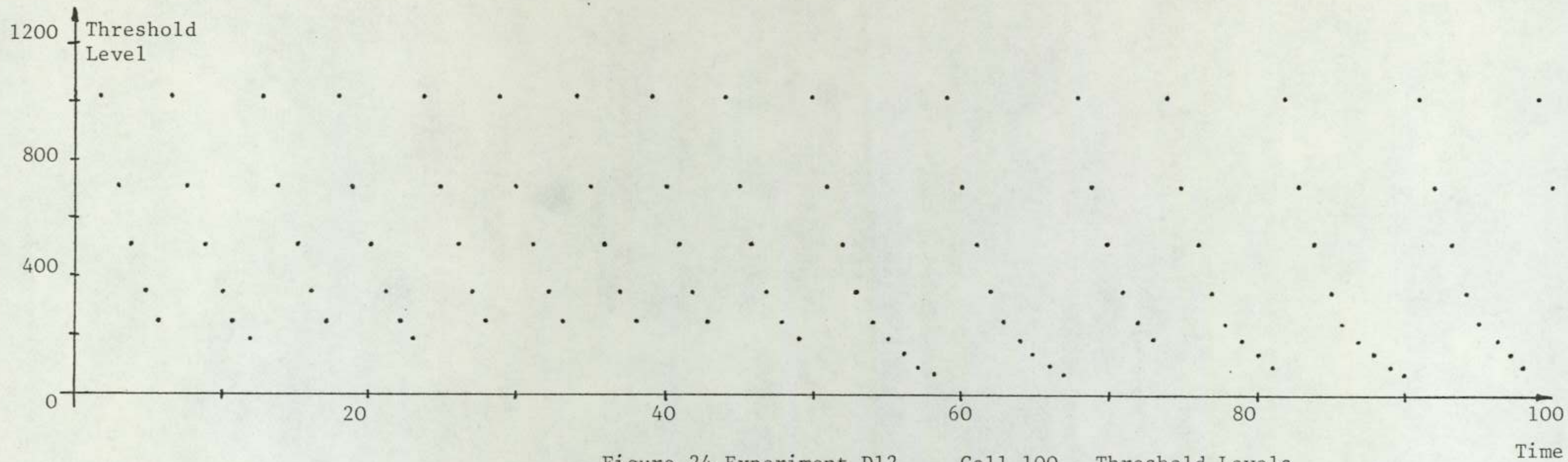
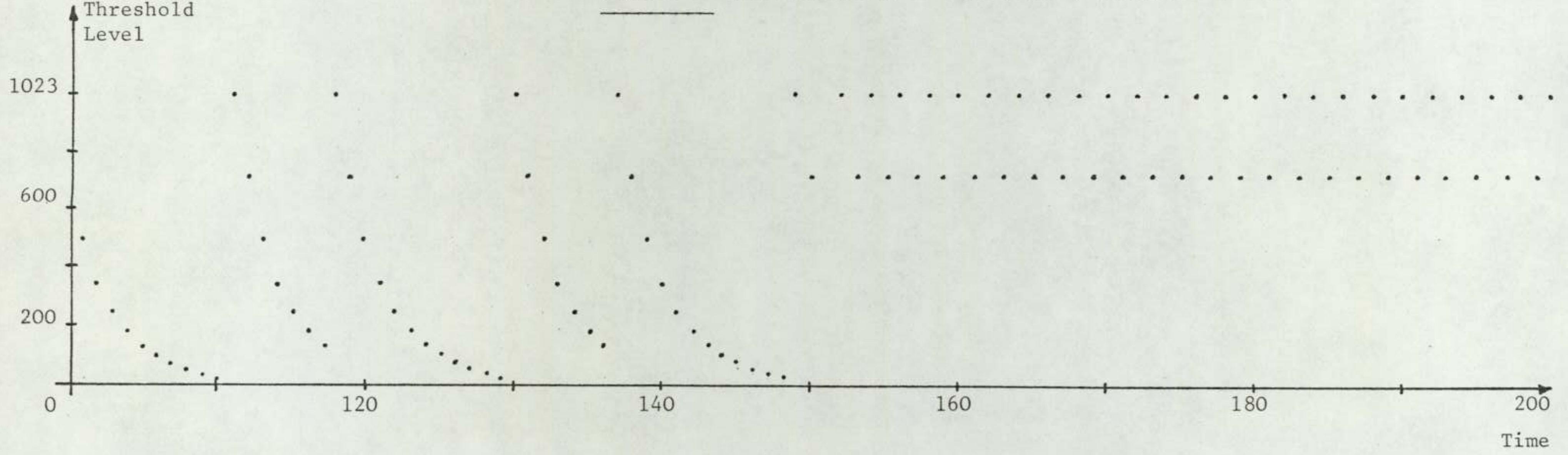


Figure 24 Experiment D12 Cell 100 , Threshold Levels



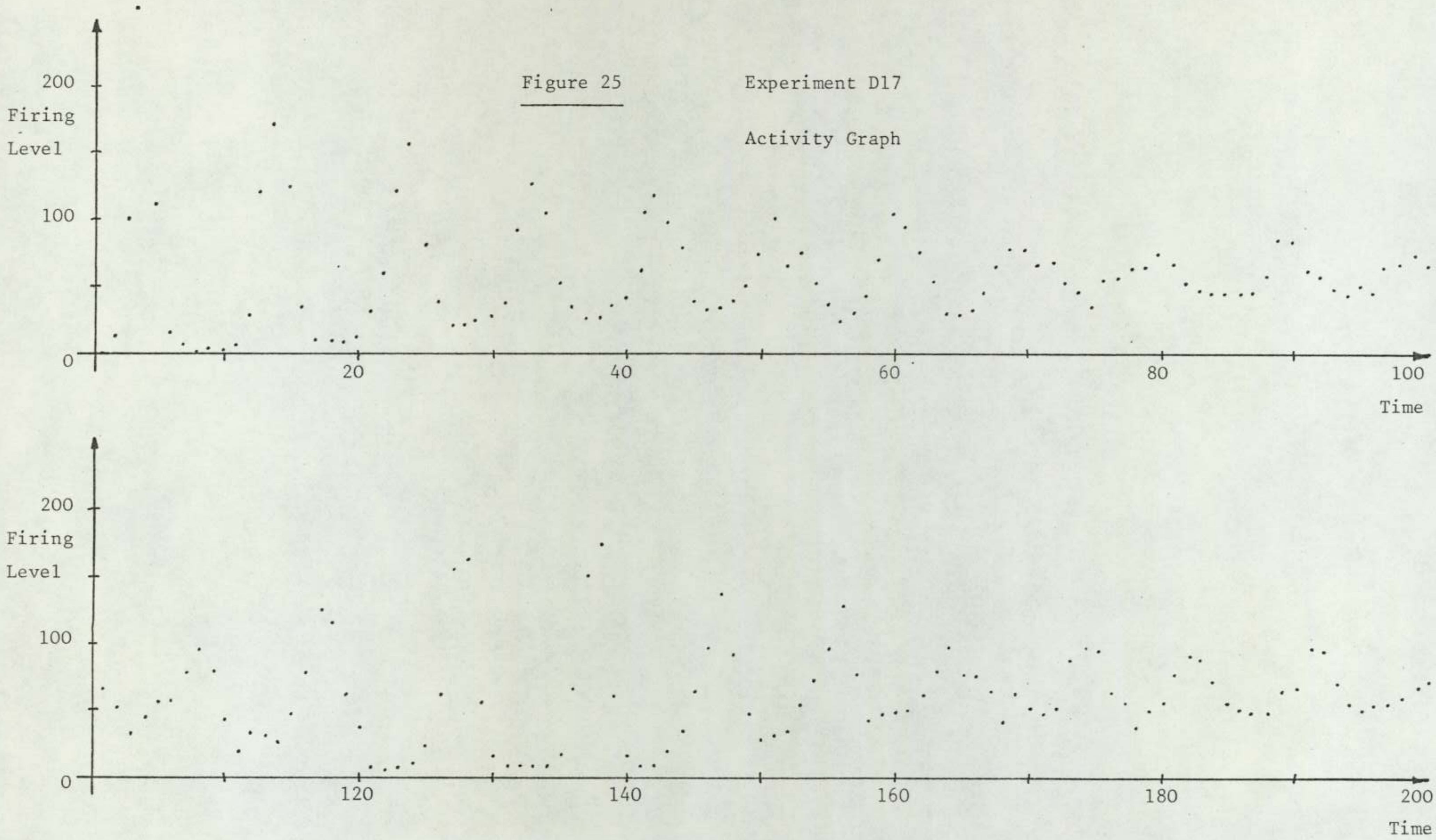


Figure 25

Experiment D17

Activity Graph

(amplitude modulation) at the signal changes and also showed amplitude changes when the input was not changing. It began to appear as if the amplitude modulations were not primarily caused by the input signal. Experiment D19 employed a new signal:

Time	Signal
1-100	50
101-200	0

Variations in the firing activity occurred but they seemed to be unrelated to the signal changes. The lack of correlation between firing level amplitude modulations and input signal changes was also noticeable in Experiment D20 which used the input centres of Experiment D13. A third input pattern was presented to the network of Experiment D17 in the Experiment D10:

Time	Signal
1-10	50
11-100	0
101-110	50
110-200	0

The net 'dies' at time unit 149 (see Fig. 26). It appears that the net needed the input to 'turn the corner' in the deepening troughs of firing level and eventually activity extinguished.

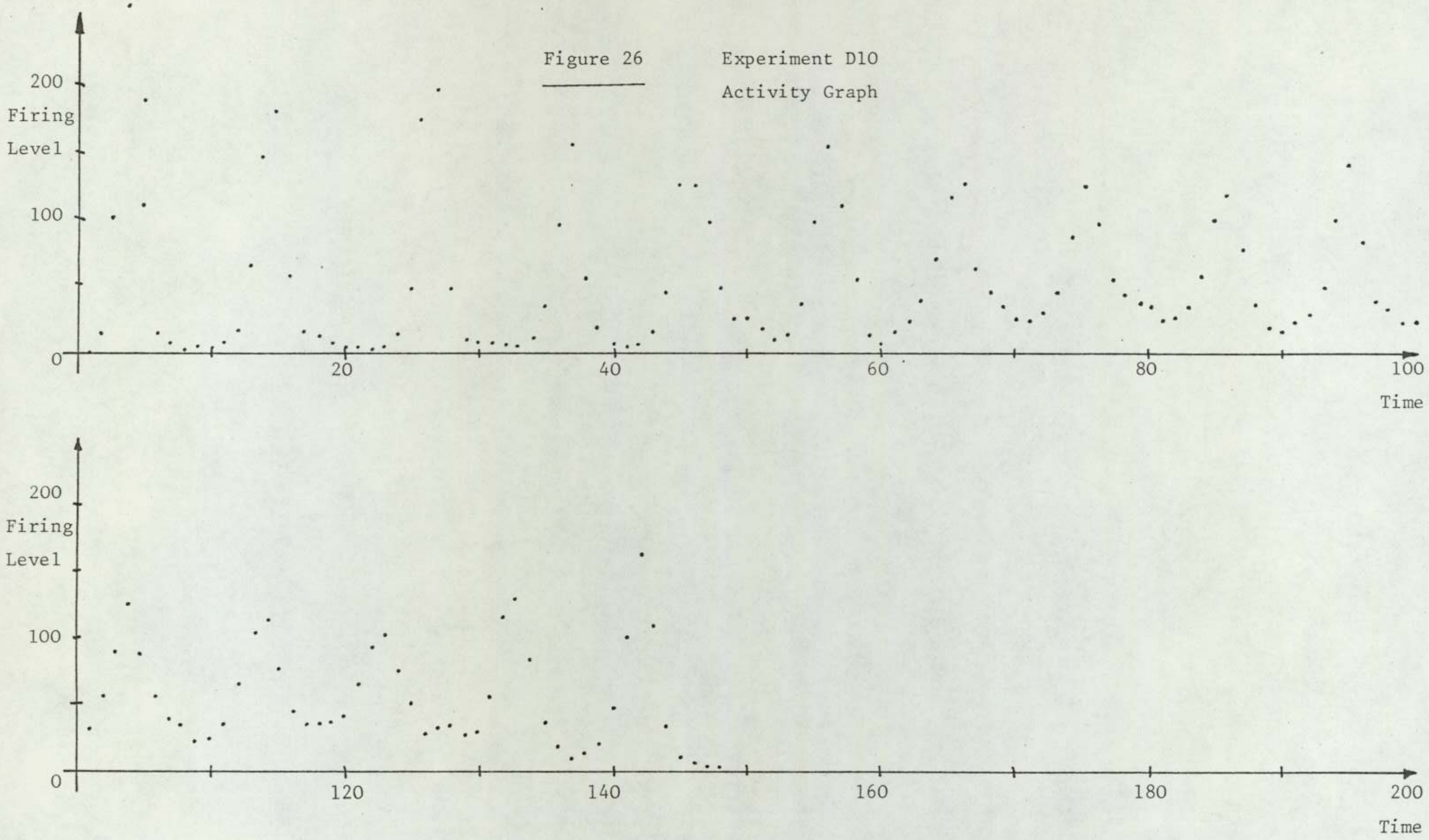
Conclusions of Experiments D11-D18

1. The effect of the input signals was not clear. It first appeared that the inputs were causing amplitude modulation of the firing data waveforms but later runs indicated that this was independent of input changes.

2. It would appear that while directly stimulated elements can show signs of afferent stimulation this ' information' is not transmitted to the rest of the net because of the internal noise of background firing.

Figure 26 Experiment D10

Activity Graph



3. Future experiments may need higher input levels to cause an effect to be widespread within the net.

4. As the activity of the networks are so complicated, it is necessary to examine the global data and generally ignore the individual behaviour. This means that subtle changes that inputs may induce in a net are not visible to the eye in the raw data graphs. What is needed is a method of data reduction that quantifies the data for comparison. Spectral Analysis is proposed as a technique that provides a suitable quantitative analysis based on frequency. The Spectral Analysis Program is discussed in Appendix A.

The remainder of the Chapter, therefore, examines networks using this technique.

Experiments Involving Spectral Analysis

As mentioned in the introduction to this Chapter, the method of description changes at this point. The aim now is to provide the evidence for the various properties noticed during the simulations and to omit a considerable amount of detail that is not so relevant.

The code numbers of the experiments were allocated when a run was completed and documented in the laboratory book used. However due to occasional failure of the machine necessitating reruns, consecutive numbering does not therefore imply a logical relationship between the runs. Also, certain experiments are candidates for providing evidence for more than one type of property and so the following method of description is adopted: A property discovered for these simulated nets will be described and examples of that property either illustrated in detail or listed for comparison. Several examples of sets of Related Experiments (see below) which illustrate the property will be given and the code numbers of the runs given in this form: ([a, b, c] , [d, e, f] , [g, h]) where the code numbers in the [ ] brackets correspond to 'directly Related Experiments' whose parameters only differ in one way, that of the property under discussion.

The frequencies mentioned in connection with Spectral Analysis are usually considered in terms of their corresponding period values as the input signals are defined this way.

Natural Frequency of Networks determined by Decay Constants.

As a prelude to this discussion the effect of varying the amount of input to a net is demonstrated by experiment sets ([F11, F11a] , [D16, D17] , [F18, F19] , [F8, F9]). In the previous section of experiments runs D16 and D17 were identical except that D17 had an extra input, centred around element (5, 5, 1). The spreading of inputs to adjacent elements that is employed in these nets implied an increase in input elements of from 4 to 13. By visually inspecting the graphs (the Spectral techniques not being implemented until Group E experiments) it was found that the number of cycles displayed was the same for each run. (21.5 in 200 time units). The mean firing level of Experiment D16 was lower but the amplitude of the waves higher than in Experiment D17. A similar change was made to Experiments F18 and F19. This time the number of inputs was almost doubled from 16 to 31 input elements and the Firing data's Smoothed Power Density Function (FSPDF) for each experiment is displayed in Figures 27 and 28. The mean firing

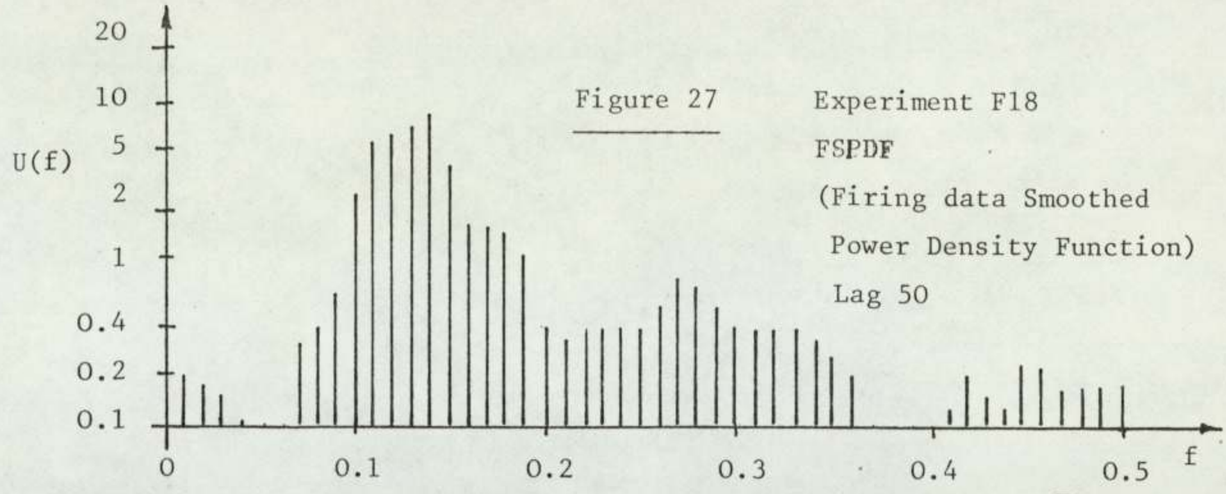


Figure 27

Experiment F18
FSPDF
(Firing data Smoothed Power Density Function)
Lag 50

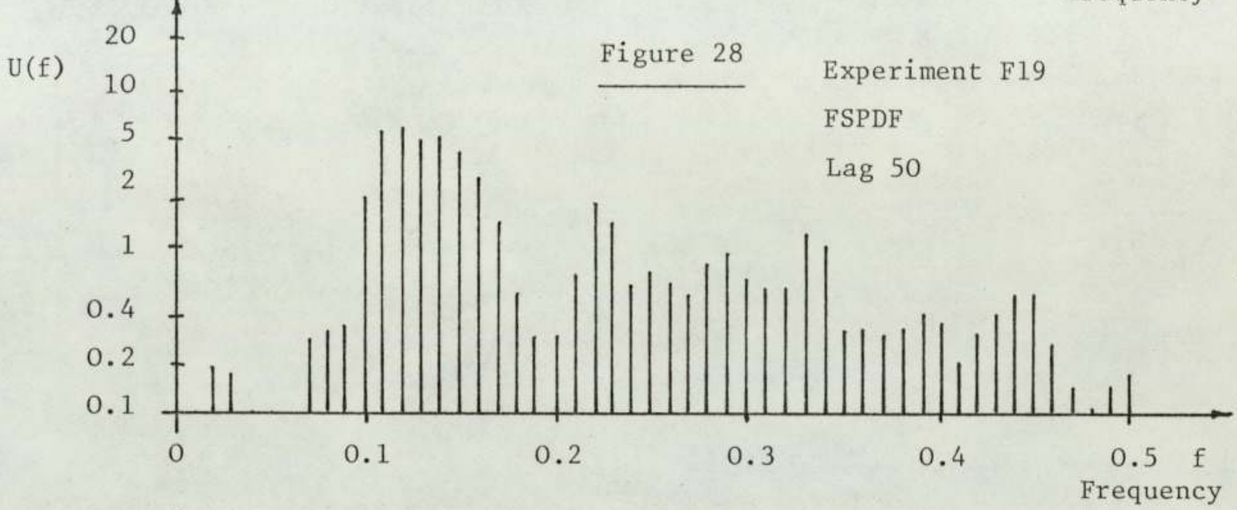


Figure 28

Experiment F19
FSPDF
Lag 50

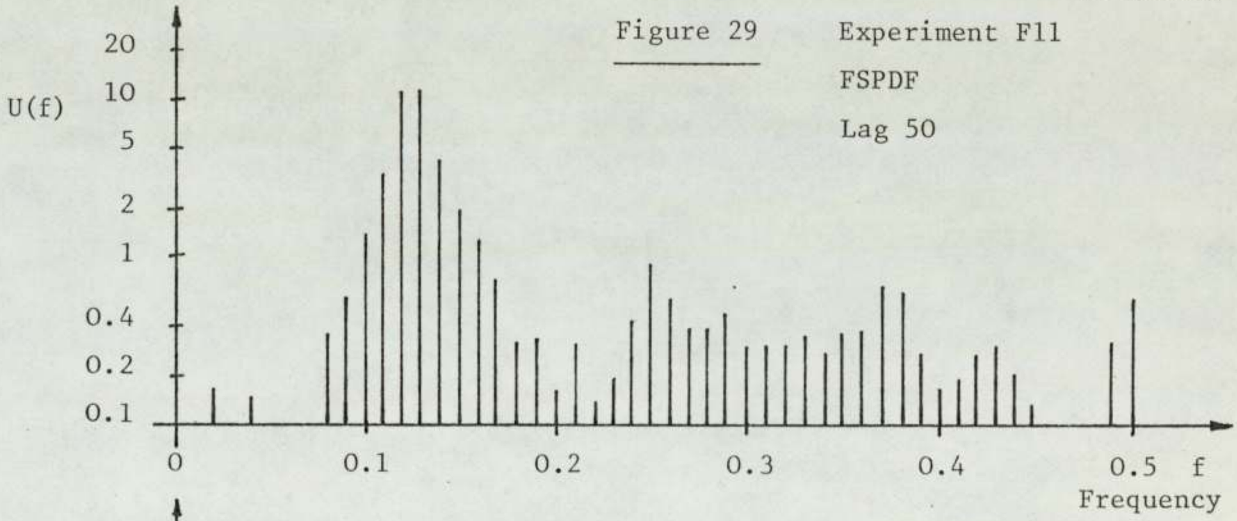


Figure 29

Experiment F11
FSPDF
Lag 50

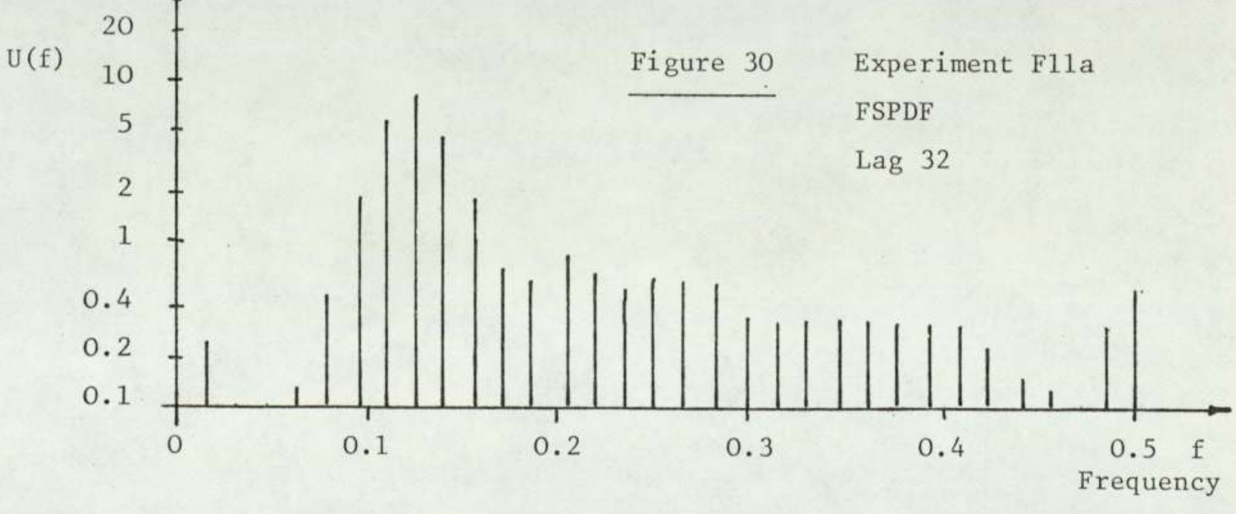


Figure 30

Experiment F11a
FSPDF
Lag 32

level for the higher input run (F19) was slightly raised (17.57 to 18.33) but the standard deviation was less (7.6 to 6.3). Experiments F11 and F11a (see Table 1) yielded the Firing data Smoothed Power Density Function (FSPDF) of Figures 29 and 30. Experiments F8 and F9 produced the FSPDF graphs of Figures 31 and 32. This data confirmed the supposition that the frequency of the net was unaltered, whilst the amplitude and mean level changed.

To examine the effect of decay rates on frequency, various sets of experiments were run that varied the decays for the same input signal: ([E2, E5, E6, E7, E8, E9, E10, F14], [F4, F5], [F6, F11], [E11, F1], [F2, E1, F10]). The first set of experiments all supplied an input of period 10 to the nets. The decay rates were varied independently as can be seen from Table 1 and in the case of Experiments E7, E8 and E10, one of the decays was generated by picking from a distribution (type 2) with the maximum value set by the range. For instance, Experiment E7 has threshold decays set randomly within the range 1 to 60% and the seed to the pseudo random number generator is 10. The Smoothed PDF graphs are displayed in Figures 33 to 41. Figure 33 is the Power Density Function of the Excitation data from Experiment E2. [At this stage the system only produced the PDF graph for this data.] It is therefore compared with the same PDF graph for E5 (Fig. 34). In Fig. 33 it can be seen that the power is centred on a frequency of 0.1 with an even area each side of the main peak. This central frequency corresponds to a period of 10. The PDF in Fig. 34 shows a wider spread of frequencies with none dominating. This wider spread is probably due to the two types of decay rate being used there being, therefore, two different 'sources of frequency'. The PDF of

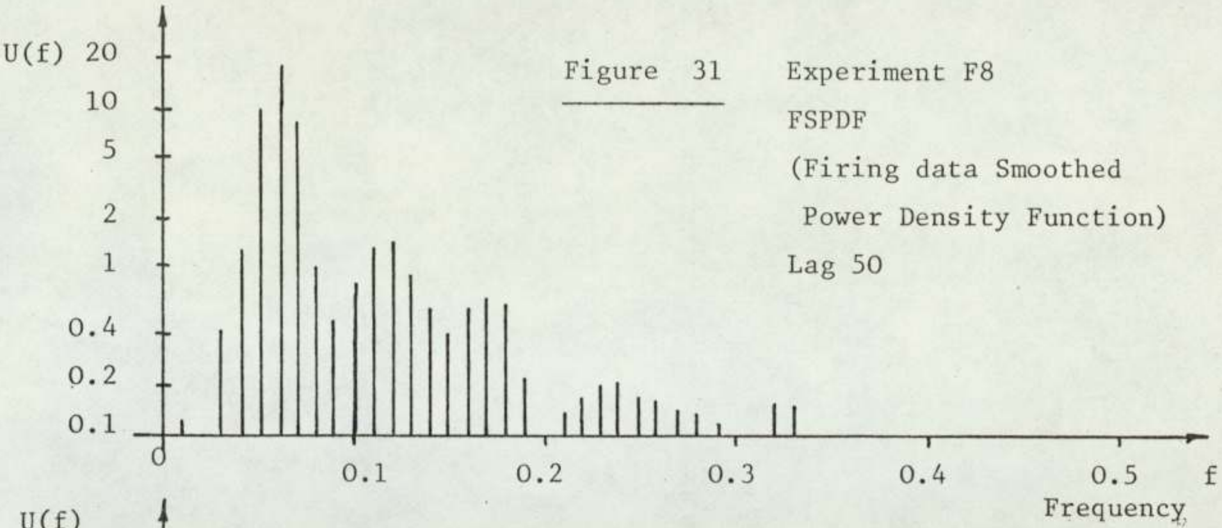


Figure 31 Experiment F8
FSPDF
(Firing data Smoothed
Power Density Function)
Lag 50

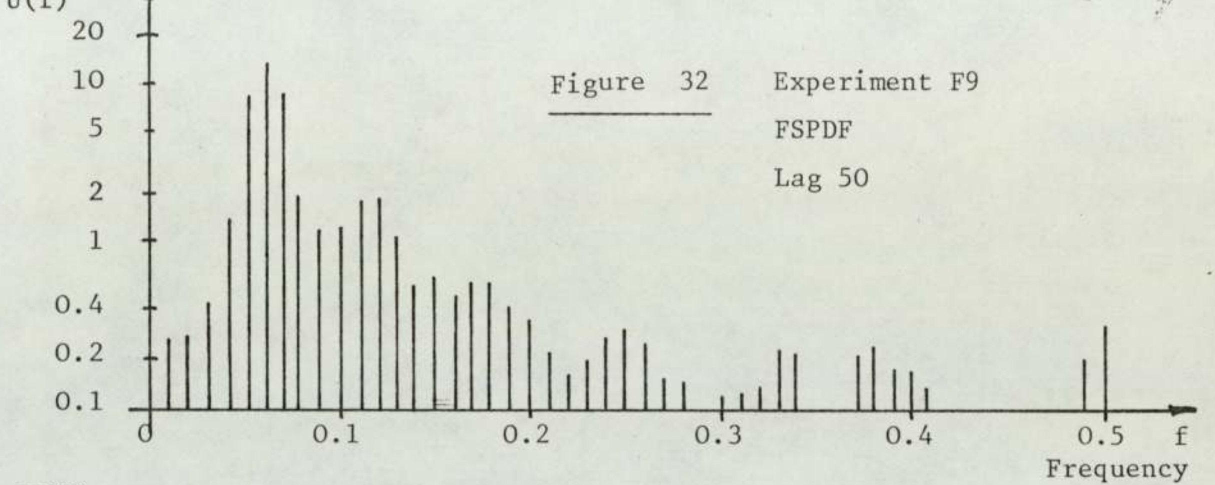


Figure 32 Experiment F9
FSPDF
Lag 50

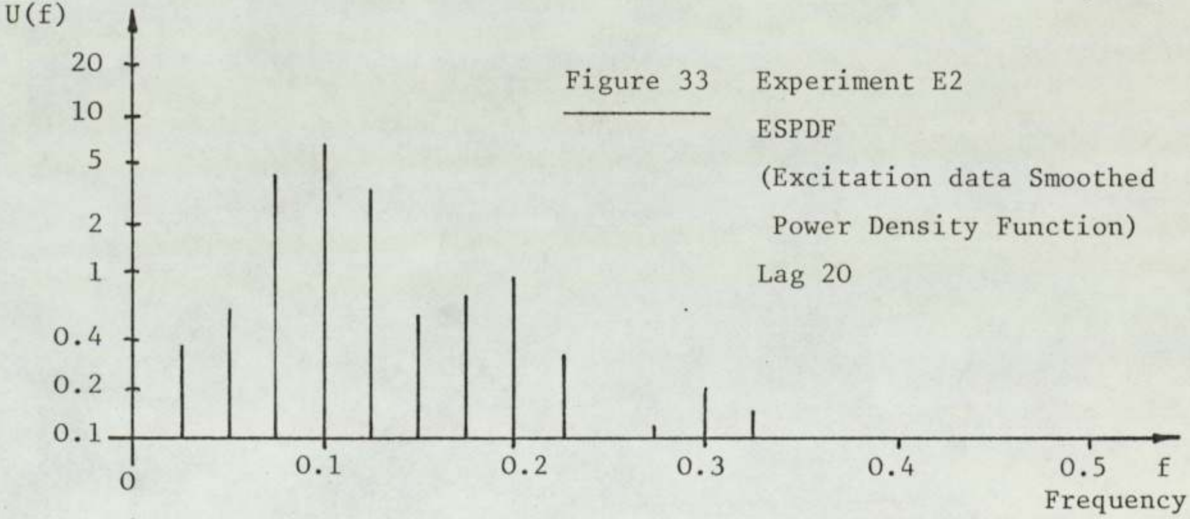


Figure 33 Experiment E2
ESPDF
(Excitation data Smoothed
Power Density Function)
Lag 20

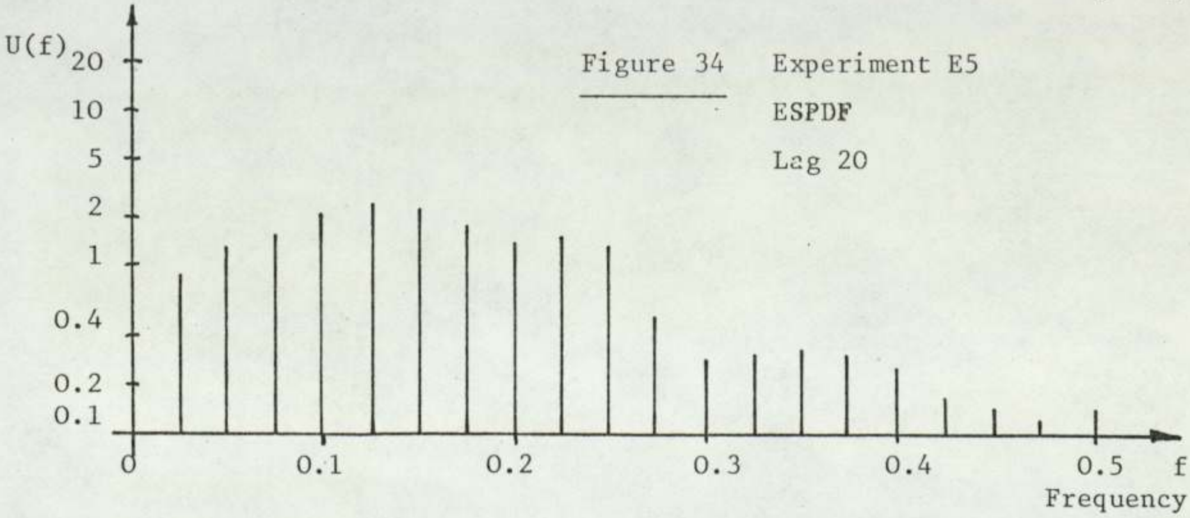


Figure 34 Experiment E5
ESPDF
Lag 20

the firing data (Fig. 35) indicates a higher frequency. This is usually the case as the remanent excitation graph is influenced more directly by afferent excitation whilst to affect the firing graph, the input has to cause a significant change in firing activity. The frequencies are still widespread but a peak corresponding to a period of 5 is now apparent. Figure 36 shows a much more defined peak, typical of nets with equal decay rates, centering around a frequency corresponding to a period of 6. The peak is not sharp and the raw data indicated low amplitude, broken waves. Figure 37, from Experiment E7, shows once again a different graph with a main peak corresponding to a period of 10 and a subpeak at period 6. In this experiment the threshold decay rates are defined by a range which may explain the wide spread of frequencies. Figure 38 is similar, with a lower peak as the excitation decays are defined by a range. Experiment E9 with fairly low decays gives rise to a wide spectral band centred around a period of 7 but being similar in shape (see Fig. 39) to that of run E6. Experiment E10 (see Figure 40) defined the decays to be equal but in the maximum possible range 1 to 63%. This produced a wide spread of frequencies with a peak at a period of 10, perhaps indicating the input's increased influence on this net. Figure 41 of Experiment F14 had equal decays, all of 40% and a frequency band corresponding to periods 15 to 5 resulted.

The second set to illustrate the effect of decay constants is [F4, F5] the FSPDF of each run being displayed in Figs 42 and 43. The change of decay rates from F4 to F5 of 20 to 30% has caused a shift of frequency from period range 14 to 20 to range 12 to 10. The remaining three sets are not 'strictly related' as the total input differed slightly between runs (see Table 1) but due to the findings of the initial section,

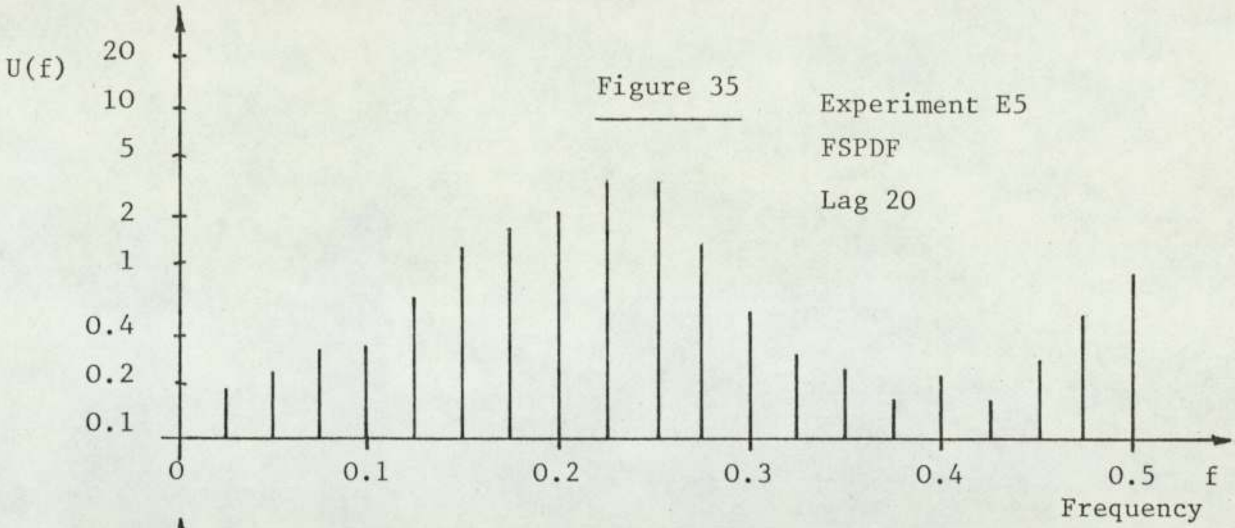


Figure 35

Experiment E5
FSPDF
Lag 20

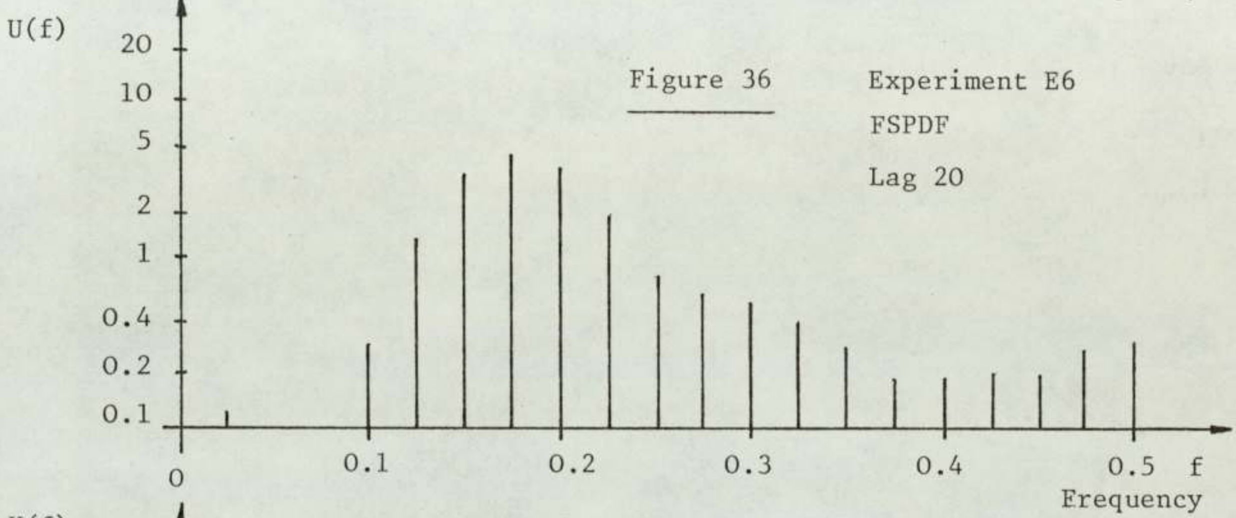


Figure 36

Experiment E6
FSPDF
Lag 20

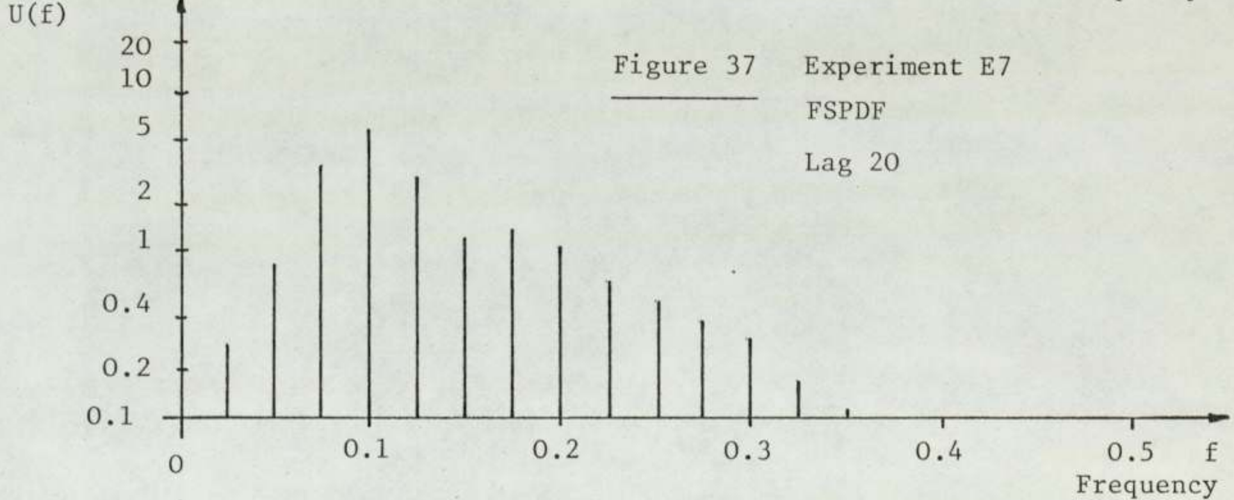


Figure 37

Experiment E7
FSPDF
Lag 20

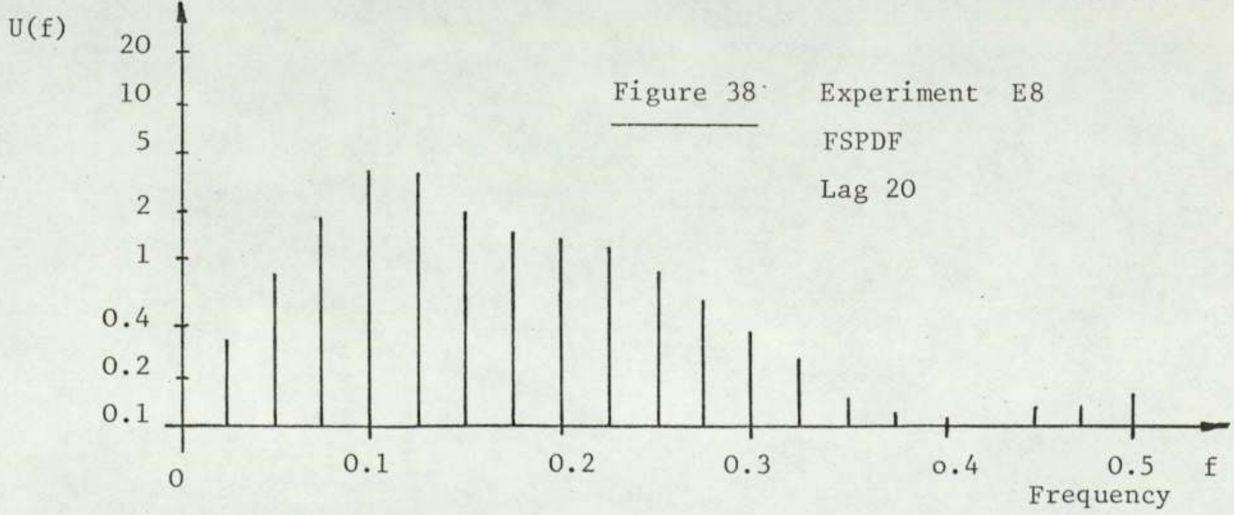


Figure 38

Experiment E8
FSPDF
Lag 20

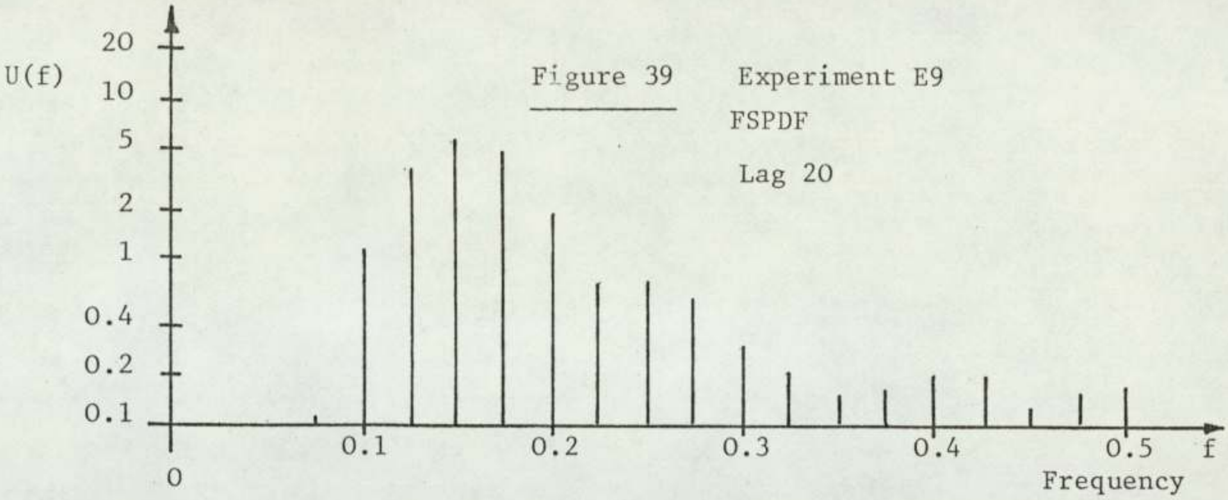


Figure 39 Experiment E9
FSPDF
Lag 20

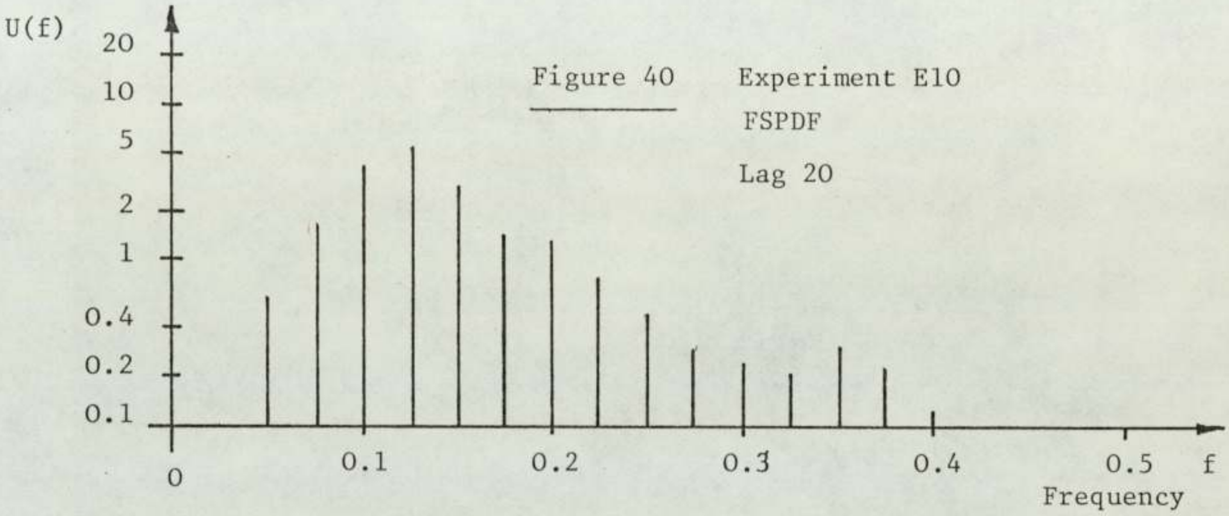


Figure 40 Experiment E10
FSPDF
Lag 20

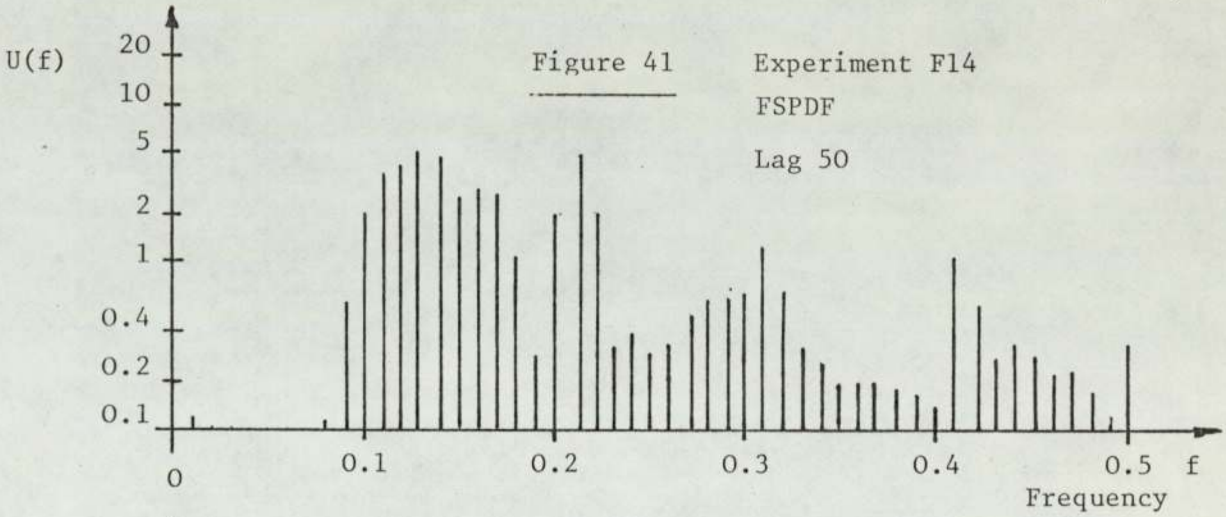


Figure 41 Experiment F14
FSPDF
Lag 50

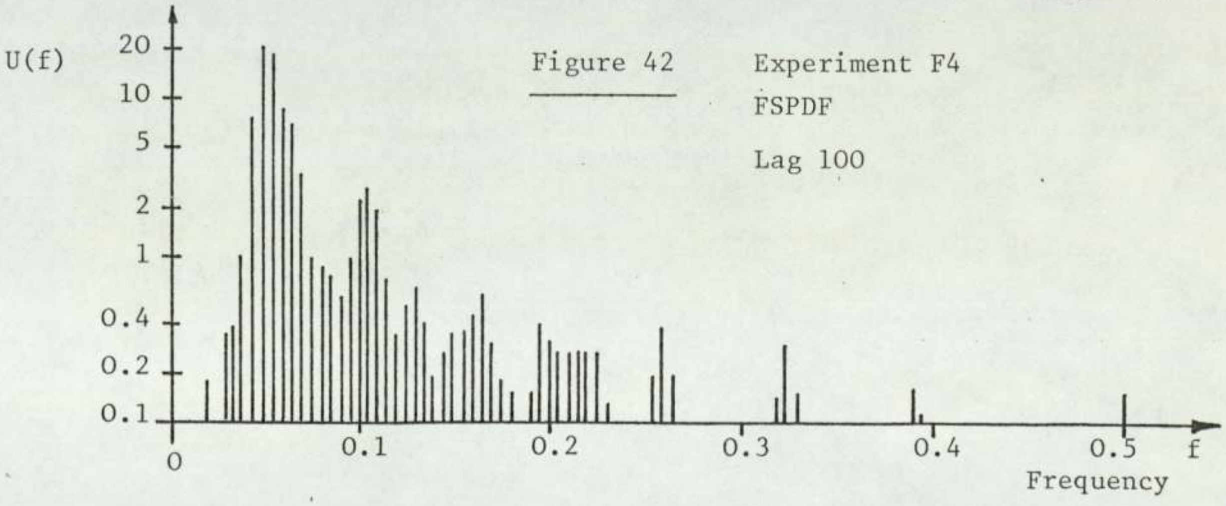


Figure 42 Experiment F4
FSPDF
Lag 100

that total input does not affect frequency in these ranges, they are included as well. The FSPDF data is displayed in Figures 42 and 29. The shift in frequency, caused by altering the decay rates from 30% to 40%, correspond to period range (10-11) (for 30%) and 7 (for 40%). Set 4 [E11, F1] have FSPDF as in Figures 45 and 46. The change in position of the peaks indicates a main component at period 20 for F1 and 13.3 for E11. Also the spread of frequency components is greater in Experiment E11, indicating a greater mixture of frequencies. Run E11 had both excitation and threshold decays as two different ranges. The median value for decays would be 31% whereas the decay for F1 was 20%. The next set [F2, F10] have FSPDF shown in Figures 47 and 48. These indicate a shift of frequencies, typified by the main component, corresponding to periods of 18 for F2 (with decays of 20%) to from 8 to 9 for F10 (with decays of 40%). As a summary of the above observations Fig. 49 shows approximately the relationship between decay values and the periodic values of the main component of those nets with equal decay rates. The data was taken from the following experiments: [F2, F8, F10, F20, F28, F29, F23]. The second half of the following split run type of experiment (to be described later) confirmed these values: [F21, F24, F26, F27].

Conclusions

1. In all the sets mentioned the frequency of the firing data changed when the decay rates of the individual cells was changed.

2. In the case of nets with excitation and threshold decays all set to the same value, it can be seen that the frequency of the net is proportional to the decay rates. The changes are more pronounced

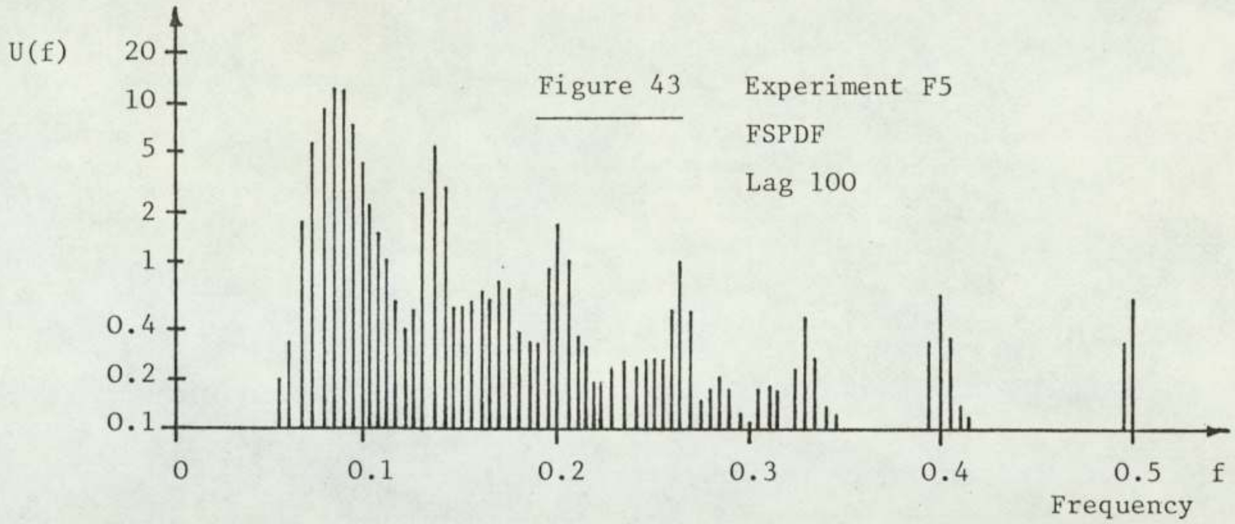


Figure 43 Experiment F5
FSPDF
Lag 100

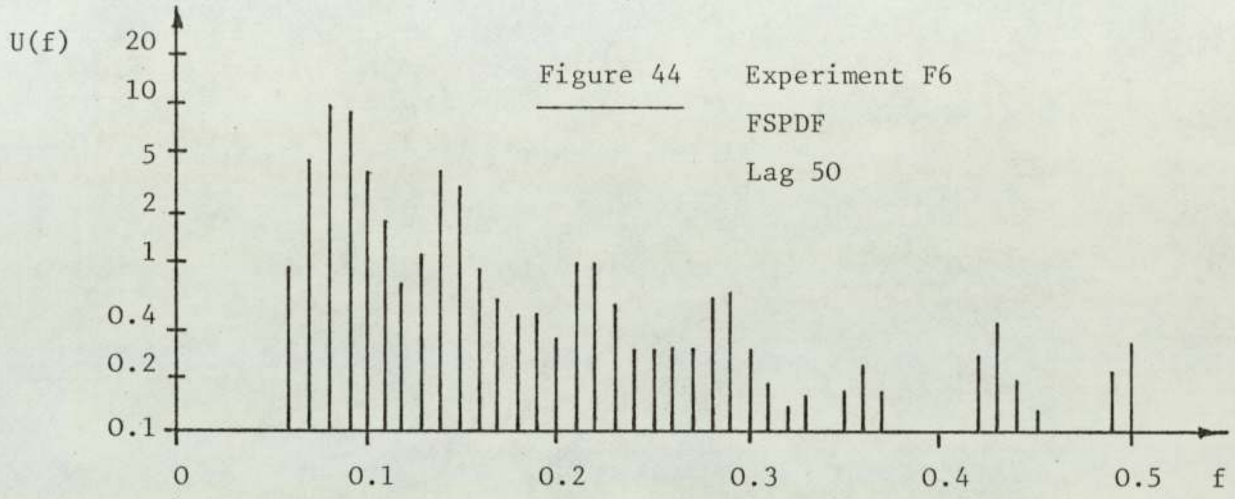


Figure 44 Experiment F6
FSPDF
Lag 50

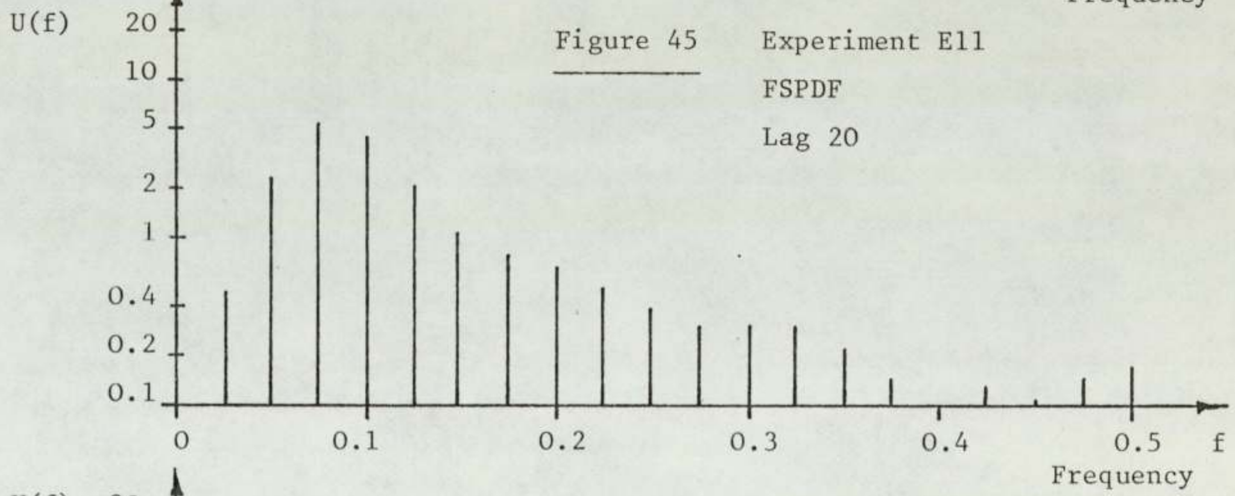


Figure 45 Experiment E11
FSPDF
Lag 20

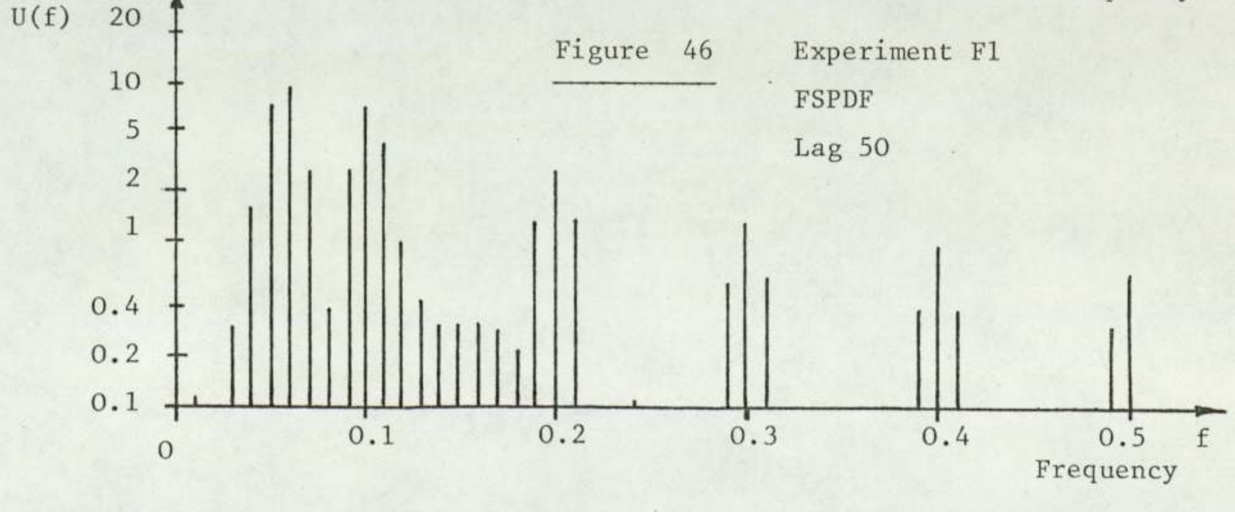


Figure 46 Experiment F1
FSPDF
Lag 50

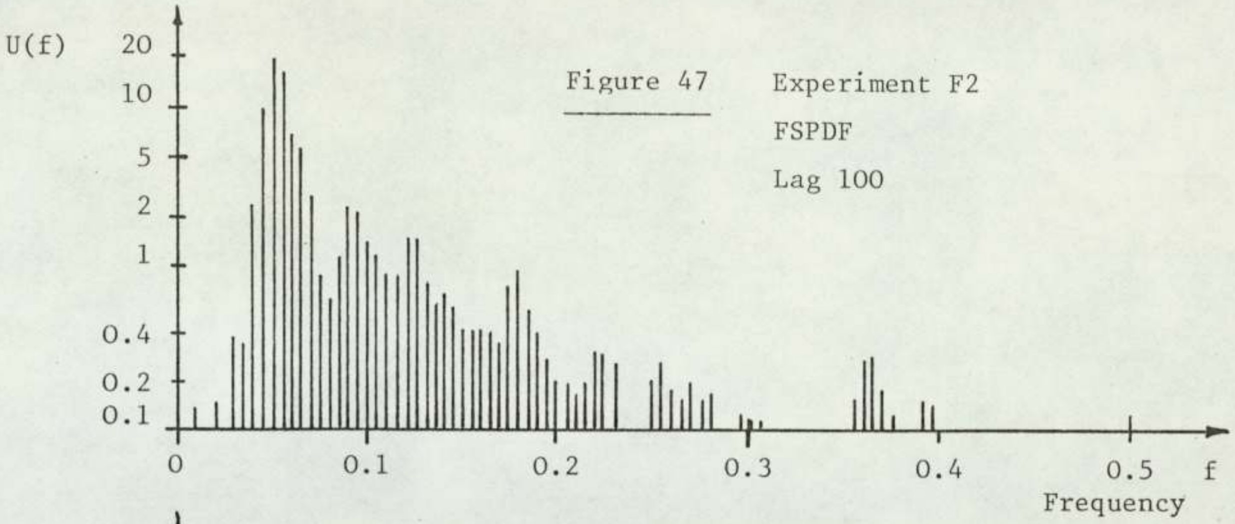


Figure 47 Experiment F2

FSPDF

Lag 100

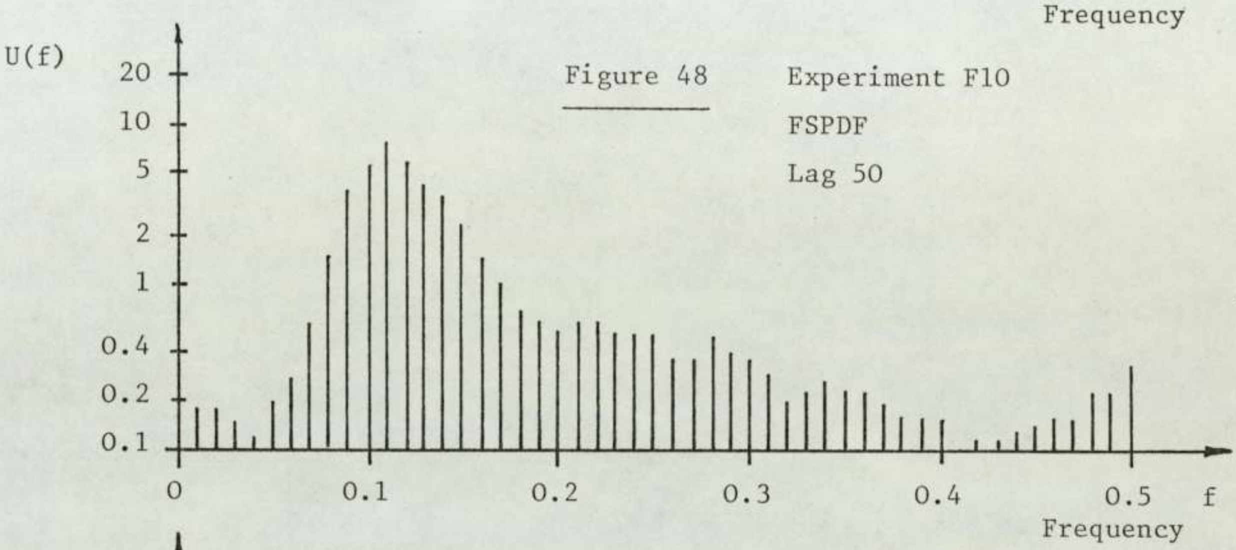


Figure 48 Experiment F10

FSPDF

Lag 50

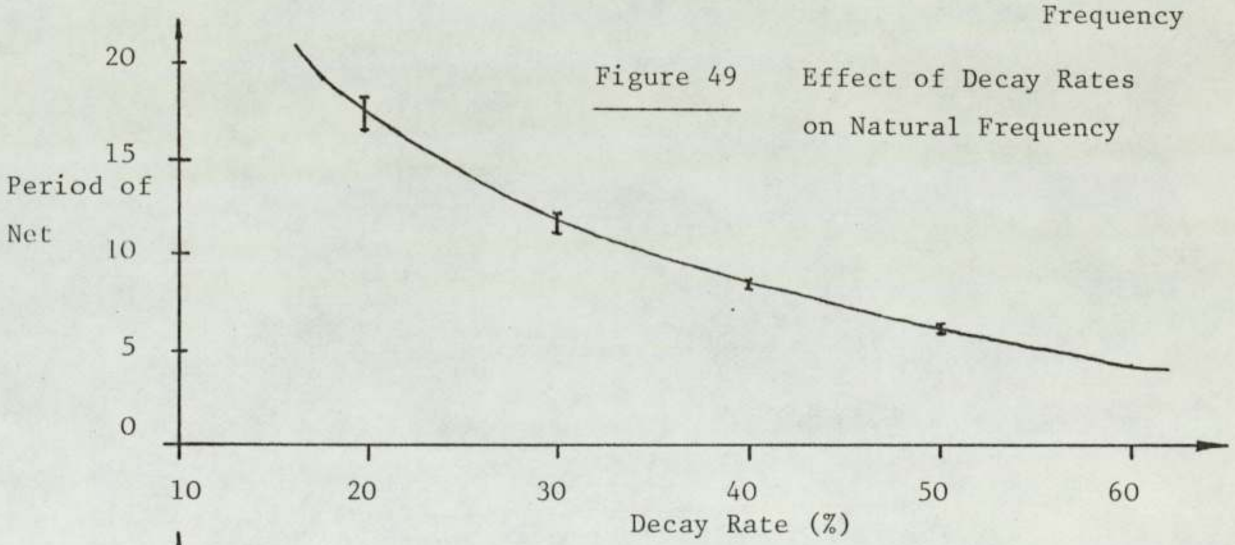


Figure 49 Effect of Decay Rates on Natural Frequency

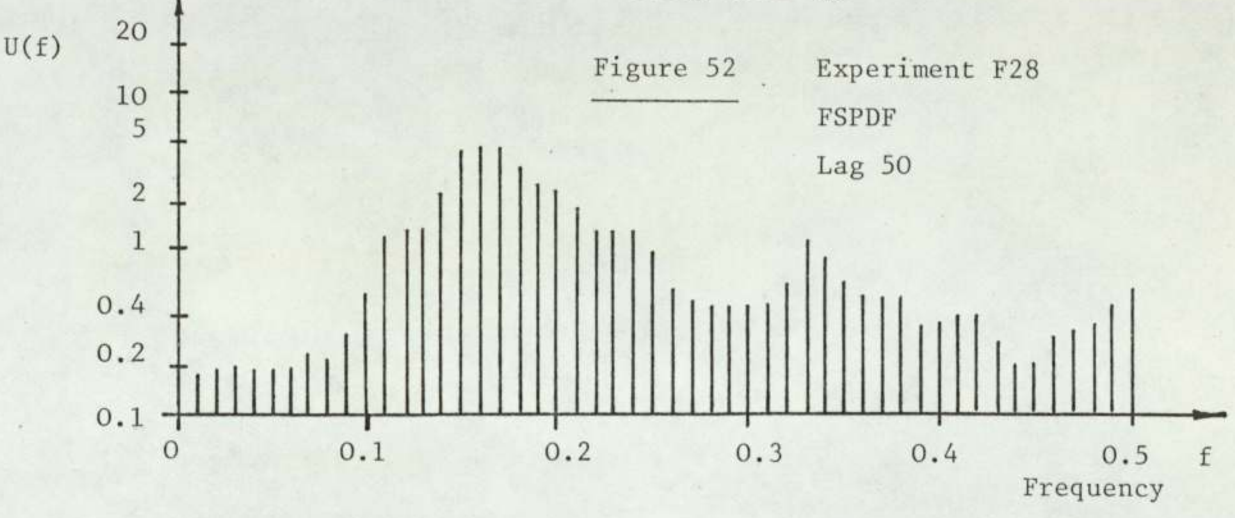


Figure 52 Experiment F28

FSPDF

Lag 50

at the lower frequencies. (i.e. $< .1$)

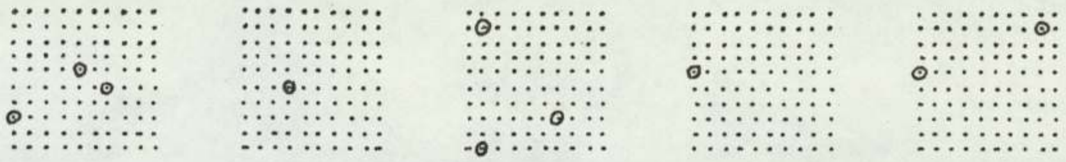
3. In the case of nets with mixed decays, either different single values for excitation and threshold or both defined by ranges, the frequency of the net is more widespread.

The Effect of Different Connection Algorithms

Several connection algorithms (described in Chapter 3) were tested and their effect on the Spectral Graphs is examined in Experiments ([E10, E11], [F28, F31, F32, F33]).

Experiment E10 employed the random algorithm GEN which generates connections to every position within the net with equal probability. Experiment E11 uses a local bias algorithm that generates connections with a probability diminishing with distance from the cell . In both cases no special effects occur at the edges, the 'outward connections' being lost. This is altered in the second set of experiments. Examples of connections from one cell with 10 connections in both modes are given in Figures 50 and 51. The difference between the spectral graphs can be seen in Figs 40 and 45 and is quite marked, as if the network of E11 had longer refractory periods. Experiment E10 yielded periodic components of 11 to 6 with the main peaks' range as 7-8. Experiment E11's equivalent ranges were 16 to 7 with a main peak between 11 and 16. This lowering of frequency may be explained by the increased probability of a connection in the local bias algorithm landing in a refractory pool. By definition of the algorithm, the cells nearby will have been most affected by other cells. Supporting this theory is the difference in the mean level of activity (E10:55, E11:45), the random algorithm being the higher.

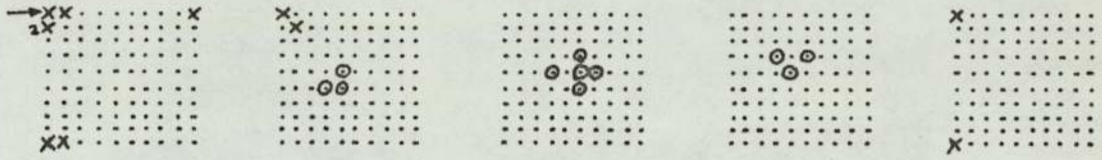
Figure 50 Example of Random Mode Connections



Input Source signal centre at (1,1,1)

Figure 51 Example of Local Bias Algorithm

○ Connections from 5,5,3
× " " 1,1,1 (Toroidal)



Toroidal connections overflow every boundary (edge).
Certain elements often receive more than one connection.

Further algorithms were tested in the second set of related experiments. Experiment F28 used a local bias algorithm and gave a spectra as in Fig. 52. The next related run used a circular net which allowed connections to pass from slice 1 to slice 5, like a strip of paper joined at its ends. At first the activity could be seen to spread around both ways from the edge of the net and meet in the middle but after this it was difficult to see refractory troughs forming in the haze of activity. The difference in the FSPDF was an increase in the period 4 component but an inherent frequency at the period of the 'circle diameter' (i.e. 5), was not observed (see Fig. 53). Experiment F32 reduced the overflow of connections to one direction only but the

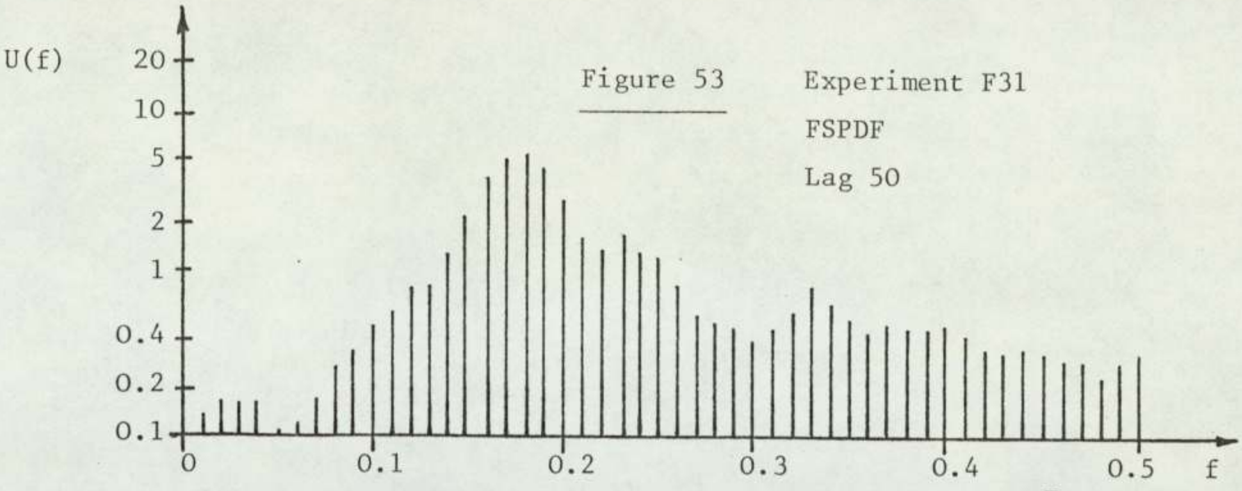


Figure 53

Experiment F31
FSPDF
Lag 50

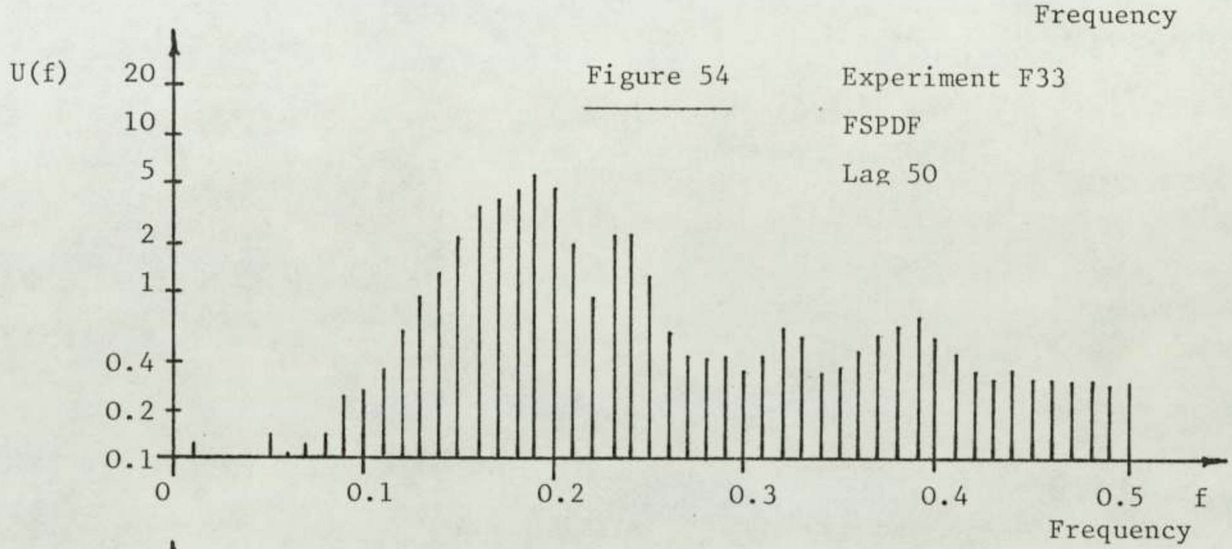


Figure 54

Experiment F33
FSPDF
Lag 50

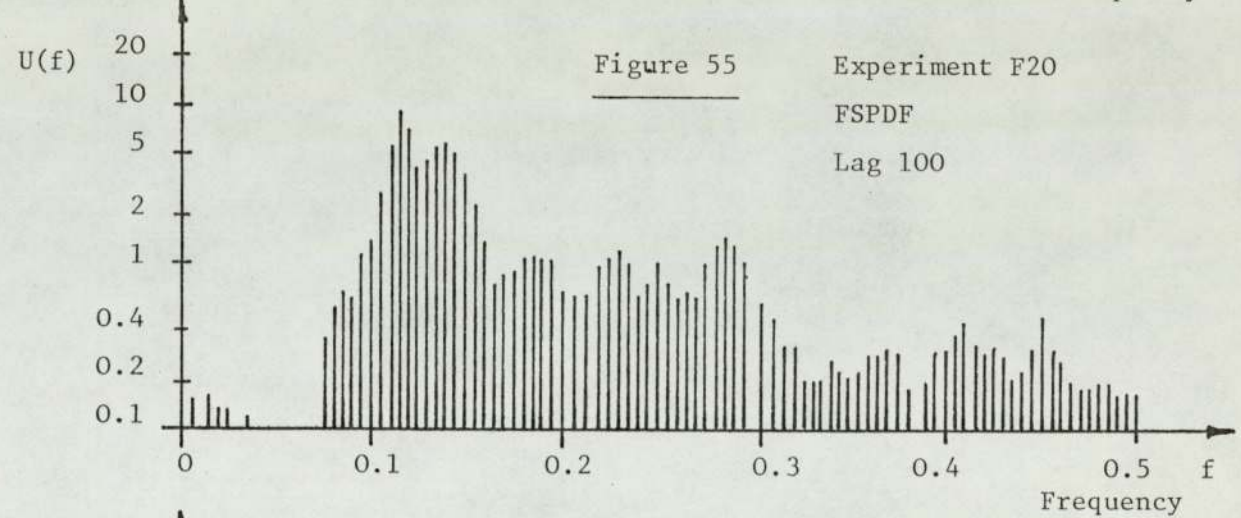


Figure 55

Experiment F20
FSPDF
Lag 100

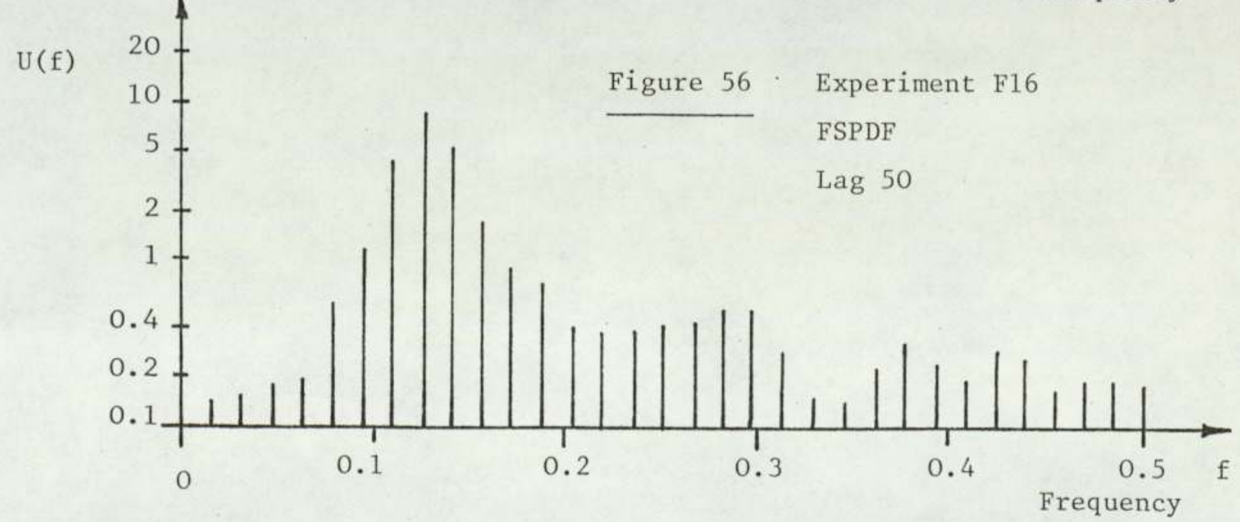


Figure 56

Experiment F16
FSPDF
Lag 50

spectral graph showed little change. Finally in Experiment F33 a completely toroidal net was generated where connections overflowed in the manner employed in Experiment F32, but in all three planes. This represents therefore a fictitious net, with no edges. Such a 'blob' might behave like a net extracted from a larger net where the overlapping connections actually pass into the surrounding cells and an equal number return. The resulting FSPDF (see Fig. 54) had a new component at a lower period, 5. The difference is small however and may only reflect the increased activity due to the higher number of connections (previous overlaps being lost).

Conclusions

Changing the number of connections inherently by a major alteration to the connection mode produced more frequency shift than a particular pattern of connectivity within the same mode. This was also noted throughout the thesis in other experiments, not directly related to the above runs but differing in parameter values found to be relatively insignificant in altering frequency. It also agrees with Anninos (1972) in this respect.

The effect of Net Size

Only two net sizes were simulated, the 5 x 5 x 5 and 10 x 10 x 5. The effect of changing the net size is illustrated with experiment pairs ([F10, F20], [F11, F16], [F12, F17], [F13, F18]). The FSPDF graphs are illustrated in Figs. 48, 55, 29, 56, 57, 58, 59 and 27 respectively. If the main peaks are compared one set [F13, F18] provide noticeable differences. There has been a shift to a slightly lower period of activity (7-8 in F18 instead of 9 as in F13). Also Experiment F20, whilst producing a similar range of periodic components (7-9) (see Fig. 48) to that of Experiment F10 (periods 7.5 to 9) the graph had a slightly different shape suggesting an absence of components between 7.5 and 8.0. This may be an artifact of the increased number of points plotted and detail shown by employing a maximum lag of 100.

Conclusions

The range of frequencies of a net is largely unchanged when switching between the two sizes of net simulated.

The Effect of Signals on a Network

After showing that the natural frequency of a net is largely dependent on the decay rates of the threshold and excitation, the effect of input signals on that "natural frequency" is examined. Two sets of experiments are used to illustrate the effects: ([F10, F11, F12, F13, F14, F15], [F16, F17, F18, F20]), the first graph being the 500 element net and the second the 125 element net. Both have decays of 40% as can be seen from Table 1. One would expect a 'natural frequency' of near 8 (see Fig. 49).

The 10 x 10 x 5 net

The net under constant input has a frequency illustrated by its FSPDF shown in Fig. 48. The net was then subject to inputs of periods 6, 7, 8, 9 and 10 and the FSPDF's resulting are shown in Figs. 60, 57, 29, 59 and 41 respectively. By comparing Figs. 48 and 60 it can be seen that the natural frequency component has been reduced to a 'bump' and the new major component corresponds to the input period

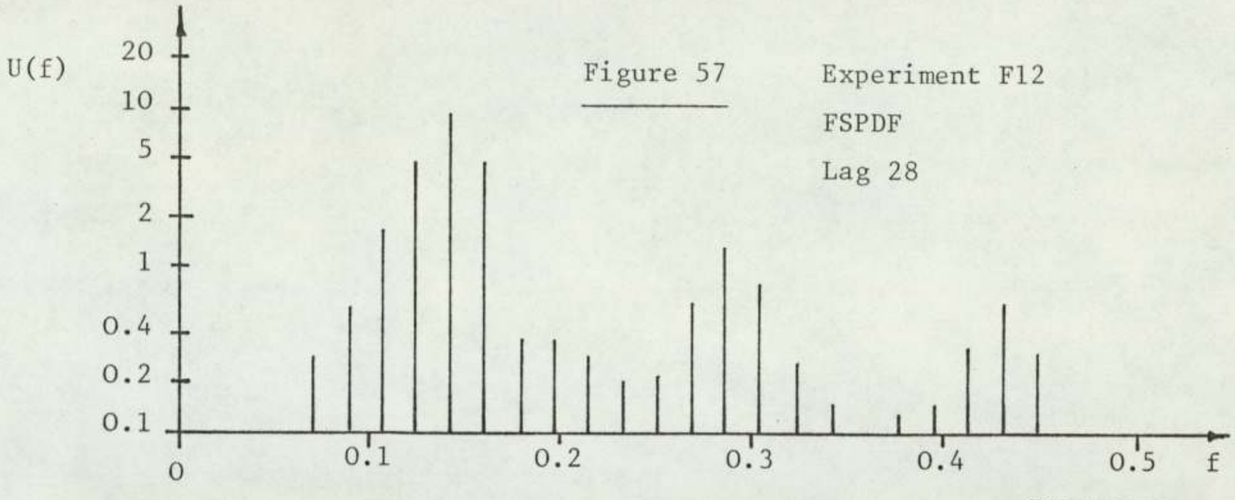


Figure 57

Experiment F12
FSPDF
Lag 28

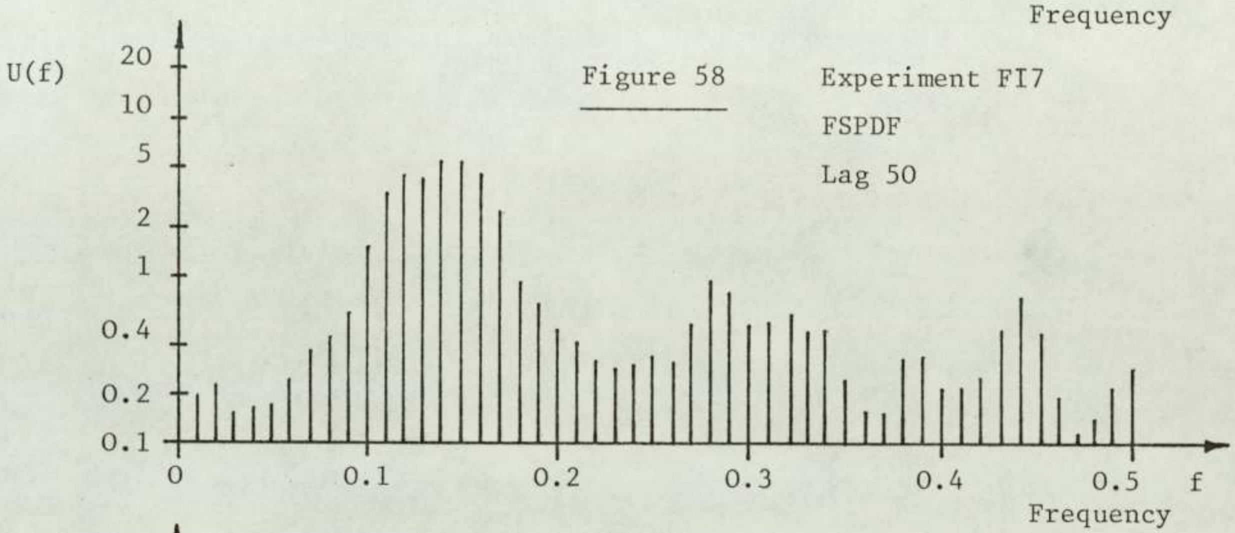


Figure 58

Experiment FI7
FSPDF
Lag 50

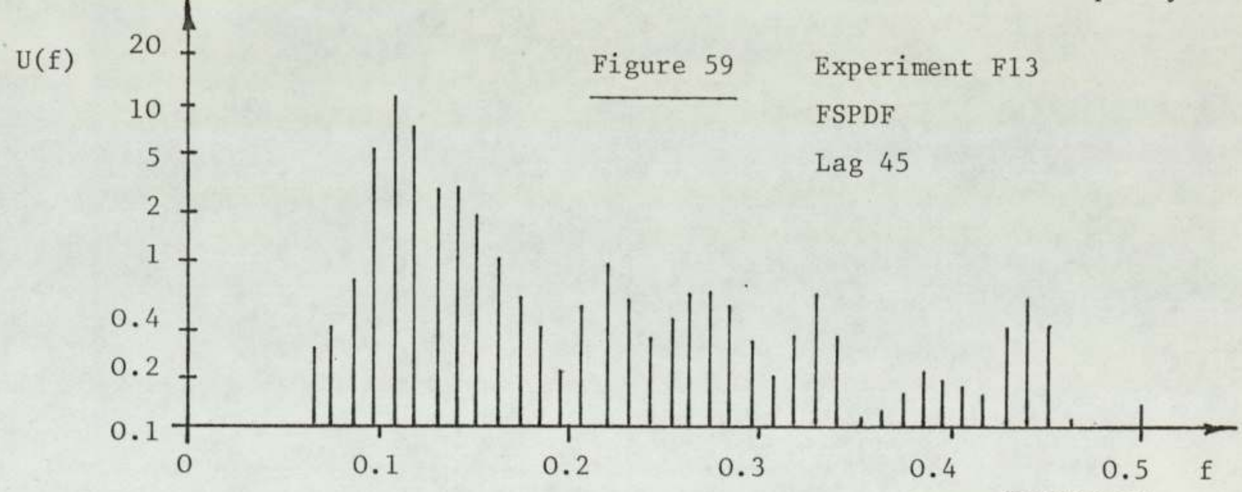


Figure 59

Experiment F13
FSPDF
Lag 45

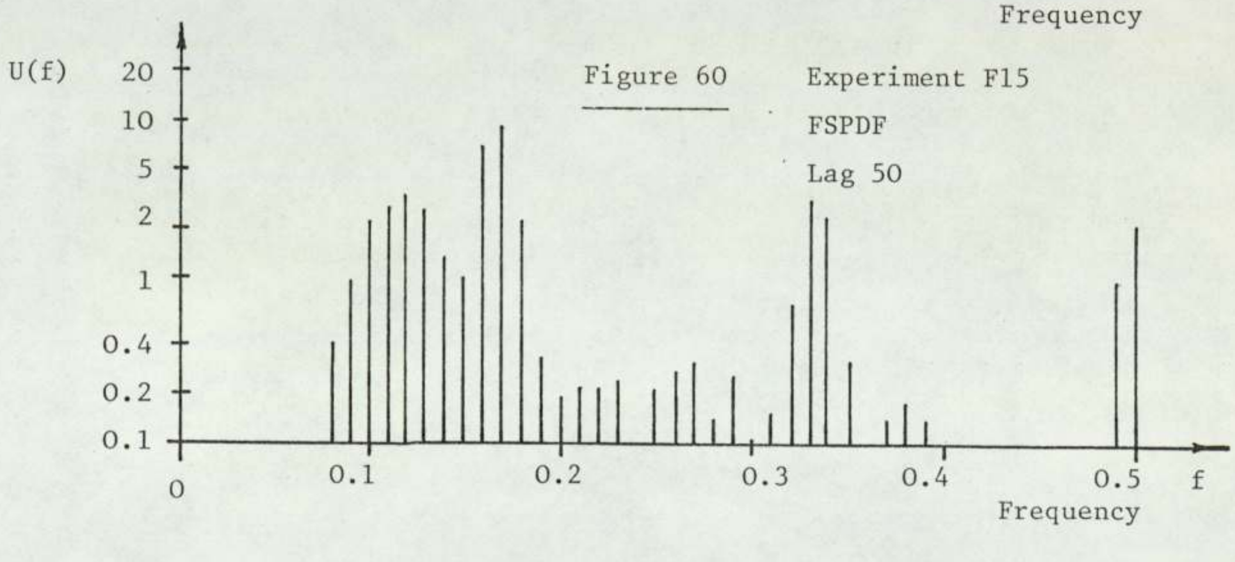


Figure 60

Experiment F15
FSPDF
Lag 50

of 6. Experiment F12 (period 7) also has the input's period as the main peak. The two components of the PDF have merged into one which encompasses the period range 6 to 8. The next experiment has the input period at the natural frequency of the net (see Fig. 29). The two main peaks are periods 7.5 and 8.0. Next, an input of 9 is applied to the net(F13) and Figure 59 displays the FSPDF and it can be seen that the input component has passed through the natural frequency band and begun to emerge on the other side. The input frequency is the main component but a significant component at the natural frequency still remains. Finally an input of 10 is applied to the net in Experiment F14 and the FSPDF of Figure 41 results. The input component is now indistinct and the highest value of the main group of components corresponds to the natural frequency. A component at period 5 becomes visible and may represent a small inversion in the larger waves noticeable in the raw data.

The 5 x 5 x 5 net

This net was subject to inputs of period 7, 8 and 9. Experiment F17 produced an FSPDF for a period of 7 and is illustrated in Fig. 58. This can be compared with Fig. 55 (F20) which used a constant input and displays the natural frequency. The periodic input produced a reduction in natural frequency and an increased input component. The large area under the graph indicates a fairly wide range of underlying frequencies (periods 6 to 9). Next, a signal of period 8 was applied in Experiment F16 (see Fig. 56) and the major component now corresponds to that period. The range under the spike is from periods 7 to 9. Finally an input of period 9 was applied (F18) and a wide range of frequencies resulted with no outstanding peak (see Fig. 27), the largest value (corresponding to the input frequency) being only slightly larger than its neighbours.

Conclusions

The natural frequency of the net was not eradicated by the input signals but is often not the main component frequency of the resultant activity. It would appear that the input signal is added onto the underlying activity of the net and does not 'drive' the net at its own frequency.

Resonance

In the previous section a series of runs tested the effect of inputs of varying periodicity and during these runs an input period was made equal to the previously observed natural frequency (Experiment F11). The resultant spectral curve showed two adjacent peaks (see Fig. 29). The interval is $7.4 < p < 8.11$ where p is the period length. The net would appear to be operating at very nearly one frequency. A second example is given by the set of experiments ([F1, F2, F3, F4, F7]). This net has decays of 20% and this would suggest a natural frequency in the range 16-18 (see Figs. 47 and 31). Several inputs were applied to the net. Experiment F1 (see Fig. 46) supplied an input of period 10 and the FSPDF shows a clear input component. Experiment F4 (see Fig. 42) uses an input period of 14 and the FSPDF of Fig. 47 shows there is a shift to a higher frequency and the period 14 component is enlarged. Experiment F7 (see Fig. 62) uses an input of 17 and the FSPDF shows a twin peak corresponding to the period interval $19 < p < 16$. However in Experiment F3 only one spike in the FSPDF (see Fig. 61) is visible, having used an input of 18. This is the sharpest spike in the signal inputs noted so far (corresponding to the interval $19 < p < 18$) and implies the net is running at one frequency.

In both cases, F3 and F11, the nets appear to be oscillating at one frequency and therefore could be resonating. If resonance was occurring then there should be a significant difference, from their related experiments, in the standard deviation calculated for these runs. Table 2 shows the figures involved. The figures reveal that the two largest values for set 1 are in fact for the 2 input frequencies closest to the natural frequency. In the second set however this is not the case, the largest value being that of F12 with an input of 7. As mentioned before the FSPDF indicated a mixture of frequencies from 7 to 10.

Conclusions

Despite the occurrence of single, sharp spikes in some FSPDF data this did not involve resonance as examination of the standard deviation score illustrated. Resonance phenomena imply larger amplitude fluctuations which would increase the standard deviation score dramatically. On examining the raw data, it became clear that for the smoothest waves (e. g. F3 or E11) the input was coinciding with the middle of a trough and synchronizing with the net's emergence from refractoriness. However this situation was very easily disturbed, by internal firing and the input became out of phase with the waveforms and this interrupted the smooth waveforms.

Persistence

If resonance had been established in the previous section, then different sets of nets with the same internal decay constants could be used to recognise incoming signals by resonating at the receipt of a signal at the correct frequency. However the activity was largely determined by the decay constants and the input frequency could only be determined using Spectral Analysis. This section therefore examines if the additional components in the spectral graphs, due to the periodic input signals, persisted for any length of time after the signal had changed to a constant one. The experiments are called 'split runs' as they had two signals input to them, one in the first half of the runs and one in the second half. The first is periodic, the second constant. Using the Back Up program BU spectral analysis was applied to either set independently. The set of experiments were ([F21], [F23-F26], [F27], [F28-F30]). The first experiment, F21, was a 5 x 5 x 5 net with 40% decays. In this run an input of period 7 was applied for the first half of the run. Figure 64 shows the first and second half spectra superimposed. A shift to the lower frequencies is noticeable and the component corresponding to the periodic input is reduced. A new net of 60% decays was generated to achieve a lower natural frequency. Several inputs were applied and their FSPDFs are displayed in Figs. 65-68, corresponding to inputs signals of 1, 7, 5, 3. As can be seen no signal dominated, the firing rates of the cells being high. No record of an input frequency is apparent and this result was also confirmed

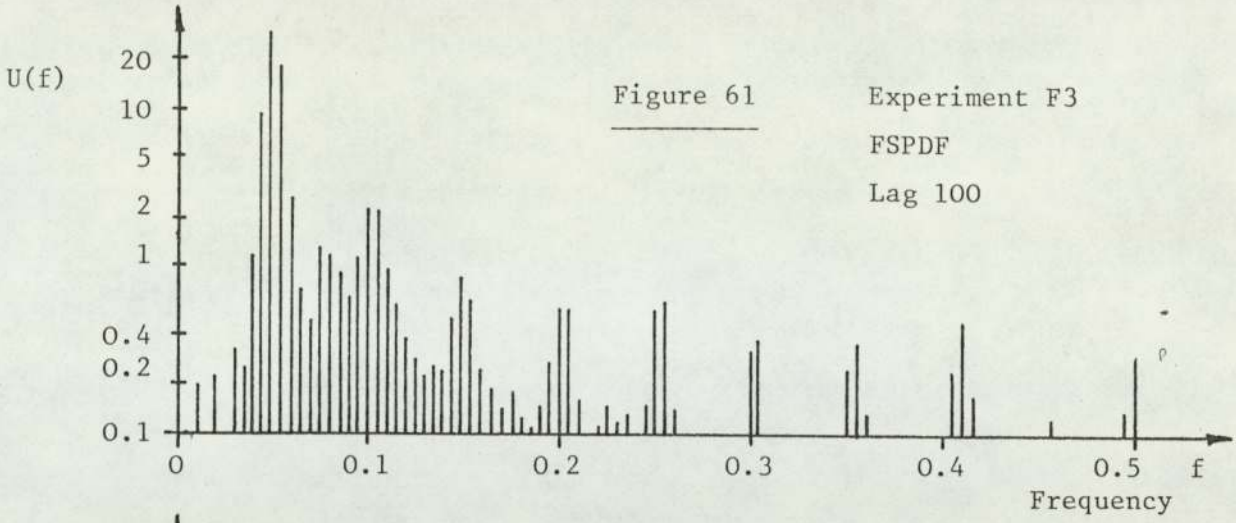


Figure 61 Experiment F3

FSPDF

Lag 100

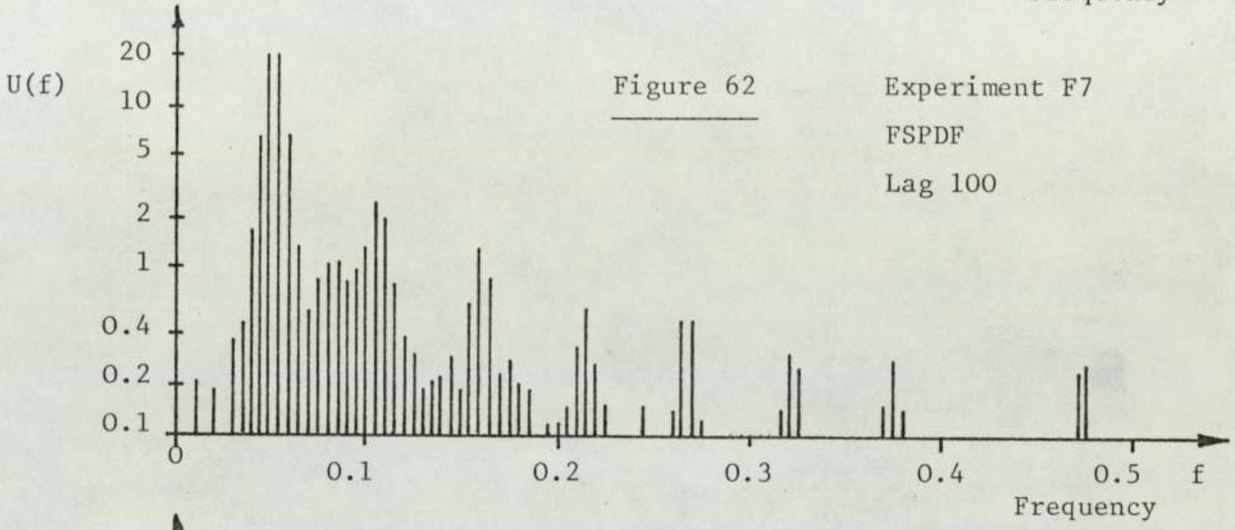


Figure 62 Experiment F7

FSPDF

Lag 100

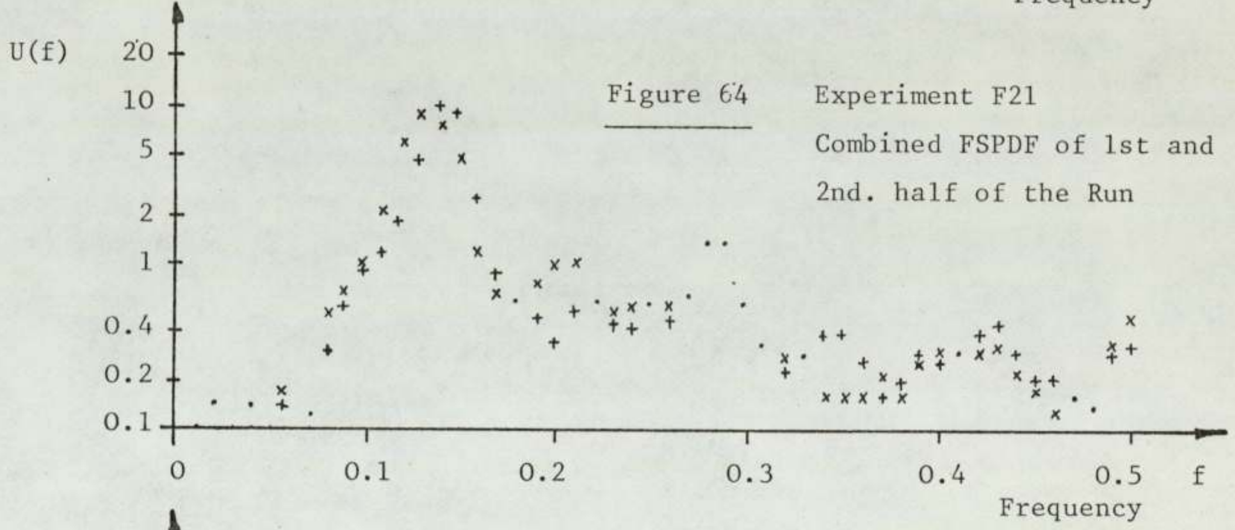


Figure 64 Experiment F21

Combined FSPDF of 1st and 2nd. half of the Run

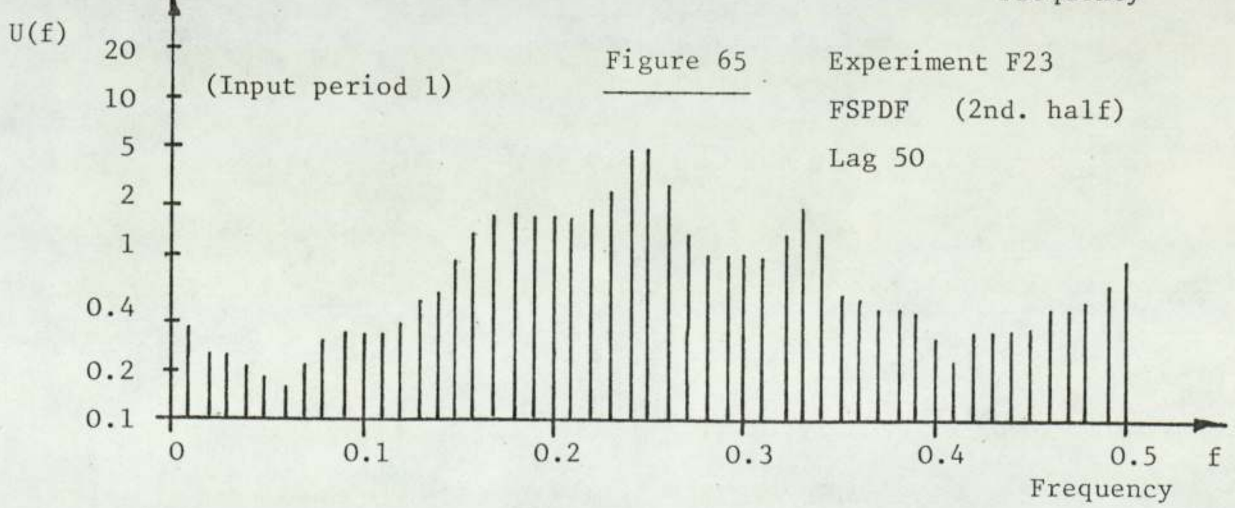


Figure 65 Experiment F23

FSPDF (2nd. half)

Lag 50

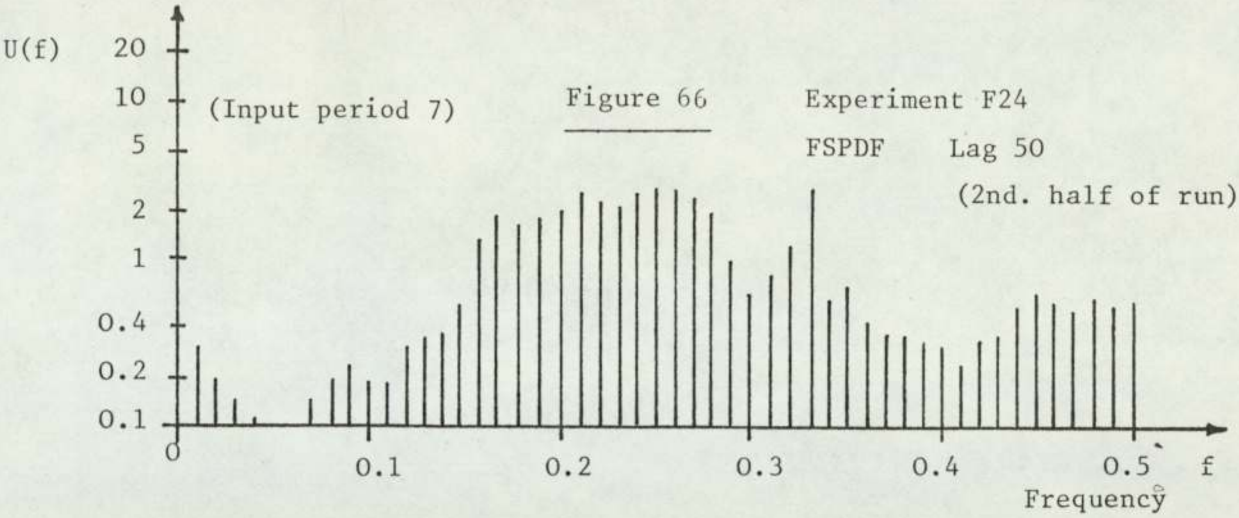


Figure 66

(Input period 7)

Experiment F24

FSPDF Lag 50

(2nd. half of run)

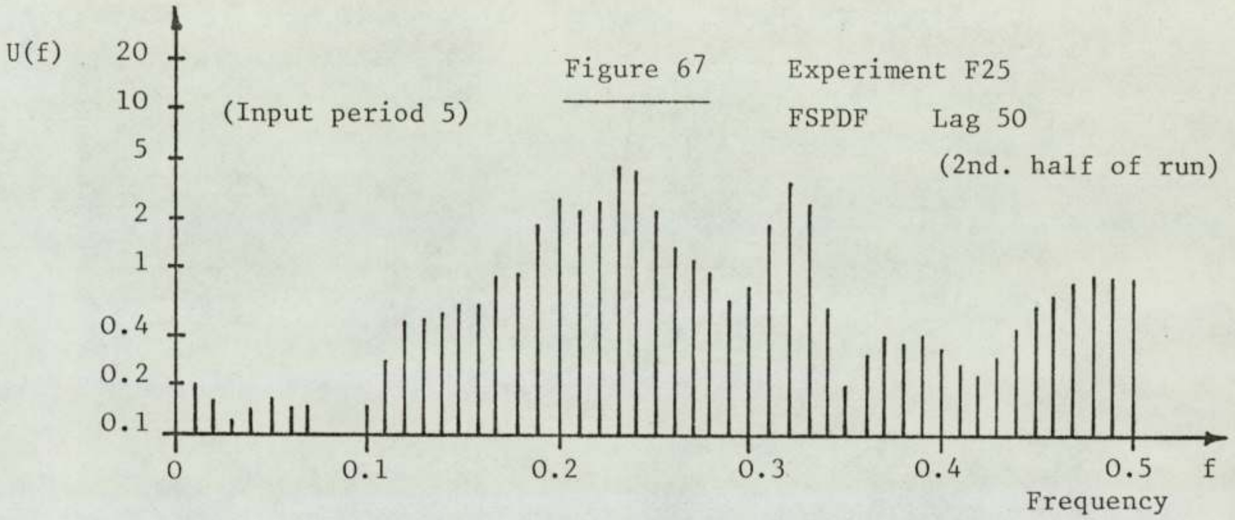


Figure 67

(Input period 5)

Experiment F25

FSPDF Lag 50

(2nd. half of run)

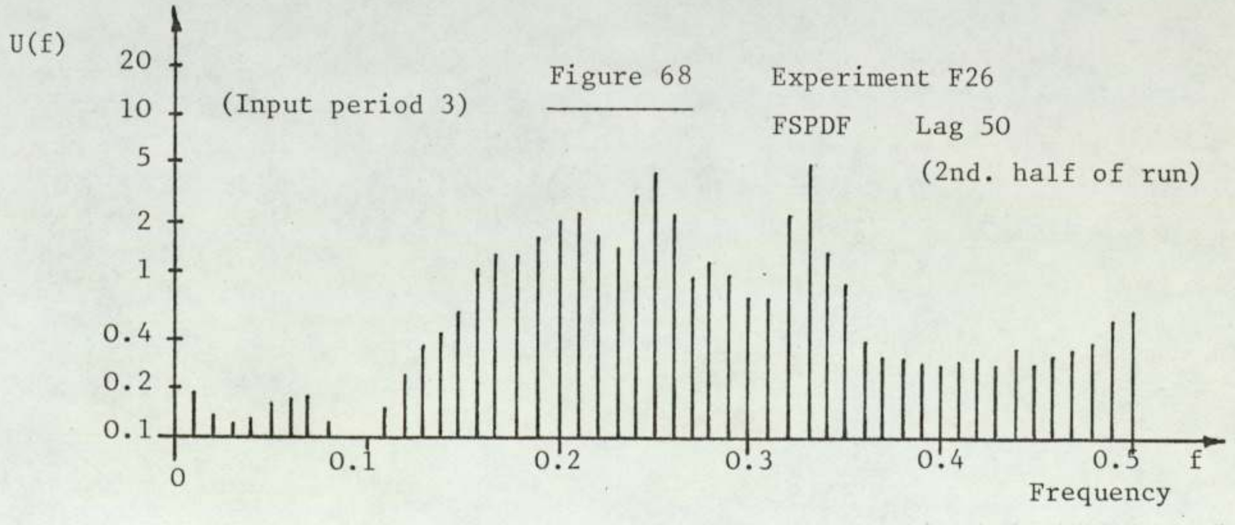


Figure 68

(Input period 3)

Experiment F26

FSPDF Lag 50

(2nd. half of run)

with runs F28, F29, F30.

Conclusions

Persistence of the effect of an input signal did not occur. The second half of the runs bore no record of the activity in the first half.

Expt. Code	Net No.	Size	Threshold Range/Type Seed	Threshold Decay Range/Type Seed	Excitation Decay Range/Type Seed	Synapse Weights Range/Type Seed	Max. No. of Weights	I.E. Ratio	Connection Multiple	Spontaneous Neurons Number/Type Seed	Set Up Number	Conn. Option
A1,A2	1	5x5x5	10/1/4	4/1/2	4/1/11	125/1/65	5	1:1	237	5/1/2	1	Random
A3,A4	2							1:5				
B1,B2, B3,B4	3			20/1/9	20/1/9							
D1,D2	4	10x10x5		20/1/20	20/1/5							
D3	5			50/1/12	20/1/11							
D4	6						10					
D5	7						15					
D6,D7, D8,D9	8					125/1/101						
D11											3a	
D12	9			30/1/10								
D13	10					125/1/65	20					
D14	11					80/1/65			321			
D15,D16	12					40/1/65						
D17,D10, D18,D19, D20											5	
D22				20/1/20	20/1/20	125/1/65						
D23	13					20/1/65						
D24	15					115/1/65						

Table 1 part 1, page 1 - Parameter details for Experiments in Chapter 4

Expt. Code	Net No.	Size	Threshold Range/Type Seed	Threshold Decay Range/Type Seed	Excitation Decay Range/Type Seed	Synapse Weights Range/Type Seed	Max. No. of Weights	I.E. Ratio	Connection Multiple	Spontan. Neurons Number/ Type/Seed	Set Up Number	Conn. Option
E1-E4	14	10x10x5	10/1/4	30/1/10	20/1/20	40/1/65	5	1:5	237	5/1/2	5	Random
E5	13*			50/1/2								
E6	14*				50/1/2							
E7	15*			60/2/10	40/1/20							
E8	16				40/2/20							
E9	17		100/2/4	40/1/2	20/1/2							
E10	18		200/2/4	63/2/7	63/2/27							
E11	19								33			Local Bias
F1-F4, F7-F9	19*		40/1/4	20/1/2	20/1/2							
F5,F6	20			30/1/2	30/1/2							
F10-F15	21			40/1/2	40/1/2							
F16-F21	22	5x5x5		40/1/4	40/1/4							
F23-F27	23			60/1/2	60/1/2							
F28-F30	24			50/1/2	50/1/2							
F31												2-way doughnut
F32												1-way dt.
F33												Toroid
F34				60/2/2	60/2/5							

Table 1 part 1, page 2 - Parameter details

Expt. Code	Max. Synapse Weight	Learn	Servo	Run Length	No. of Inputs	Positions	Types	Radius of Spread	Max Lag	Period of Input Signal	Learn Factor	Signal on Value	Duration of Signal	Signal off Value	Total Input (per 100)
A1-A4	-	-	-	51	1	5,5,1	1	2	-	1	-	50	1	0	5000x4
B1,B2		N,Y		72											
B3		N	Y												
B4		Y	Y												
D1,D2			Y,N	69,78		10,10,1									
D3-D11		see text		200											
D12-D16		N	N				pattern a								
D17					2	5,5,1/ 10,10,1									5000x13
D10							pattern b								
D18						1,1,1/ 10,10,1	pattern a								
D19							pattern c								
D20						5,5,1/ 10,10,1									
D22-D24		Y	Y		1	10,10,1	1								
E1		N	N		2	5,5,1/ 10,10,1			20						
E2							3			10		100			1000x13
E3										7					1400x13
E4						5,5,1/ 4,5,1	-	5							1400x38
E5-E10						4,5,1/ 10,10,1		1		10					

Table 1 , part 2, page 1 - Parameter details of Chapter IV Experiments

Expt. Code	Max. Synapse Weight	Learn	Servo	Run Length	No. of Inputs	Positions	Types	Radius of Spread	Max Lag	Period of Input	Learn Factor	Signal on Value	Duration of Signal	Signal off Value	Total Input per 100
E11	-	N	N	400	2	4,5,1/ 10,10,1	3	1	20	10	-	100	1	0	1000x13
F1				1000				5	91						1000x71
F2										1		50			5000x71
F3										18		100		10	1540x71
F4,F5										14					1630x71
F6										8					2170x71
F7										17					1540x71
F8				500			1		50	1		30			3000x71
F9												40			4000x71
F10												20			2000x71
F11,										8		119		9	2330x71
F11a												95			1932x71
F12				280					28	7		91		8	1962x71
F13				450					45	9		100		10	1990x71
F14				500					50	10				11	
F15										6					2026x71
F16				320	1	3,3,1	3	1,typ2	32	8		95		9	1932x16
F17				500				2	50	7		91		8	1962x16
F18										9					1990x16
F19					2	3,3,1/2,3,1									1990x31

Table 1 , part 2, page 2 - Paramater details of Chapter IV Experiments

Expt. Code	Max. Synapse Weight	Learn	Servo	Run Length	No. of Inputs	Positions	Types	Radius of Spread	Max Lag	Period of Input	Learn Factor	Signal on Value	Duration of Signal	Signal off Value	Total Input per 100
F20	-	N	N	1000	2	3,3,1/2,3,1	3	2	100	1	-	20	1	0	2000x31
F21, F24								3,4 split		7/1		91/20		9	1962x31/ 2000x31
F23, F28, F31										1		20			2000x31
F25										5/1		91/20			2270x31/ 2000x31
F26										3/1					
F27										7/1		300/20		9	4974x31/ 2000x31
F29										10/1		200/20		10	2900x31/ 2000x31
F30										8/1					3280x31/ 2000x31
F32- F34										1		20			2000x31

Table 1 , part 2 , page 3 - Parameter Details of Chapter Experiments

Experiment Code and Figure No. of FSPDF graph		Net No.	Spectral Spike Periods (in order of size)	Input Period	Mean Firing Level	Standard Deviation
F1	46	19	22 to 15,10	10	31.1	390
F2	47	19	17 to 19	-	35.8	320
F3	61	19	17 to 19	18	31.9	410
F4	42	19	14, 17 to 19	14	31.5	380
F5	43	20	12 to 11	14	48.5	260
F6	44	20	12 to 11 , 8	8	49.1	290
F7	62	19	17.3 to 19, 17.3 to 15.8	17	31.2	410
F10	48	21	8 to 10	-	70.6	200
F11	29	21	8	8	69.6	200
F12	57	21	7 to 10	7	68.5	230
F13	59	21	9,7	9	69.1	210
F14	41	21	10,8,5	10	69.2	190
F15	60	21	5 to 6, 8 to 11	6	69.6	210

Table 2 (Fig 63)

Table giving the standard deviations for Experiments at or near Resonance conditions.

CHAPTER V

Adaptive Nets

Introduction

The results of Chapter 4 indicated that networks, as simulated in these experiments, do not have an inherent memory capability, as the effect a signal has on a net is swiftly lost when the signal is removed. When the signal is present there is no simple means of identifying it by, for example, recognising a unique feature of the resultant activity. It was felt, therefore, that the nets must be made adaptive and then, perhaps, the resulting changes would produce different behaviour, in the form of activity, to be able to distinguish between input signals.

The method of adaption was based on the modification algorithm of Hebb (1949), which rewards coincidence of pre- and postsynaptic activity by increasing the synaptic weight values and, conversely, decaying them for non-coincidence. The changing of synaptic weight values was shown, in Chapter 4, to have a significant effect on the resultant activity, although not to the same degree as changing the decay rates had. However, altering the interconnections between cells rather than the properties of the cells themselves implies greater flexibility, as the number of potential sites for modification is so much larger.

The Hebbian type of algorithm was chosen in preference to a global form of Reward (e. g. as was used briefly in Chapter 4) as it was felt that any processing performed by the latter type was inherent within the algorithm. The local type of adaption this Chapter's algorithm uses can be thought of as a property of the cell fibres and therefore 'automatic' in function. The first few experiments test out the various forms of the algorithm, the details of which are illustrated for explanation. The implementation of the basic algorithm (HEBB) has been described in Chapter 3. This Chapter is divided into three sections, the first dealing with the effect of various algorithms, the second with the spectral analysis of the nets and the third using the new form of analysis, the Cell Firing Histogram. All the Experiments' important parameters are listed in Table 1 which can be found at the end of the Chapter.

Testing the Algorithm

Whilst the basic method of adaption is always the same the parameters governing the rate of reward are altered to find the most promising algorithm. Much of this early work is similar to, but independent of, the theoretical discussion in Uttley (1976).

Figures 1 to 6 indicate the various percentage changes in synapse weight, in Reward and Punish Mode, that are used in this group of experiments. Method 1 (Fig. 1) was to apply a 5% increase in value in the Reward case and 0.1% reduction in the Punish case. As the Punish Criterion was more likely to be satisfied, in a low activity net, the change in this case was less. However, due to the very low Punish reduction percentage employed, this Mode had no effect. At the end of the run (Experiment TL3) most of the synapses'

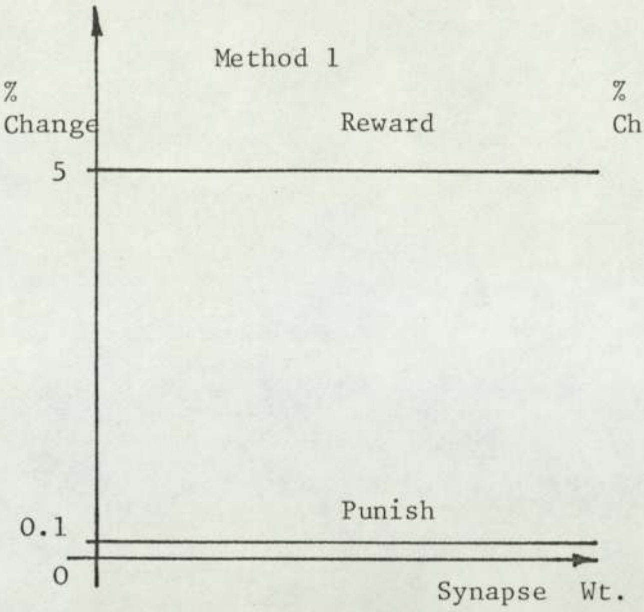


Fig 1

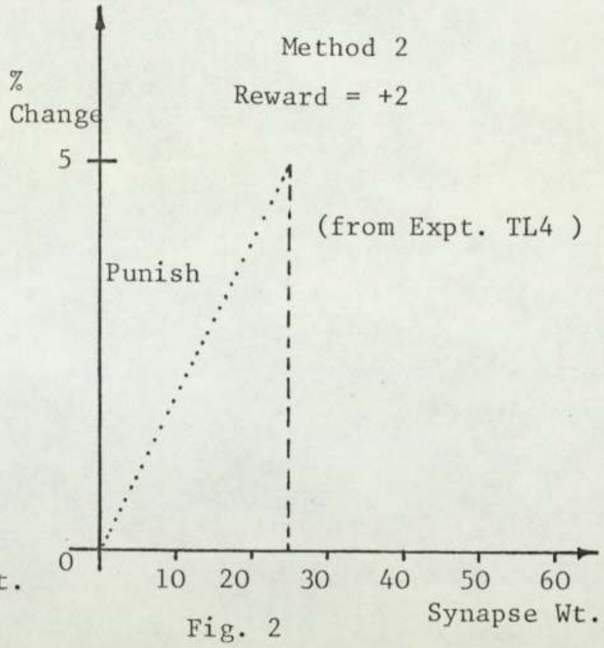


Fig. 2

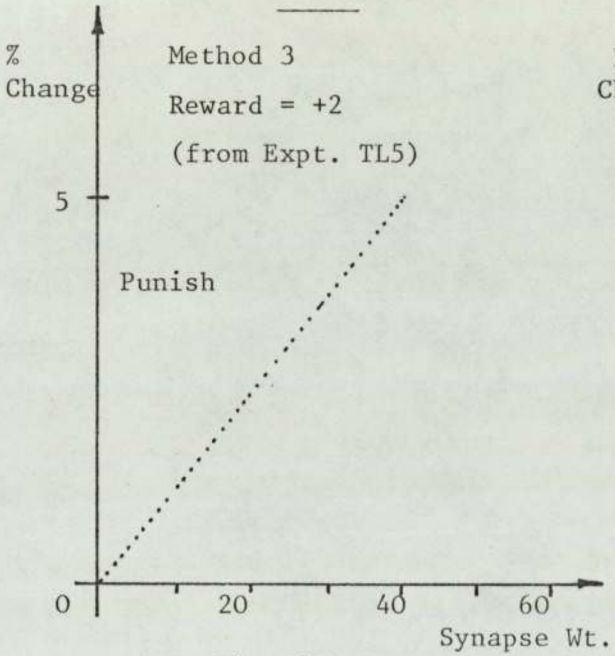


Fig. 3

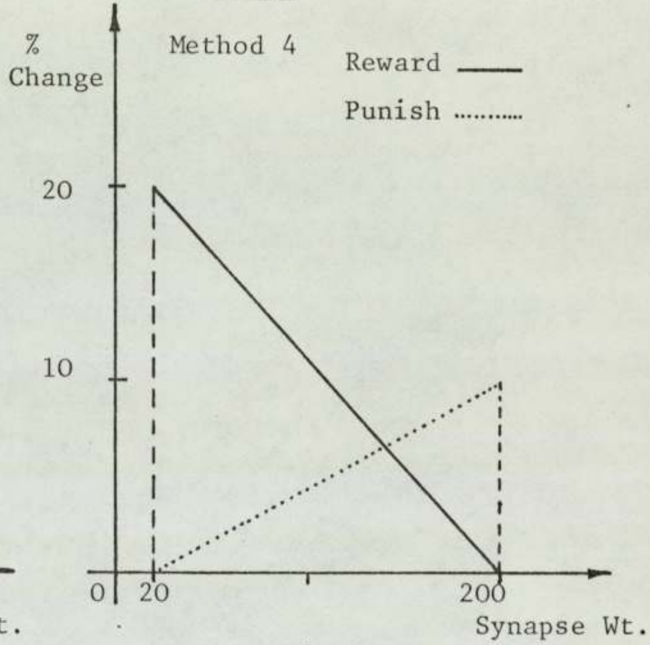


Fig. 4

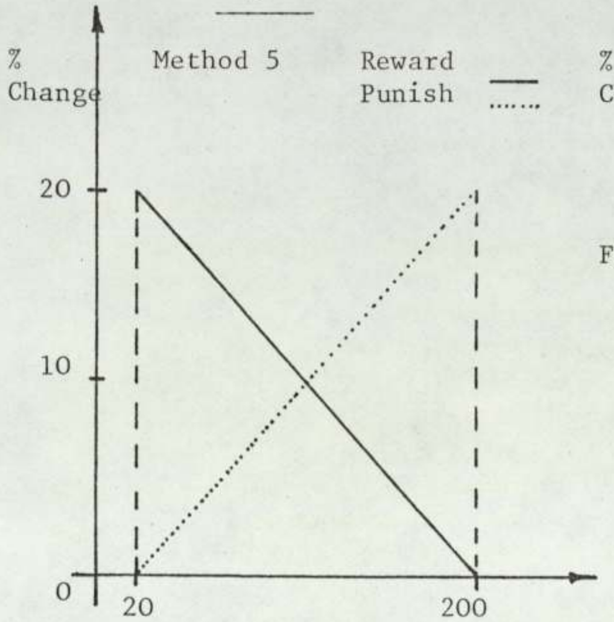


Fig. 5

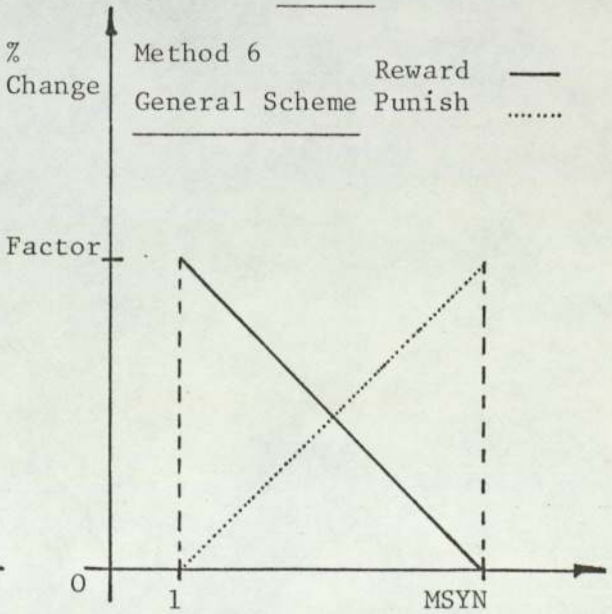


Fig. 6

weights had veen vastly increased and many were on the maximum value of 512. This obviously provided no discrimination.

Method 2 (Fig. 2) produced more stable behaviour, in Experiment TL4, but a trend of activity was indicated by large values in the 'lowest' frequency cell of the Firing data Smoothed Power Density Function (FSPDF). This method had a simple Reward increase of 2 synaptic weight units, rather than a percentage. Method 3 (Fig. 3) produced a larger trend, which was visible in the raw data, as a gradual increase in the mean level of activity, of Experiment TL5. The values of the Punish factor were smaller (see Fig. 3) for a particular firing level than in Method 2 and therefore had less of an effect in reducing the synapse weights and consequently the activity level. Method 4 (Fig. 4) produced, in Experiment TL13, an indiscriminate increase in synapse weights with, for a randomly chosen element, 47% of the weights having reached the maximum value. Method 5 (Fig. 5) involved increasing the Punish factor with the result that 18% of the final synapse weights were at the maximum value. (Experiment TL14). An attempt was made to reduce the difference between the maximum and minimum values of the final synapse weights to prevent certain pathways becoming totally dominant. This, hopefully, would increase the number of possible final connection states of an adapted net. Method 6, therefore, employs a maximum synapse weight of 100. Most weights became zero and the few that remained, approximately 10%, were at the maximum. For a system that could be retrained on new signals, the minimum value must be capable of being 'resurrected' to any level. Two methods to achieve this were employed, the first involved adding various rounding terms to the calculations to prevent terms going to zero and the second used a higher adaption percentage to make significant changes to the small values. The general scheme of Reward and Punish Percentages is illustrated in Figure 6. This general scheme was employed, with a few modifications, in the later runs, and the final weights typically indicated many small non-zero values, a few maximal and fewer still in the middle range. This was considered satisfactory.

During the running of Experiments TL2-TL23 to test various algorithms, their global effects on the net were also examined. As in the previous Chapter Spectral Analysis was employed and features such as Persistence of input signal were looked for. The adaption changed the frequencies of firing in some cases, but a dominant frequency, after adaption, usually bore no relation to the input frequency.

By their nature, the algorithms tend to emphasize certain pathways at the expense of others and it was hoped that circuits would be formed of reinforced fibres and hence contribute a significant frequency component of their own. It was further hoped that these frequencies might be different for different inputs. An example of the final major pathways, typical of that produced with these algorithms is shown in Fig. 7 taken from Experiment TLB1.

The elements in the first slice number 1 to 25. In this Experiment all cells bar 10 and 20 receive periodic input of 6. It can clearly be seen that as the cells in the first slice generally fire

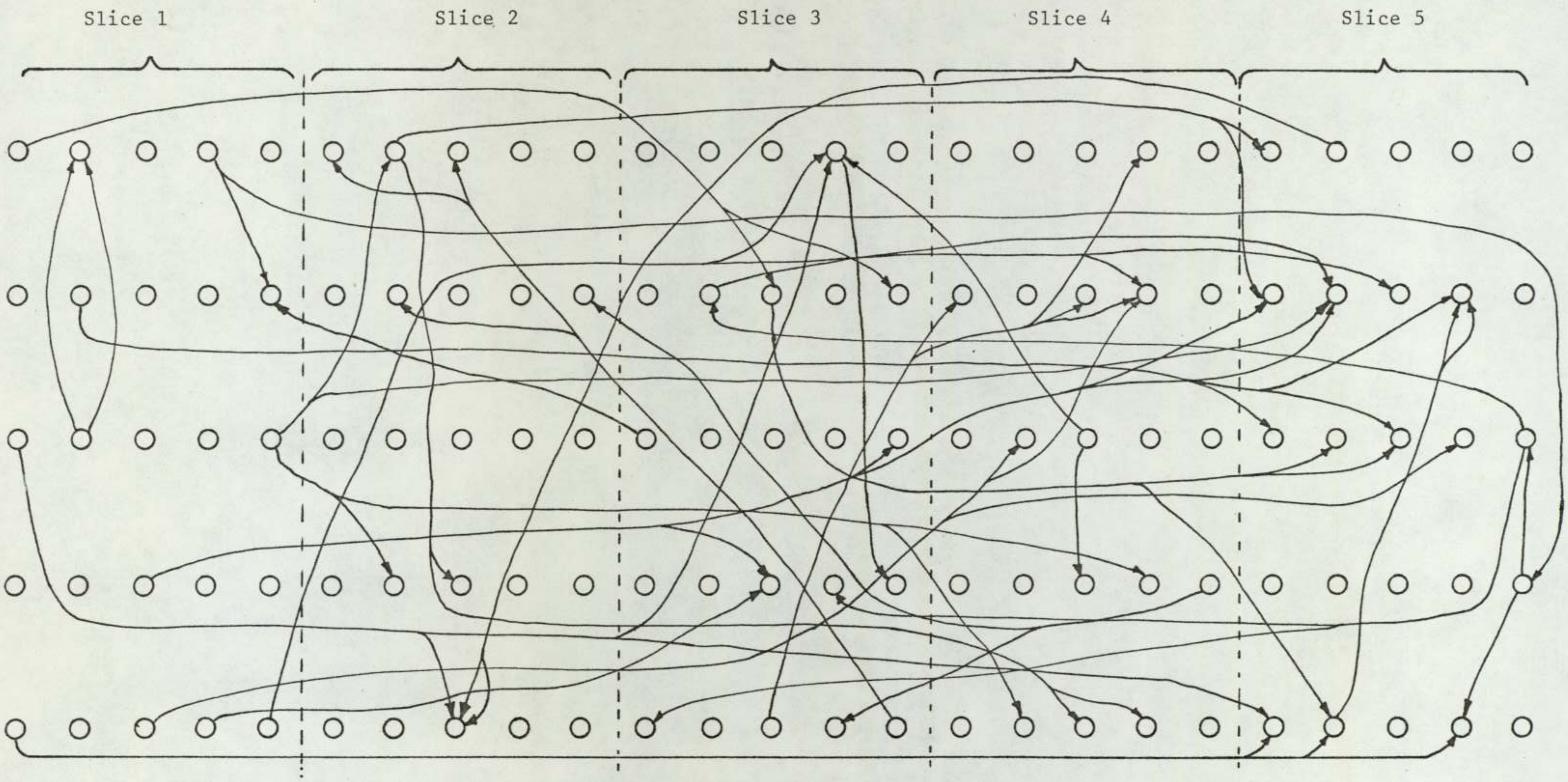


Figure 7 Major Connections from Experiment TLB1 (At the end of run)

together, they do not form strong links between each other. For reinforcements to take place the two cells involved must fire one after the other. This is far more likely in the centre of the net where the rhythmic effect of the input is soon lost in the background firing (as discussed in the previous chapter). The main links from the input cells are to the fifth slice to which they are directly joined. There are no return links from this area as the first slice will then be in a refractory state and unable to fire "in sequence". Long chains are rare but one involving medium and strong connections is (4, 120, 115, 57, 107). There are 3 chains of length 5 and 7 length 4. No circular paths can be seen. There are other connections, not shown on the diagram, of low synapse weight and so cells that appear to be isolated may not be. There may in fact be loops, formed from the visible chains plus several "small" synapses. A strong link has a synapse weight of over 80 and a medium link has one of over 30 (excitation units).

Conclusions of the Initial Group of Experiments

Despite quite drastic synaptic changes, frequencies typical of the input are not noticeable at a global level. The major pathways formed made no complete circuits which may explain this. The threshold and excitation decays (all 60%) were such that elements would tend to fire every four or five units of time and return links to the input elements would be expected to have been built up. However, the algorithm may be too harsh by only allowing reinforcement if the post-synaptic activity occurred one time unit after the pre-synaptic activity. Despite this, final synaptic weights were different for different inputs indicating a certain amount of discrimination had been recorded.

To attempt to maintain the stability of the nets and retain high activity levels the relatively common occurrence of inhibitory reinforcement will be prevented. From this point on, only excitatory synapses are modified.

Frequency Analysis of Adaptive Nets using Spectral Analysis

For this and subsequent sections, the approach of Chapter 4 is re-adopted of providing groups of strictly related experiments to illustrate a particular property. The experiments in this Chapter are all variations of the 'split-run' type in which a periodic signal is applied to the net for the first half of the experiment, whilst the net is allowed to adapt. In the second half the input is changed to a constant signal and the adaption is inhibited. In this way any remanent frequency that is not part of the net's natural rhythm must be due to the signal in the first half of the experiment.

The Effect of the Maximum Synapse Weight and the Rate of Adaption on Frequency

Several runs using different values for the Maximum Synapse Weight (MSYN) and the Adaption Rate (FACTOR) were performed ([TLB20, 21, 22, 24, 25, 26], [TLB23, 27, 30]). The first set varied MSYN. Examining the raw data it became clear that the net was virtually cycling, as very regular types of waveforms were being produced. They were never exactly the same, but one of the closest, in this thesis, to the type of repetitive activity noticed in Anninos' nets (1972). In the second half of the run the waveform changed as the input signal became constant but was still cyclic. This continued throughout the run. The patterns of the waveforms produced in this type of run often contained sequences of 'sub-waves' which although perhaps being different in shape were picked up as the same component in the Spectral Analysis. The FSPDF does show only small components as contributing to the power but, by examining the raw data, the length of the main cycle was seen to be around 24 units. A section of the waveforms for Experiment TLB21 is displayed in Figure 8 (showing two consecutive points at the same level beginning at time units 957, 981) and the FSPDF in Fig. 9. The nets, by elimination of the majority of pathways, have become 'simple nets', with a reduced number of states. All the FSPDF produced by these experiments were very similar, indicating only the high frequency sub-components of the main cycles produced, but the pattern of these cycles in the raw data was always very different. The major connections for Experiment TLB21, which are typical of the set, are displayed in Figure 10. The connections formed in this set did not differ very much, particularly in the input slice, but the connections showing the greatest change, in the centre of the net, often , when connected to the same elements, had different strength of connection to those elements . The raw data indicated that changes were taking place quite abruptly in the firing rates, by an upturn in the level of activity. Figure 11 is a plot of the Maximum Synapse Weight and Rate of Reward (FACTOR) against the time of the first occurrence of a major change in the firing rate. Assuming that this is an equivalent state between simulations, the effect of the rate of reward in speeding up the adaption to reach an almost final state of connection path can be seen. The effect of MSYN is not a simple linear relationship (see Fig. 11).

A medium value, for the Maximum Synapse Weight, of 50 was chosen for Experiments TLB34 onwards. This means that the difference between the largest and smallest synapses is not too great.

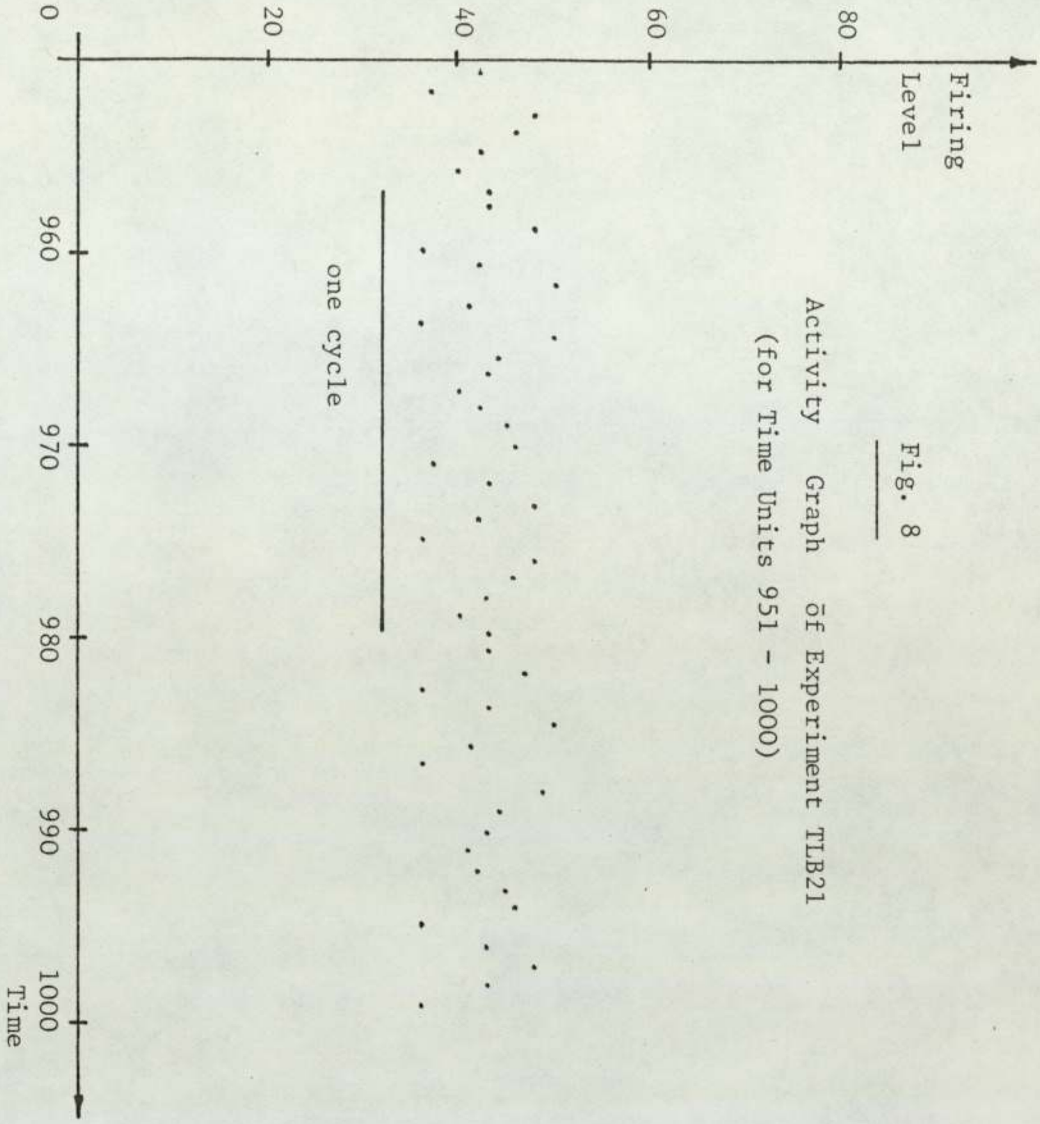


Fig. 8

Activity Graph of Experiment TLB21 (for Time Units 951 - 1000)

Figure 8 Graph showing cycle of 24 Time Units.

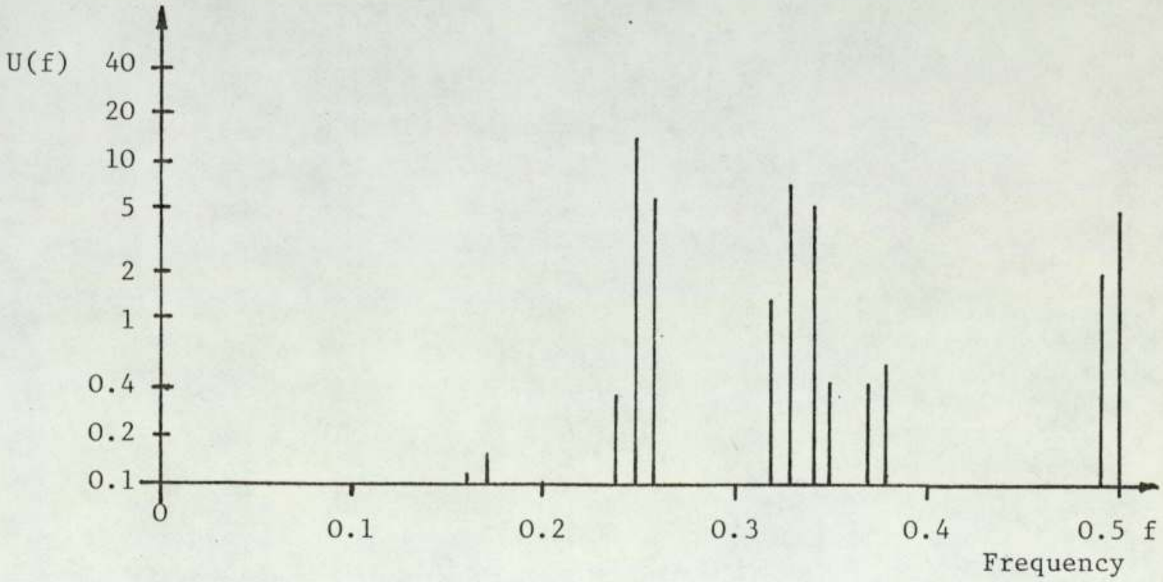


Figure 9 FSPDF of second half of TLB21

No indication of the 24 unit cycle is shown as only the sub-frequencies have been recorded.

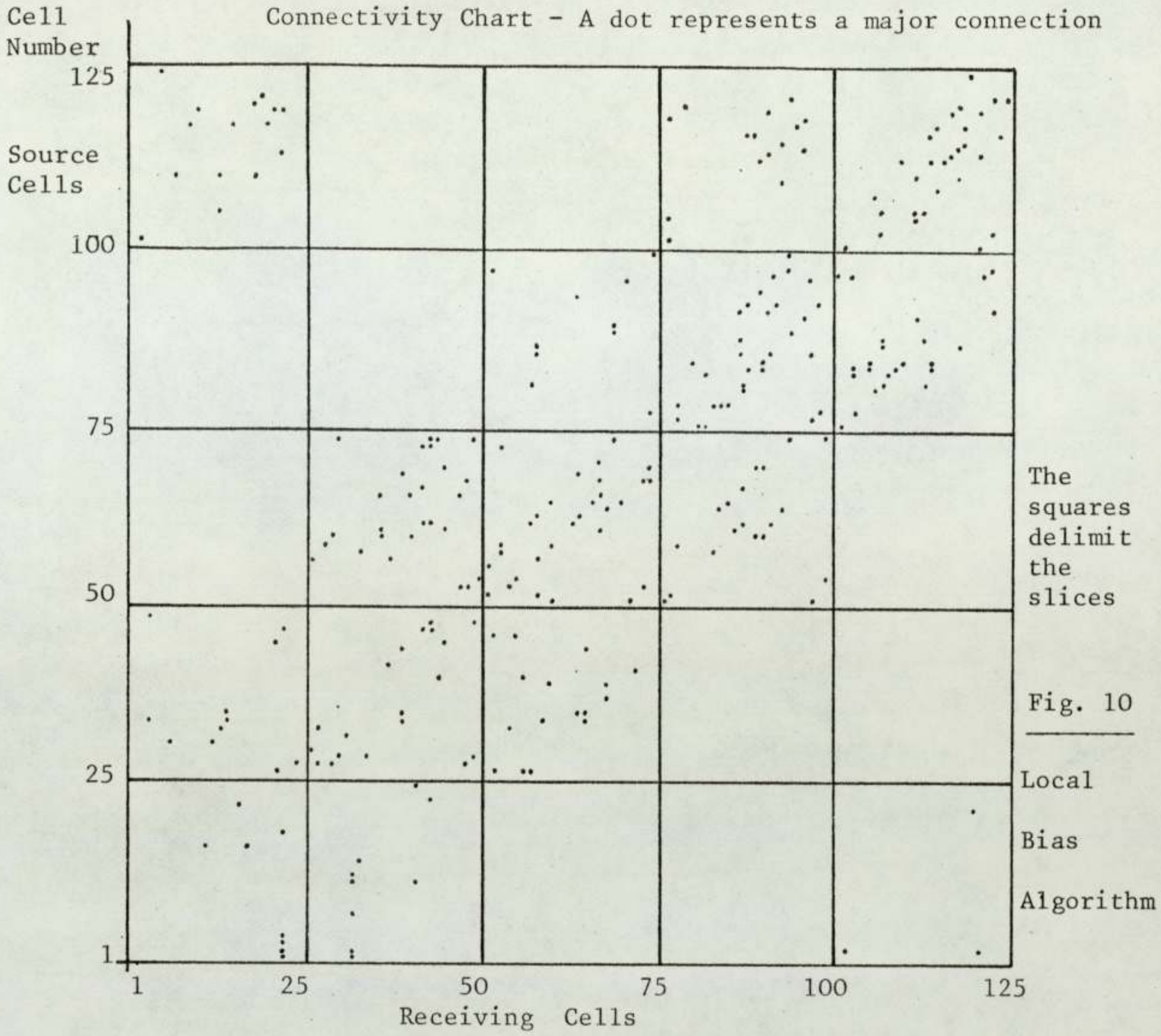


Figure 10 - The major connections left after adaption in Expt. TLB21

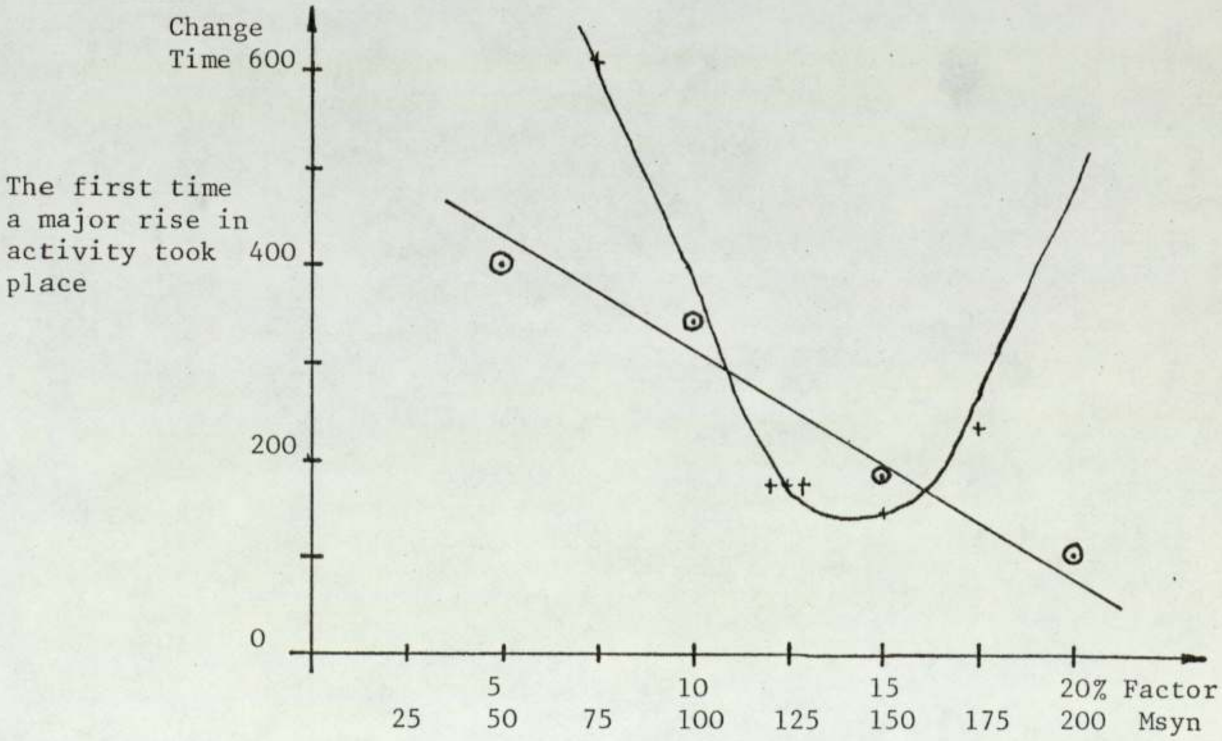


Figure 11 Graph of the Maximum synapse Weight and the Adaption Rate against the time of the first main change in Activity level

The choice of the rate of Adaption was taken to be 20%, to achieve the quickest alterations in weight value and thus increase the net's sensitivity to small changes in input. From the graph it can be seen that major changes will have occurred within the first 50 time units.

The Effect of Decay Rates on the Formation of Cycling

This section employs Experiments ([TLB31, 32, 33]) to investigate how cycling is affected by the natural frequency of the net. The runs of Experiments TLB9-12 had decays of 60% and several exhibited cycling of period 24. Experiment TLB31 with 50% decays exhibited cycling, in the second half of the run, of cycle length 40. TLB32, with 40% decays, exhibited cycling in the first half of the run when the periodic input of 6 was stimulating the net but in the second half patterns of activity could be seen that were similar but they did not repeat exactly. This also happened in Experiment TLB33 with 30% decays. No exactly repeating sequence of firing levels could be seen over the entire length of the second half of these last two Experiments.

Conclusions

It would appear that, as the decays increase and the number of states an element can be in decreases, so the likelihood of cycling increases also. The nets with slower decays therefore can be compared using Spectral Analysis techniques as these would not be adversely affected by cycling.

The Effect of Signal Input on Frequency and Form of Activity

The Experiment group testing the effect of signals on the net is ([TLB9-12], [TLB13, TLB14], [TLB15-17], [TLB35-39], [TLB40-43], [TLB46-49], [TLB35], [TLB36, 43, 46], [TLB37, 42, 47], [TLB38, 41, 48], [TLB39, 40,49]) named Sets 1 to 11 respectively.

The first Set employs the local bias connection algorithm GEN1, and applies signals of period 6, 5, 7, 8, respectively. TLB9, with a periodic value of 6, achieves cycling after the input changes to constant and repeats every 24 time units. As usual, this confuses the spectral routines which display large low frequency components, which usually suggest a trend and a few components arising from sub-cycles within the main cycle. The activity of the last 50 time units is displayed in Figure 12. Experiment TLB10 of periodic input 5, produces a cycle of 24 again with clear subcycles of length 3 and 4, which were picked up by the spectral analysis. The final 50 time units is displayed in Figure 13. TLB11, of period 7, does not achieve cycling but TLB12 does with a period 12 (see Fig. 14). The sub-components of 7 and 5 are picked out by the FSPDF. The next two sets employ the random algorithm GEN. Set 2 uses periodic input values of 8 and 7 respectively. TLB13 produces, from an input period of 8, cycling of period 24 which was made up of subcycles 2 and 6, see Figure 15. TLB14, with a period of 7, did not produce cycling but a mixture of low frequencies, 4, 3 and 2. Set 3 used a net with 45% decays and input periodic values of 7, 8 and 5. They did not produce perfect cycling although there were similar patterns being produced which became broken up into new patterns. An example is the final activity levels of TLB15 with an approximate cycle of 21 (see Fig. 16).

In the next experiments the signal is more complex and is defined by two parameters X and Y. These have been defined in Chapter 3 and are the length of the 'off' signal and the length of the

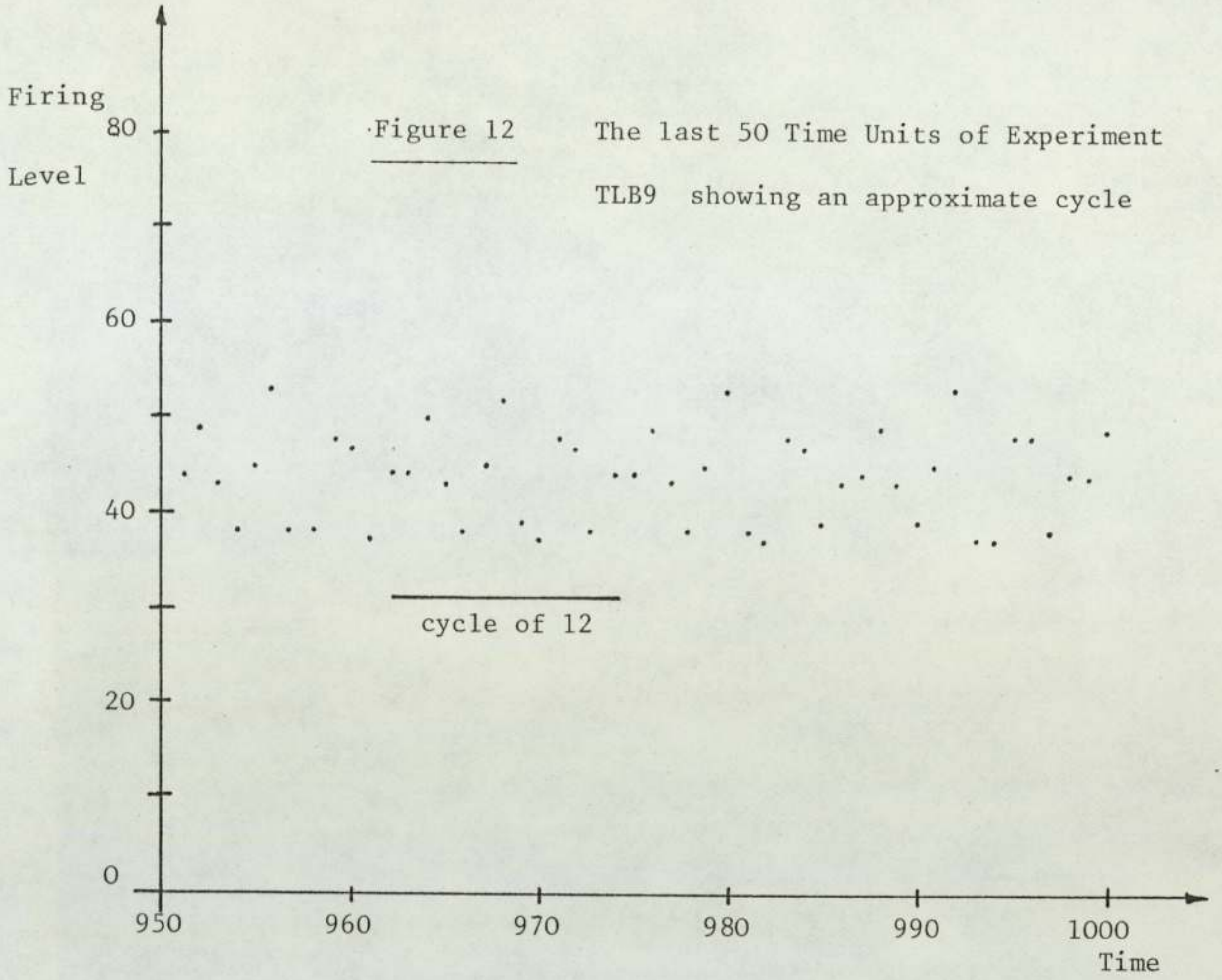


Figure 12 The last 50 Time Units of Experiment TLB9 showing an approximate cycle

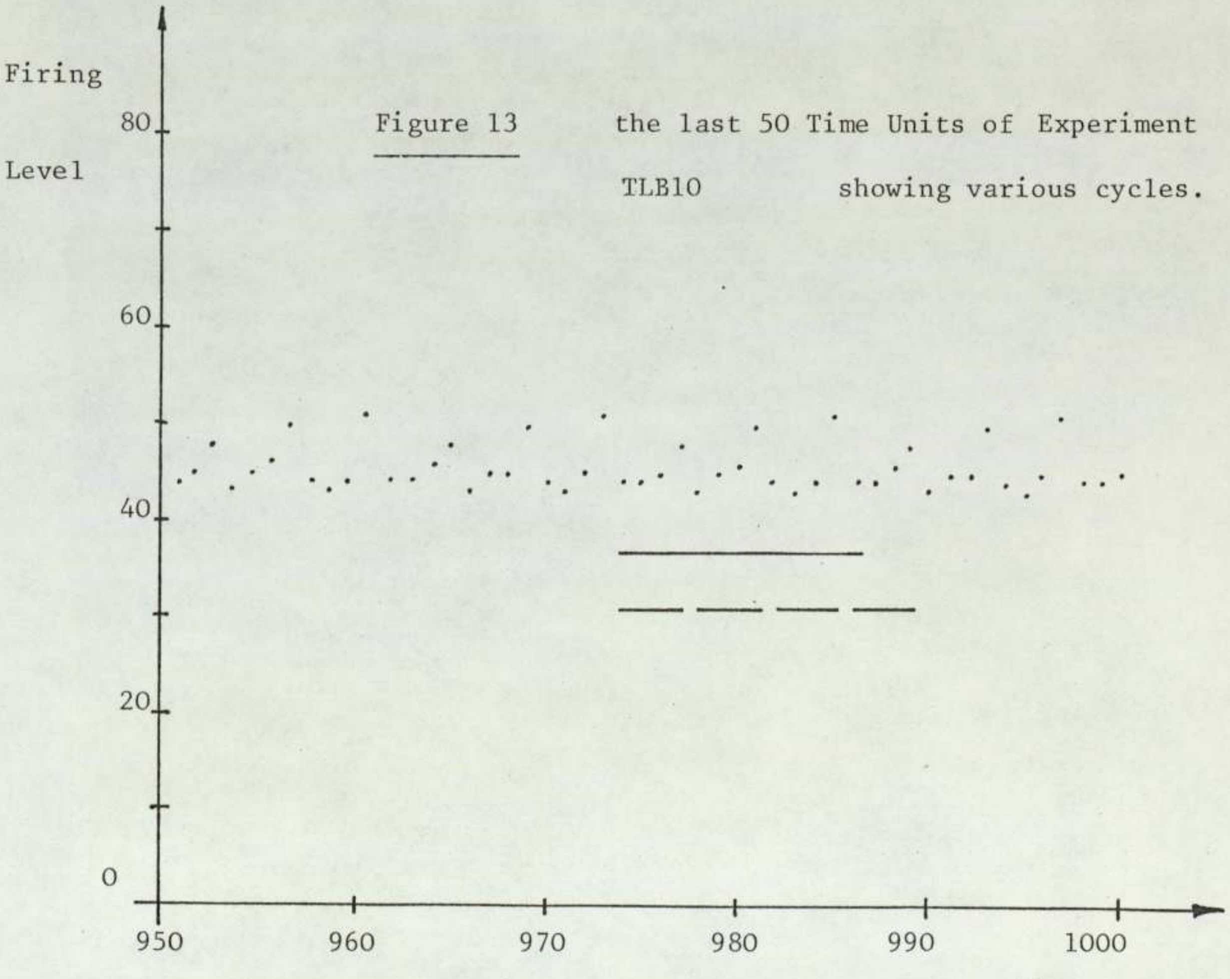


Figure 13 the last 50 Time Units of Experiment TLB10 showing various cycles.

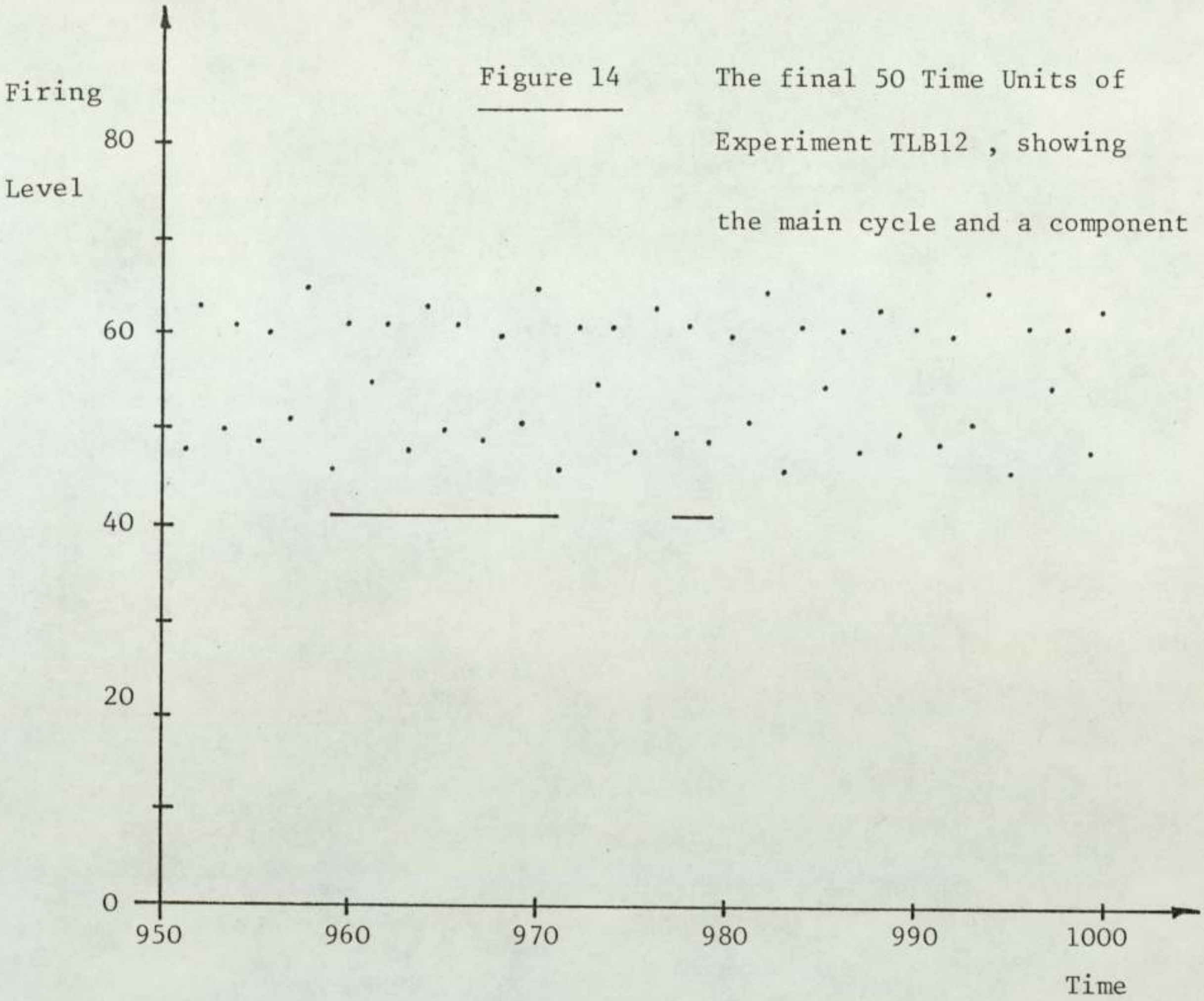


Figure 14 The final 50 Time Units of Experiment TLB12 , showing the main cycle and a component

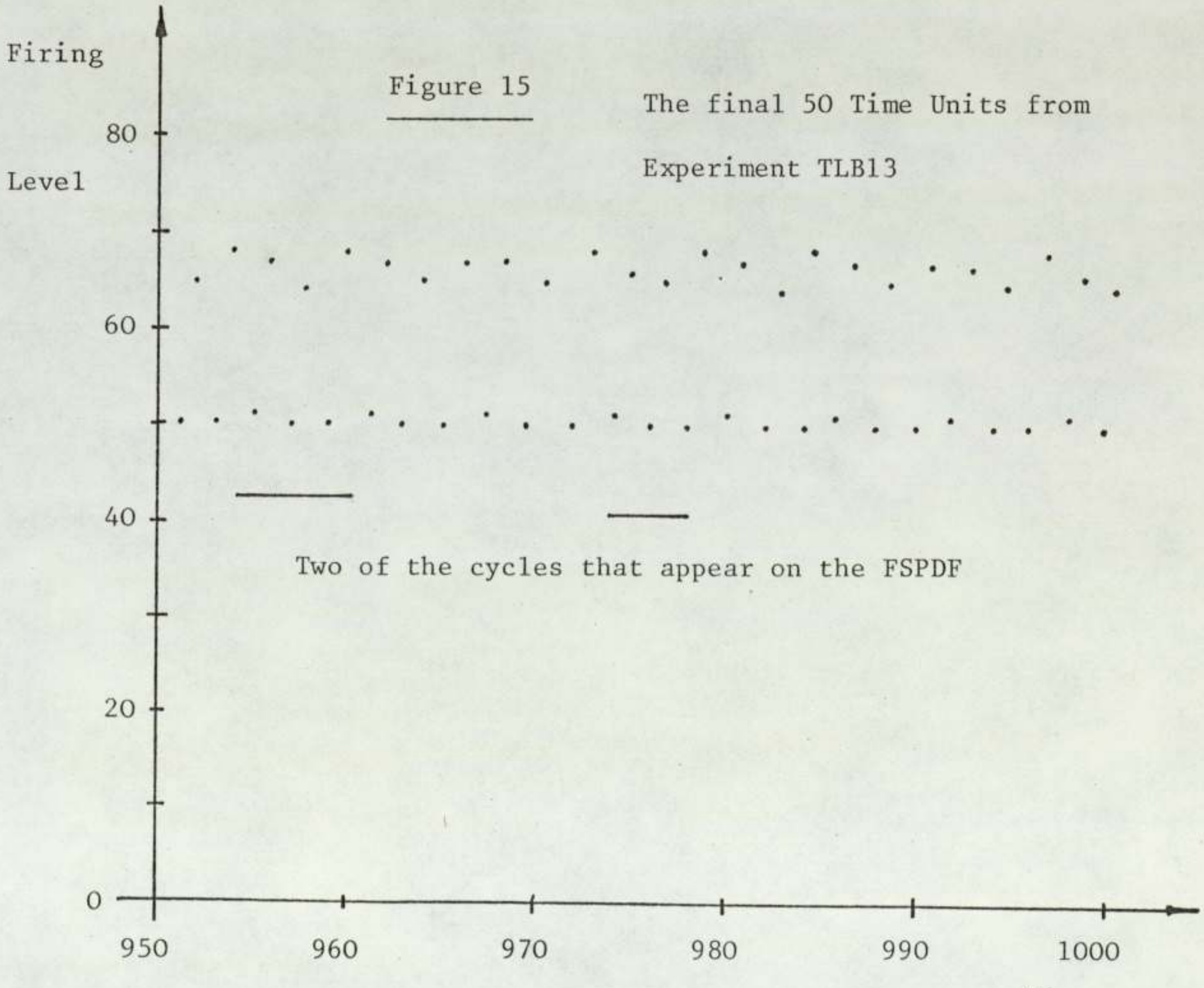


Figure 15 The final 50 Time Units from Experiment TLB13

Two of the cycles that appear on the FSPDF

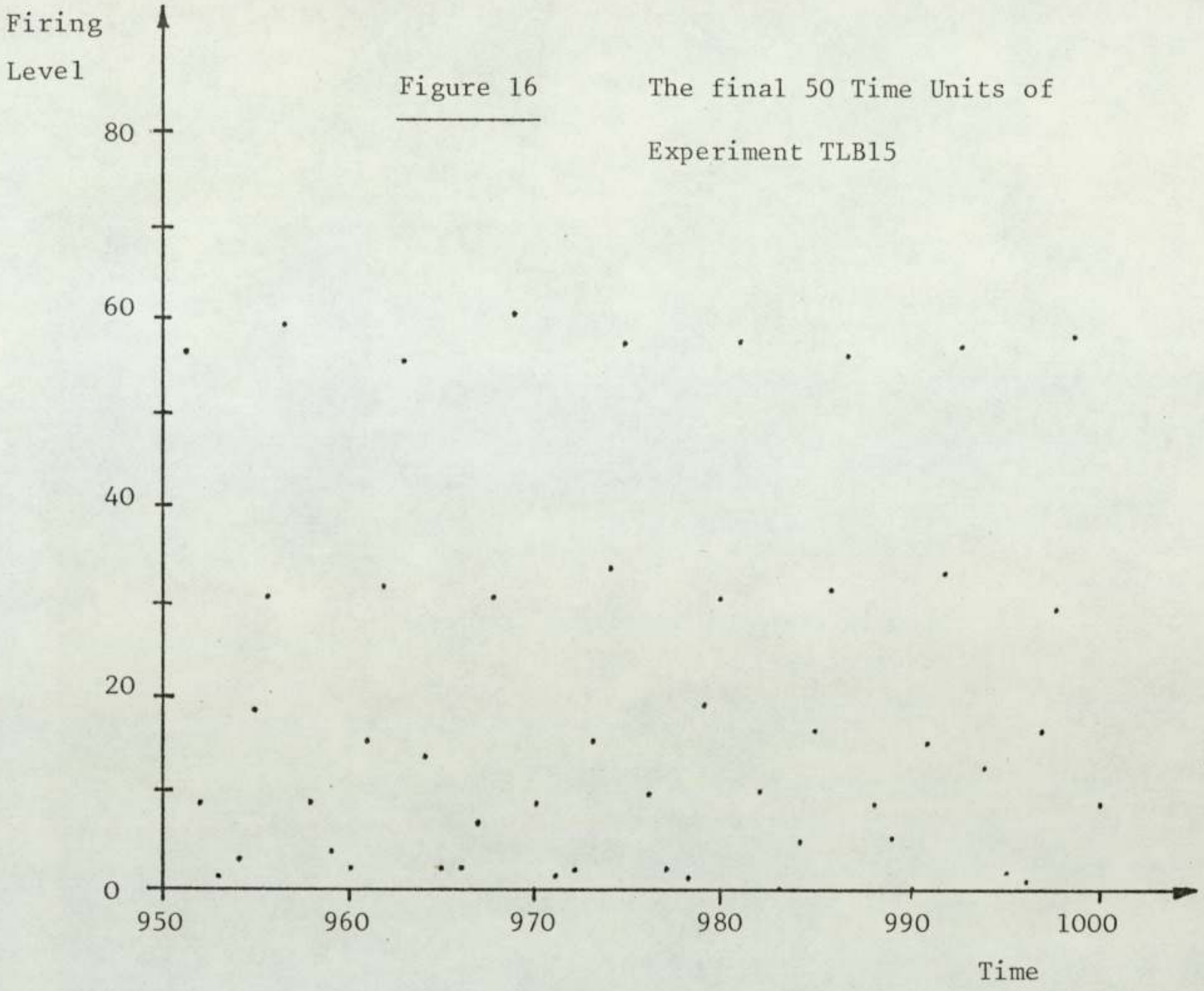
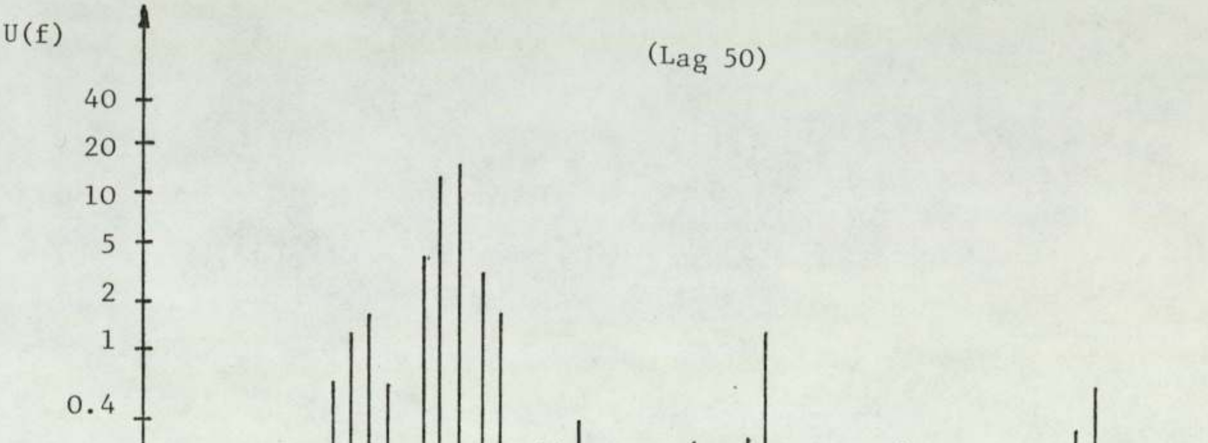


Figure 16 The final 50 Time Units of Experiment TLB15

Figure 17 FSPDF of Experiment TLB35

(Lag 50)



'on' signal. They are both varied, in turn, in the remaining Sets (see Table 1). The nets used had 40% decays, Maximum Synapse Weight of 50 and a Rate of Adaption of 20%. From the section on effects of decays on cycling it would appear that nets with this rate of decay are less likely to have fixed cycles as there are more states each cell can be in , so the FSPDF should be more useful. The first Experiment of Set 4 used an X value of 6 and a Y value of 2. The resulting spectra is shown in Figure 17. The Y value for subsequent experiments in this set was increased by one and the resultant spectra are reproduced in Figures 18-21. As can be seen, the spectra vary considerably for these very slight changes. This was true for all the remaining Sets and brief descriptions of all the main components of the spectra are given in Figure 22.

Conclusions

The very slightest change in an input signal produces vastly different final activity in the nets after adaption. For nets of short refractory period perfectly cyclic activity is often produced, the pattern of which is unique for each input signal.

Clearly, from the exceptions to the exact cycling shown in Experiment TLB11 for example, from Set 1, the factors determining whether exactly repetitive signals are produced is complex. As the conditions for reward in the HEBB algorithm are so precise it may be that, with certain signals, these conditions are not satisfied often enough for major connections to form and subsequently "dominate" the activity flow. Nevertheless, in the non-cyclic cases, similar shapes of the activity graph were seen to repeat and indicated some

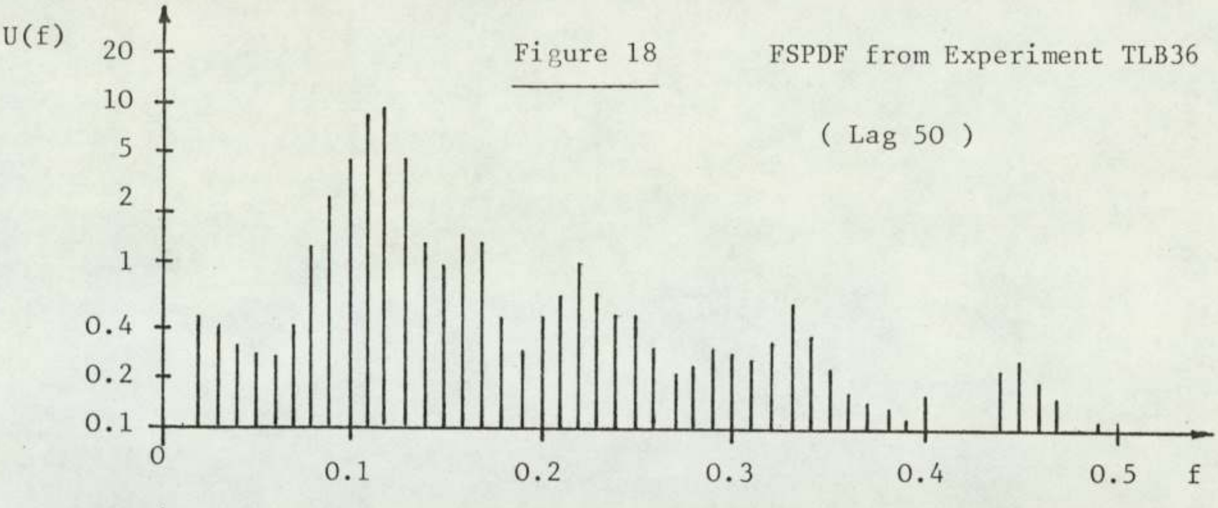


Figure 18 FSPDF from Experiment TLB36

(Lag 50)

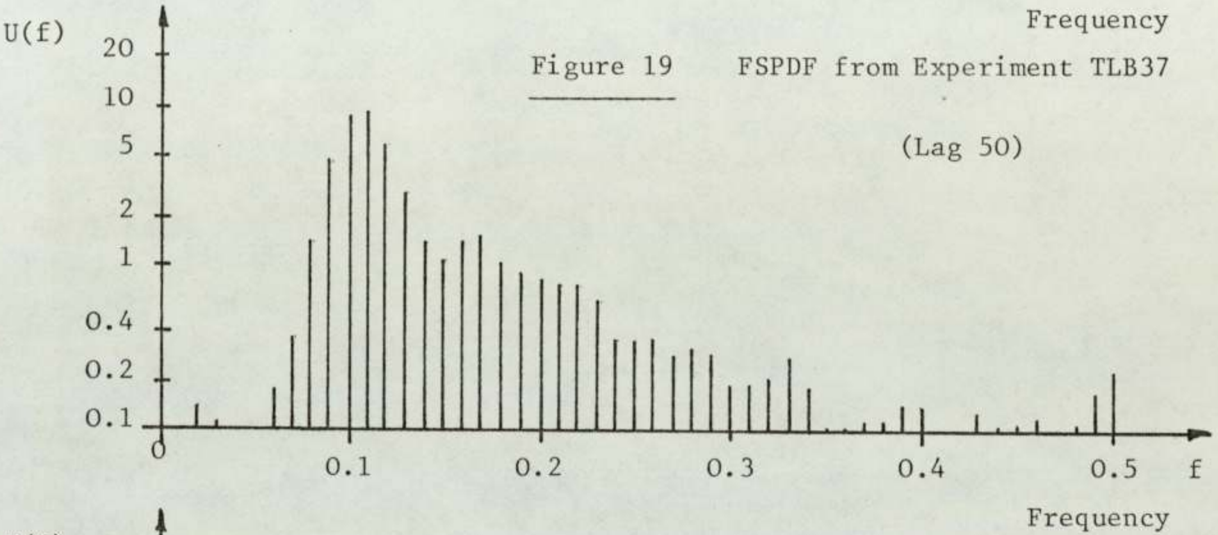


Figure 19 FSPDF from Experiment TLB37

(Lag 50)

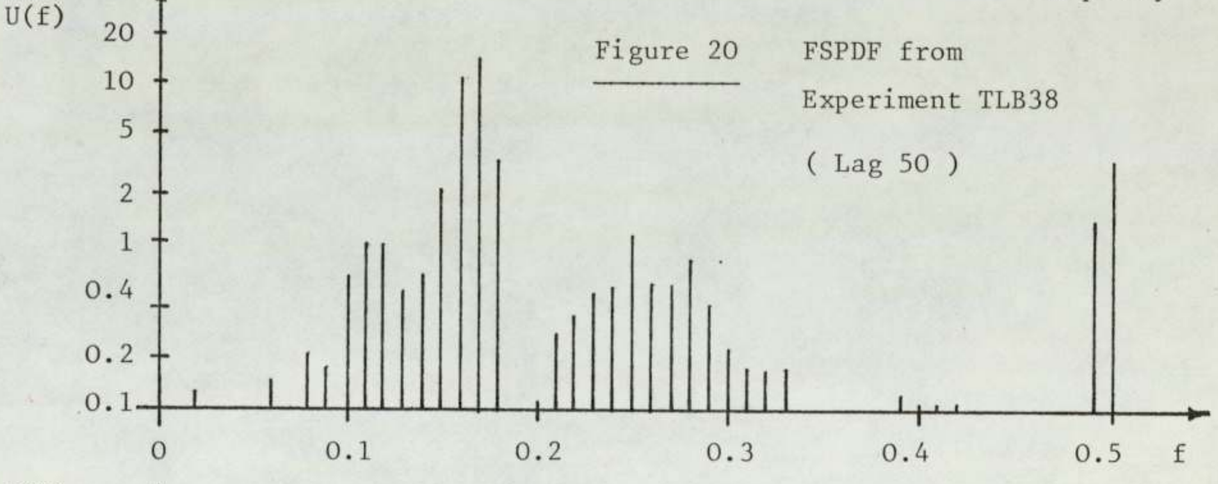


Figure 20 FSPDF from Experiment TLB38

(Lag 50)

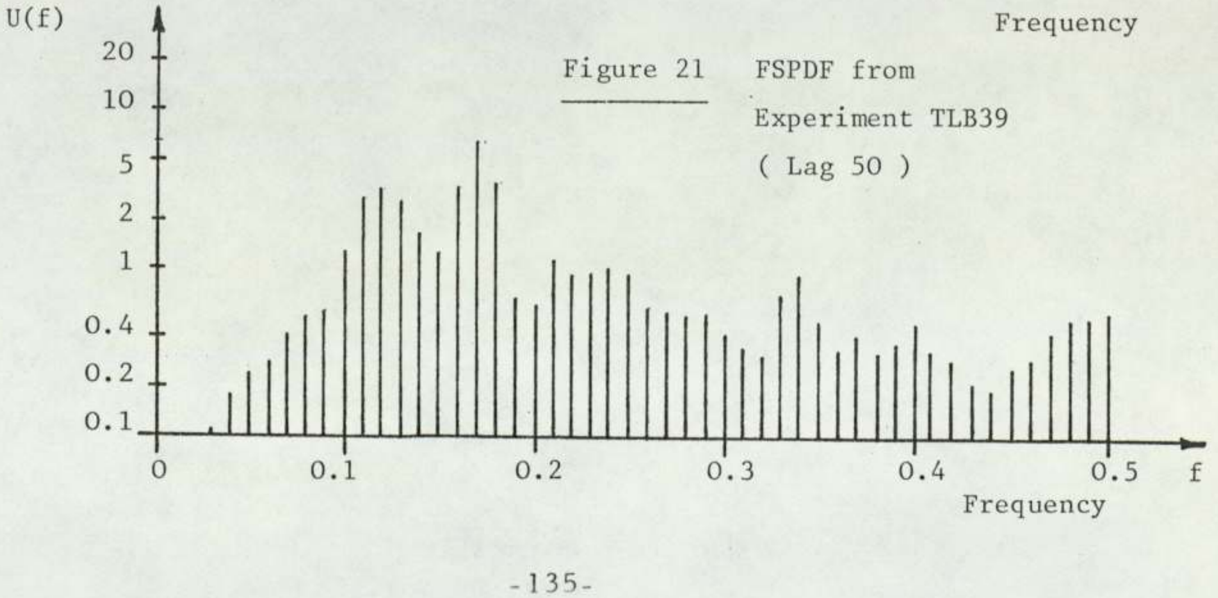


Figure 21 FSPDF from Experiment TLB39

(Lag 50)

Set	Expt. Code	Figure	Brief description of Main Components of FSPDF produced
5	TLB40		Components at 6 ,9,10,3 ; Small at 2;
	TLB41		" 6 , 3 , 2 larger;
	TLB42		" 6 , 5 increased, 3 reduced, 2 missing;
	TLB43		" 8, 9 , 6 reduced , 5 up;
6	TLB46		" 7 , 6 , sub-peak at 4;
	TLB47		" 6 to 12 without 9, sub-peak at 10
	TLB48		Wider spread, 3 peaks : 5,7,8
	TLB49		Large spike at 6 ,5; Base of spike at 10-5, sub-peak at 3;
7	TLB35	17	Main peak at 6 , sub-peaks 8 , 9;
8	TLB36	18	Components at 9,8,7, minor peak at 6,4, small trend value (very low frequency)
	TLB43		Very similar with increase at 5;
	TLB46		Sharper spike, components at 7,6
9	TLB37	19	10,9,8 , sub-peak at 6 ;
	TLB42		Lower period spikes 6,6.5, sub-peaks at 5 and 3;
	TLB47		Components at 6 , spread around 10 ,lowest periods now absent;
10	TLB38	20	Component at 6 with slight spread but not to next periods,slight peaks:10,4,2;
	TLB41		Very similar but 3 larger and 10 reduced;
	TLB48		Vast change : 8,9,5 and very wide spread;
11	TLB39	21	Components at 6, sub-peaks at 5,8,3;
	TLB40		Similar but component at 3 increased;
	TLB49		Components at 8,9,10,6 and 3 reduced;

Figure 22 Brief description of FSPDF from Experiment Sets 5-11
Components are described in terms of period with the main spike's period underlined.

reinforced pathways were having a considerable effect. It was as if the net had produced a coded version of its own for each signal. The problem remains, however, of detecting these signals produced, but the net now has this record permanently in its "wiring". The third main section of this Chapter deals with the analysis produced employing the Cell Firing Histogram.

The Cell Firing Histogram (CFH)

In previous sections it was often necessary to re-examine the raw data to see the effects of various signals. As a result of adaption, many pathways had been virtually eliminated and there arose the possibility of activity passing along a relatively small set of "preferred pathways" and that these pathways were different for different inputs. In other words specific sequences of firing cells may be produced depending on the input value the "naive" net was "trained on". The adaption algorithm rewards successive firings between cells and chains have been shown to be forming (see Figs. 7, 10) which would make specific firing sequences tend to repeat. The volume of data, however, describing every pathway is vast and so a considerable amount of data reduction is necessary before printing the data on a lineprinter. It was argued that, if "preferred pathways" had been reinforced at the expense of others, then the firing rates of the cells on the preferred pathway would be higher than those on the less used ones. So a necessary condition for similar firing sequences to take place is that certain cells should be shown to fire at higher rates than others. Also, if those sequences were different for different signals then the graph of the firing rates of each cell should be different as well. The Cell

Firing Histogram displays the number of times each cell has fired. The actual display used superimposes several histograms, calculating the data at equal intervals of time throughout the simulation. This was done to try to obtain a visual picture of changes in cell firing rate, which would be represented by the widening or narrowing of the gap (if any) between successive component histograms. The Cell Firing Histogram is defined as the display of a set of histograms taken at specified intervals. The method of calculation is described in Chapter 3. The Back Up program, BU2, displays a CFH for several intervals of the simulation and using different values of the increment between each successive histogram. For the sake of clarity, only a subset of the data displayed on the lineprinter is reproduced in this chapter.

The Effect of the Maximum Synapse Weight and the Adaption Rate on the CFH

It was decided to examine the effects the Adaption parameters had on the CFH produced. If certain settings of parameters produced CFH graphs whose individual cell values differed considerably, then this would make recognition of signals easy to achieve, by testing certain cell's firing rates. Two sets of Experiments were performed which varied the Maximum Synapse Weight (MSYN) and the Learning Rate: ([TLB20-22, TLB24-26, TLB29], [TLB27, 30]). Set 1 had an Adaption Rate (FACTOR) of 10%.

Considering the Experiments in order of increasing MSYN, the Maximum Synapse Weight, (see Table 1) it became clear that as MSYN increased, so the level of activity of the elements in the slices that did not receive external afferent excitation, increased very sharply.

The CFH for the maximum and minimum values of MSYN are displayed in Figures 23 and 24. The input area slice tended to remain constant, with a few of its elements matching 'background' cells for firing rate. The top value of MSYN (150) meant that certain cells fired continuously. This must mean the synapse weights are so large that certain elements are always receiving more than 1023 units of excitation (the maximum threshold value). Only 7 connections at this maximum weight would be needed for this to occur. The advantage of this value for MSYN is that there is considerable difference between the cell's firing rates which, if different for different inputs, make input identification easier. This net had decay rates of 60% so the firing rate and therefore the likelihood of reinforcement is going to be high anyway. The Second Set examines the effect of varying the Adaption Rate percentage, FACTOR. It uses MSYN value of 100. Considering these runs in order of increasing FACTOR value the effect is even more dramatic (see Figs. 25 and 26) than by varying MSYN. The experiment using the final value of FACTOR (Experiment TLB28) had to be aborted as so many weights were at the maximum that the whole net was almost saturated with activity. The simulation, which works fastest with low activity, became intolerably slow. Clearly this rate of activity was not going to discriminate between different signals.

Conclusions

Despite the variability of individual cell response when the Maximum Synapse Weight was very large, it was felt that such a net's discriminatory ability would be small as most of the synapse weights would be the same. Consequently, subsequent experiments, bearing in mind the natural frequency of the nets concerned, used low MSYN values

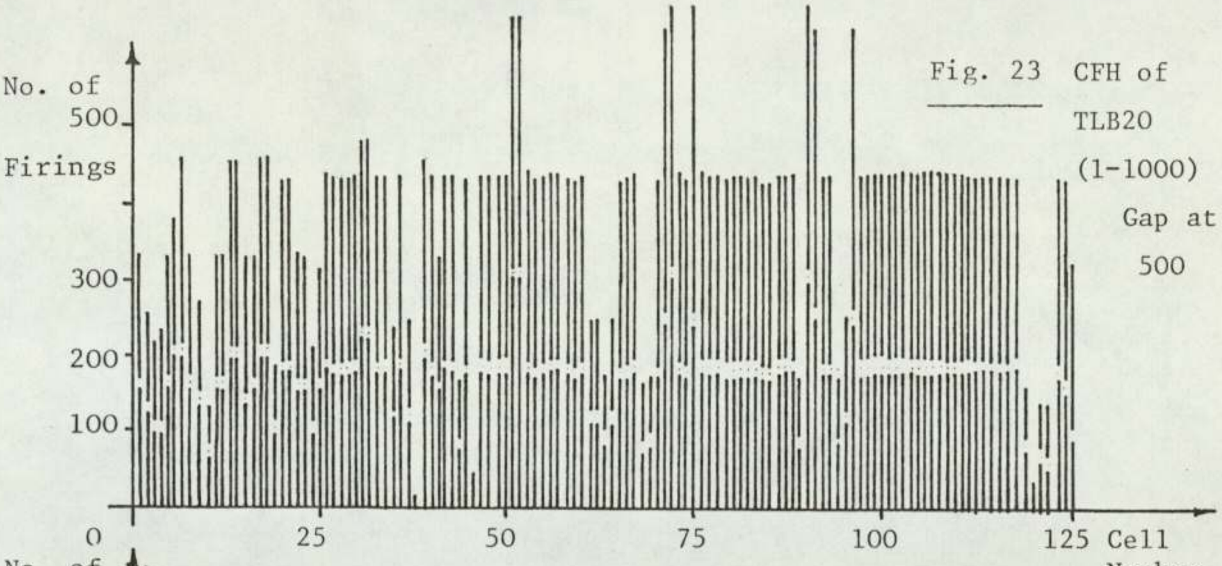


Fig. 23 CFH of TLB20 (1-1000) Gap at 500

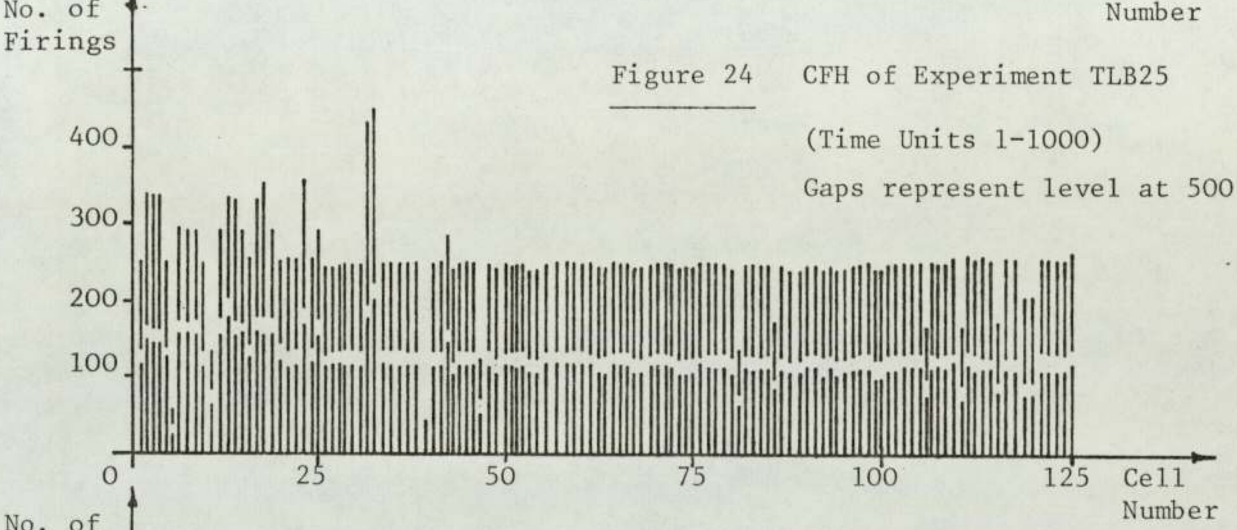


Figure 24 CFH of Experiment TLB25

(Time Units 1-1000)

Gaps represent level at 500

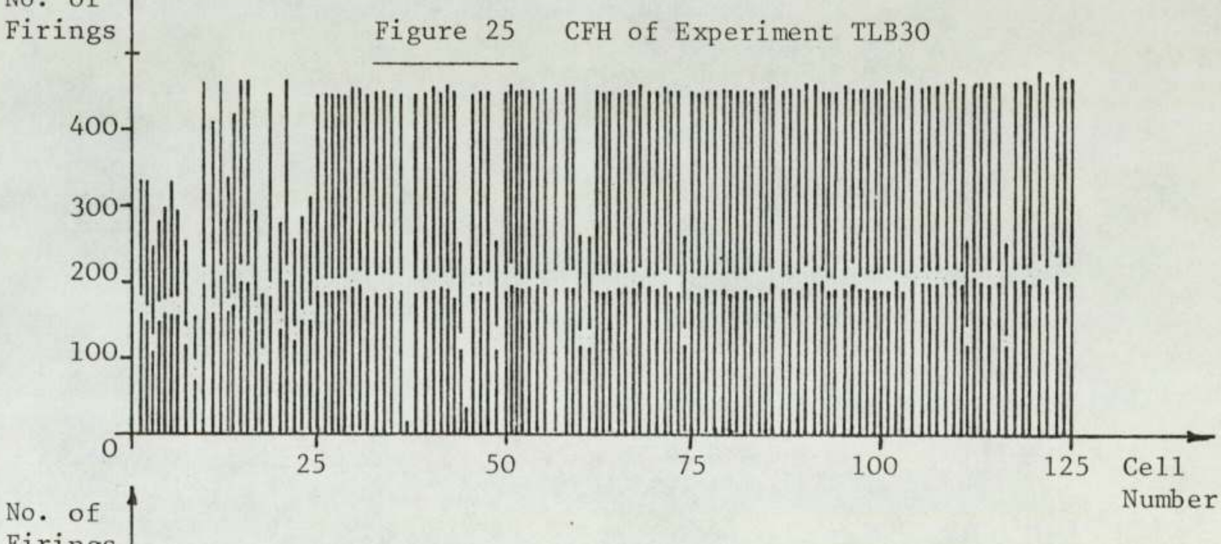


Figure 25 CFH of Experiment TLB30

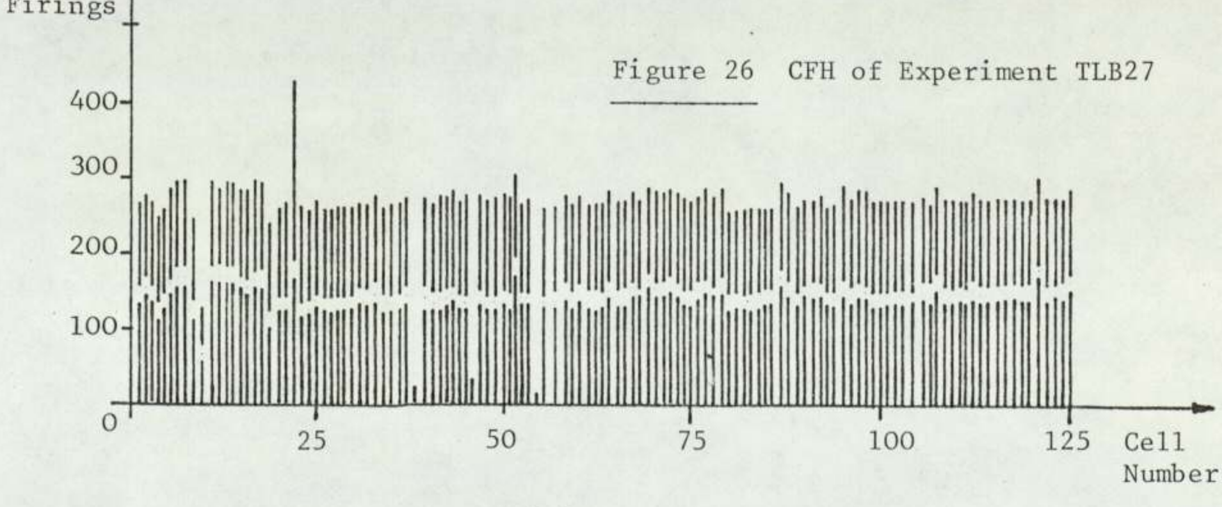


Figure 26 CFH of Experiment TLB27

and high FACTOR values which did not cause saturation of the net.

The Effect of Different Signals on the Cell Firing Histogram

The experiments in this group are ([TLB9-12], [TLB15-17], [TLB34-39], [TLB40-43], [TLB46-49], [TLB36, 43, 40], [TLB37, 42, 47], [TLB38, 41, 48], [TLB39, 40, 49]) where Sets 1 to 5 examine the effects of varying the X parameter in the signal definition and Sets 6-9 examine the effect of varying Y. If the effect of an input on the net was to make certain cells fire more than others, then these cells could act as indicators of particular input patterns. To examine the effect a signal had on a net, the CFH of the second half of the experiment was examined. With every change of signal the CFH changed, as displayed, for example, by the CFH of time units 501-600 for experiments TLB34-39 (see Figs. 27-32). The CFH of the remaining Sets differed as well, supporting the view that different preferred circuits were being formed for even the smallest change in input. The cells in the first slice had higher levels as they were receiving constant input and therefore fired more frequently. Only in a few cases did cells from other slices fire at a noticeably higher rate than their neighbours and then they tended to do so for several inputs. This may be because of an unusually strong connection path, perhaps caused by two connections being generated to the same cell or one cell receiving pulses from more than one input element.

Conclusions

Whilst different preferred circuits have probably been formed for small input changes, detecting them is still difficult. The 'readout' problem is that it is difficult to tell which pattern has

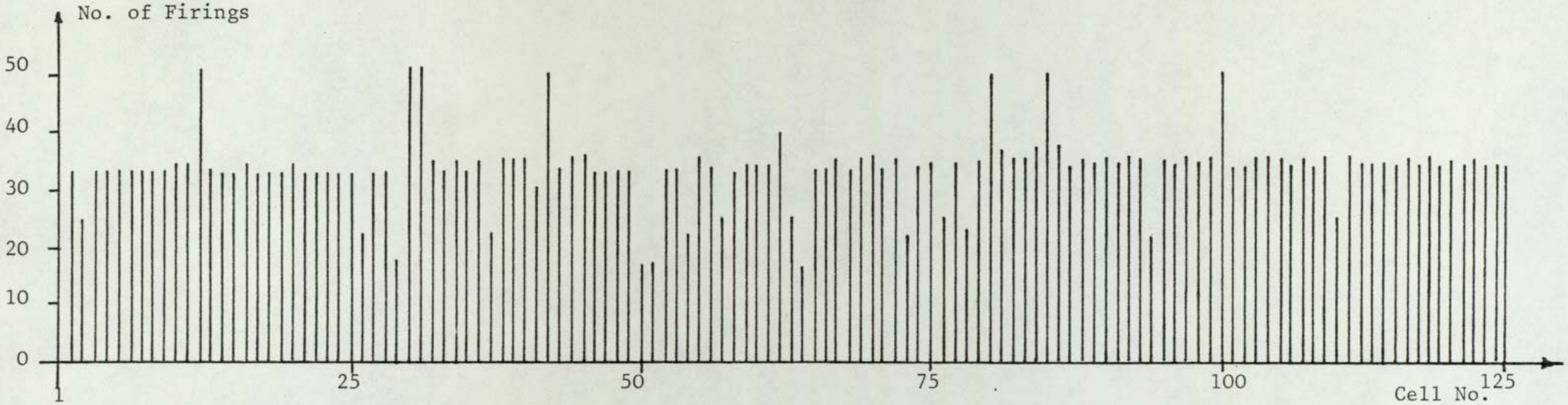


Figure 27 Cell Firing Histogram of Experiment TLB34 (Time Units 501-600)

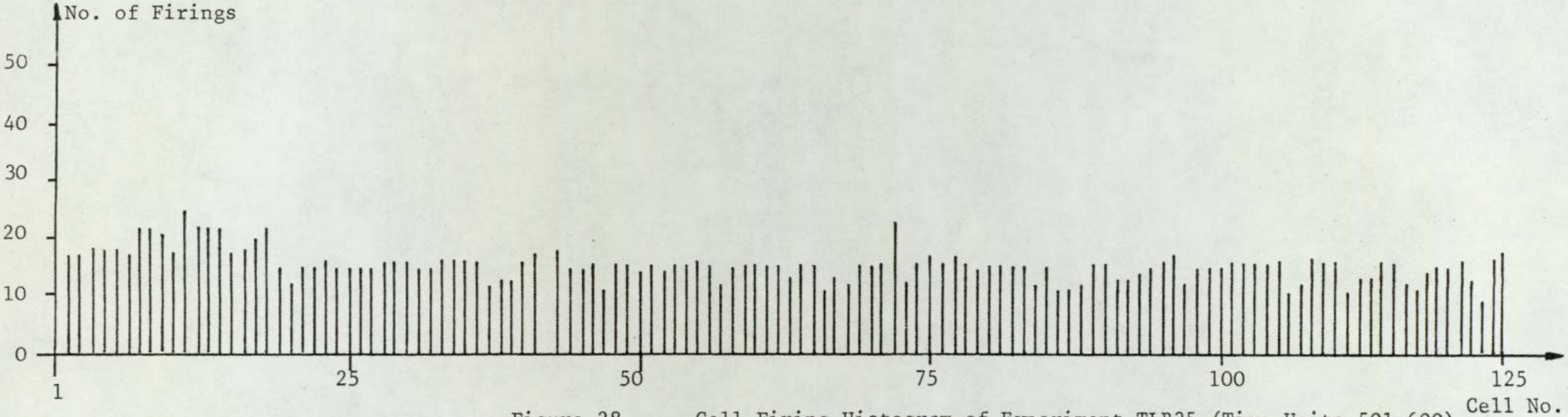


Figure 28 Cell Firing Histogram of Experiment TLB35 (Time Units 501-600)

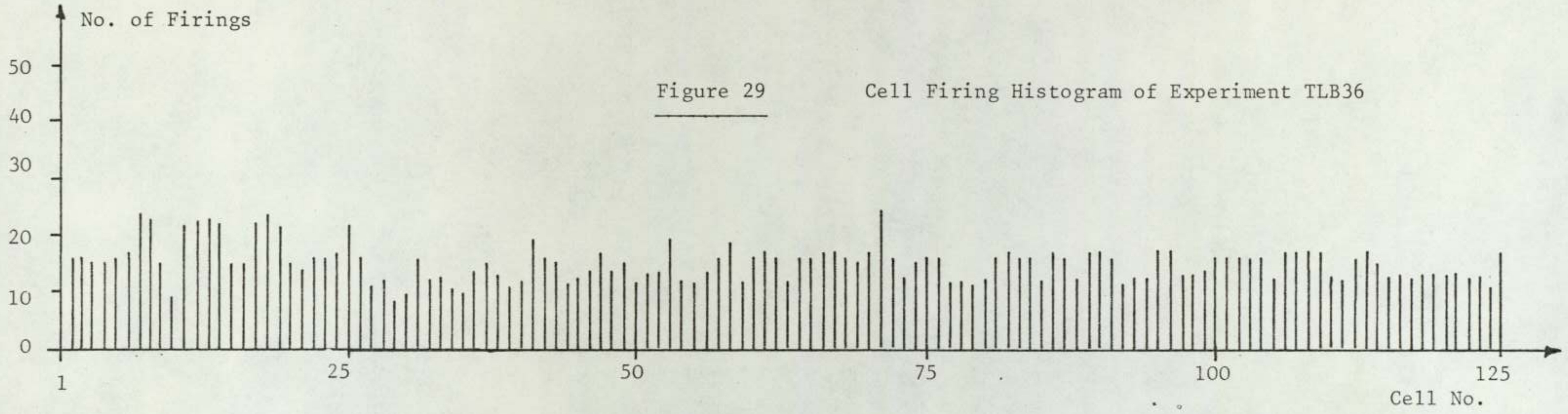


Figure 29 Cell Firing Histogram of Experiment TLB36

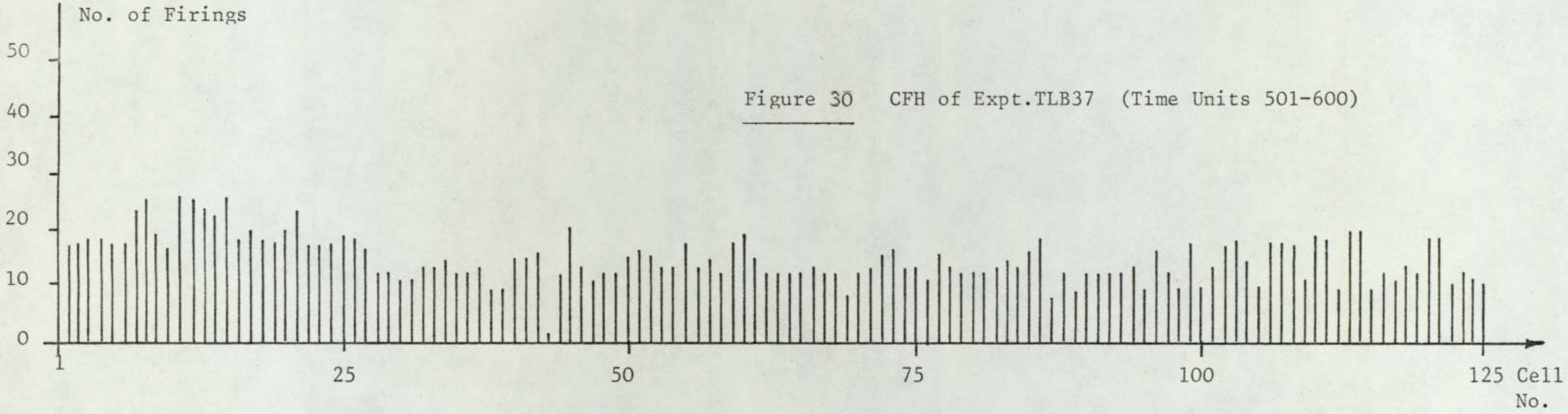


Figure 30 CFH of Expt.TLB37 (Time Units 501-600)

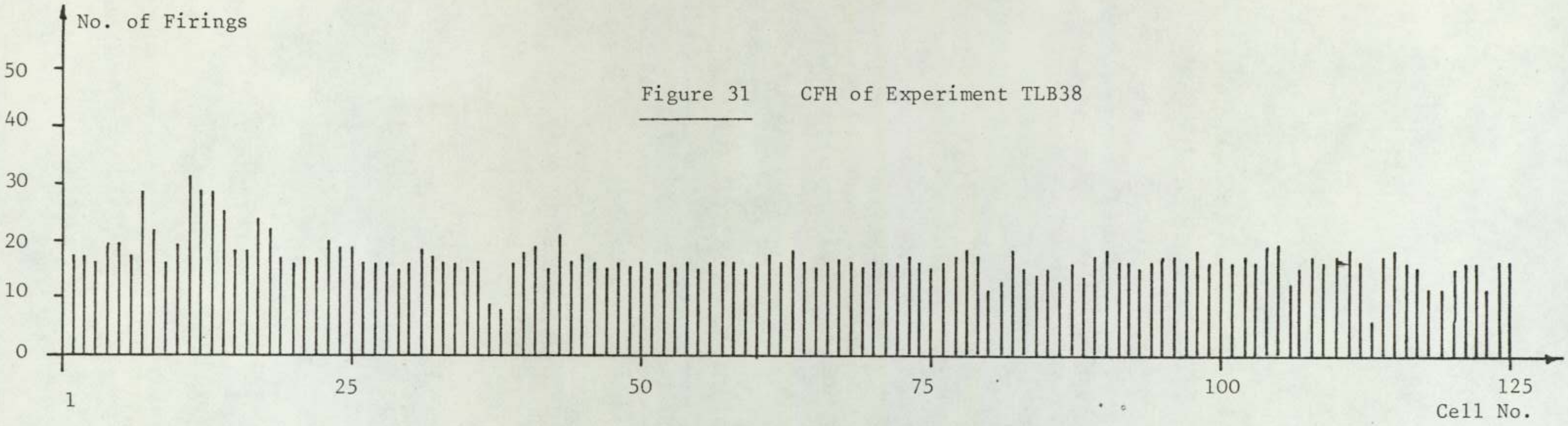


Figure 31 CFH of Experiment TLB38

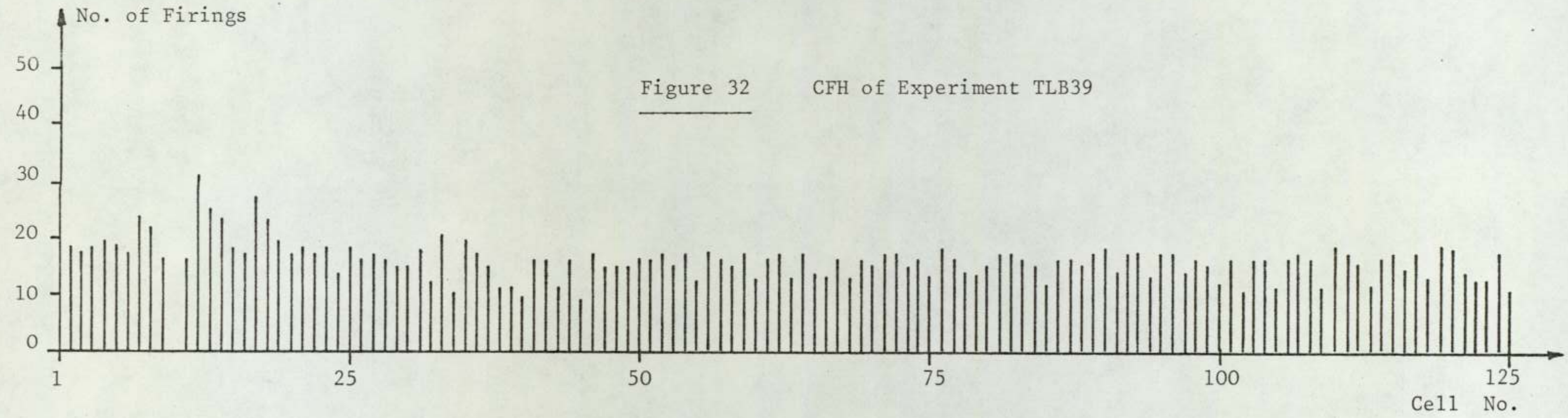


Figure 32 CFH of Experiment TLB39

presented itself, as very few individual cells fire at a greater rate than their neighbours and consequently the information, these high firing cells contain, is limited. Perhaps different values of MSYN and FACTOR would improve this situation. The input elements fire at a higher rate than the rest of the cells so an attempt was made to try and see if it was possible to control this effect by an association property.

Conditioned Reflex Behaviour

The idea was to provide the net with two inputs in the first half of the run and then remove one of them in the second half.

The two inputs were applied to two different areas of the first slice of the net. The input that was on continuously, the permanent input, was applied to the top two rows of cells in the input slice and the input which was removed at the halfway stage of the run, the temporary input, was applied to the bottom two rows of cells. This was simply to keep those cells in the same area, contiguously displayed on the Cell Firing Histogram. As a result of the higher levels of input the two areas receive in the first half there should be a greater chance of the Conditions of Reward to occur. If, as a result, there are links built up to these areas, then even when one of the areas receives no more external excitation, the reinforced pathways to it should raise its activity level above those cells in the other slices. Two groups were run: ([TLB55, 56, 57], [TLB68, 69 70, 71, 58, 59]). The first experiment of Set 1 did not produce any associations as the firing levels of the input sites were not appreciably larger, in the first half, than the other elements in the net as the input level was so low (20 units every time unit, see Table 1). The next experiment used two identical periodic signals in the first half and in the second half the 'permanent signal' became constant. The reason the permanent signal becomes constant is that the second half of the permanent signal could be thought of as an 'enquiry' signal, stimulating the net for a record of what it had just adapted to. If the net showed any retention of the temporary signal in terms of frequency of subsequent behaviour or special type of pattern of activity, then it would be misleading, in the investigation of this, to be supplying the net with just that frequency all through the Experiment. Again no association took place. The third experiment yielded a "disassociation", that is the "temporary" input area had lower firing levels than the surrounding elements. This is probably because the temporary input area either fired exactly with the permanent one or just before it and was therefore highly refractory when the permanent input area fired. Hence the conditions for reinforcement of connections between the areas was rare. Also, as the local bias algorithm was employed, nearby cells will have been triggered by either input and the pulses returning from them will also reach the temporary input site when it is refractory. The decay of connections that are not reinforced means the temporary area will soon receive very little excitation and when the source of its input is removed in the second half, its firing rate will be lower than its neighbours.

The second Set of experiments did provide some associations, however. It was felt that the constant input signal of TLB55 was too low and so various other values were tried (see Table 1).

Experiment TLB68 provided a constant input of 30 units of excitation each time unit but again this did not make the input areas fire sufficiently quickly. An input level of 50 units of excitation, in Experiment TLB58, did provide an association, in that two cells of the temporary input area fired at rates greater than those in the other four slices, but less than those in the permanent area. An input level of 60 units of excitation provided an association of 5 elements (out of ten possible in the temporary input area) in Experiment TLB69. Their subsequent firing levels were the same as the permanent input area. There were also three other cells in the net which now fired at the same rate, situated in the fourth and fifth slice. The CFH of the last half of the experiment is shown in Figure 33. Increasing the input further to 90 (Experiment TLB70) brought the number of associations down to 3 and two others fired at a slightly less rate but more than the rest of the net. (see Fig. 34). Increasing the input to a level of 100 excitation units per time slice brought the associations down to 1 and increasing the level to 120 (Experiment TLB71) means no associations formed at all. In fact, three disassociations formed. The increasing of the input may have forced the exactly synchronous firing of the two areas, which from the discussions concerning the first set of the group, meant the satisfying of the adaption criterion increasingly unlikely. As a result certain cells had their afferent connections "decayed away".

The Effect of Delaying the Signal on the Formation of Associations

To test further the sensitivity of association forming, a periodic input was applied to the net as the temporary input incorporating a delay. The delay was varied to see how it affected the associations built up. The group of Experiments is denoted by

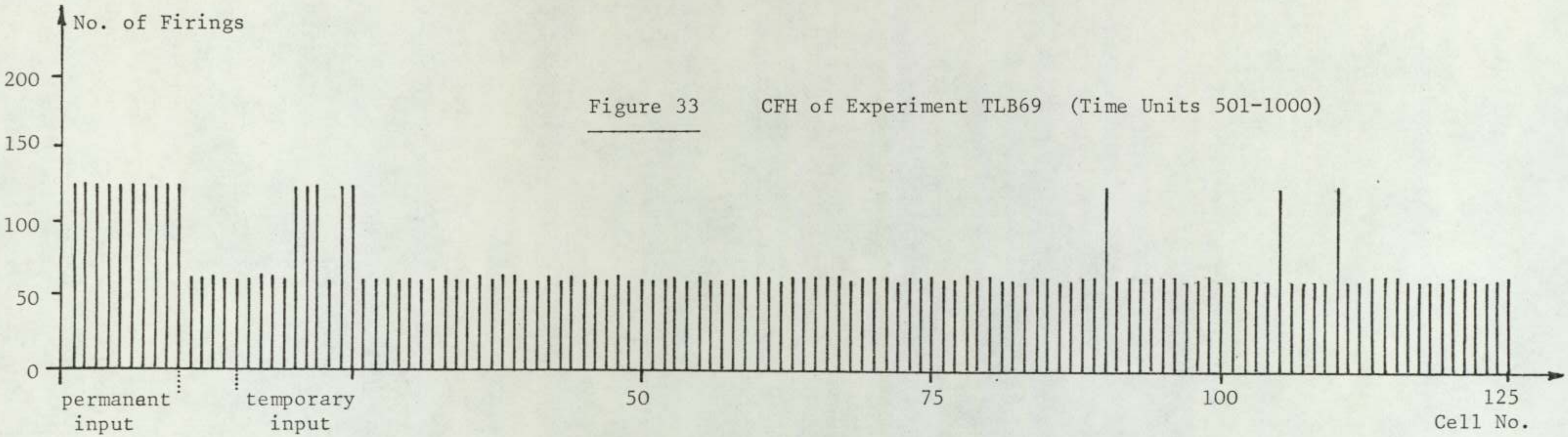


Figure 33 CFH of Experiment TLB69 (Time Units 501-1000)

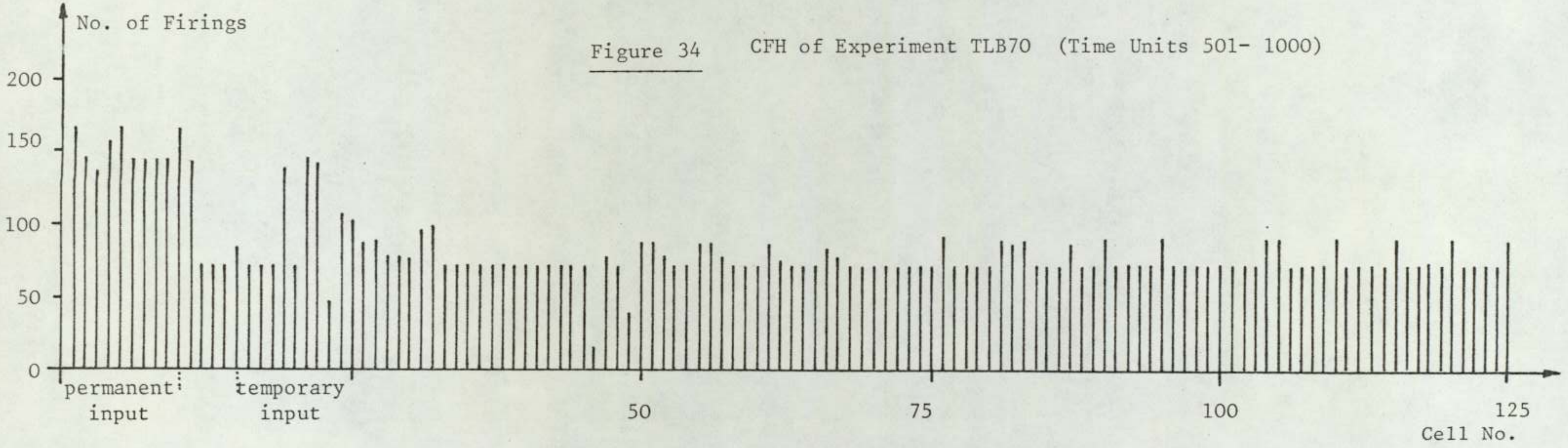


Figure 34 CFH of Experiment TLB70 (Time Units 501- 1000)

([TLB72-76]). The input signal had X, Y values of 6, 1. (see Table 1).

Two runs, using delays on the signals of 3 and 5, produced associations (Experiments TLB 73 and 75). The remainder all produced disassociations, the most exaggerated case involving a delay of 4. (Experiment TLB 74). The resulting CFH of these last three runs are displayed in Figures 35 to 37.

Conclusions

It would seem therefore, that the associative ability of a net is highly sensitive to the relative temporal occurrence of the pair of signals. If the cells of the temporary input area do not fire in the time unit following the instant the permanent input cells fire, then those cells are likely to be inhibited when the temporary input is switched off. Perhaps more 'generous' conditions for Reward would reduce this sensitivity. Nevertheless, this association or disassociation does seem to provide a mechanism for matching signals, as those signals not satisfying the Reward criteria cause strong inhibition in the area in which they were 'compared'.

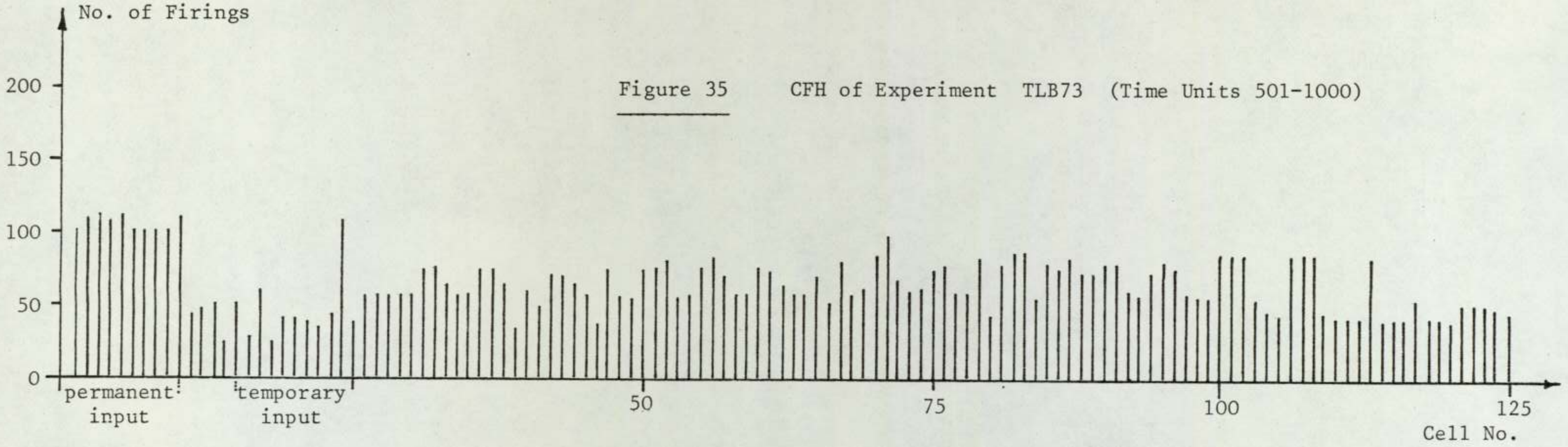


Figure 35 CFH of Experiment TLB73 (Time Units 501-1000)

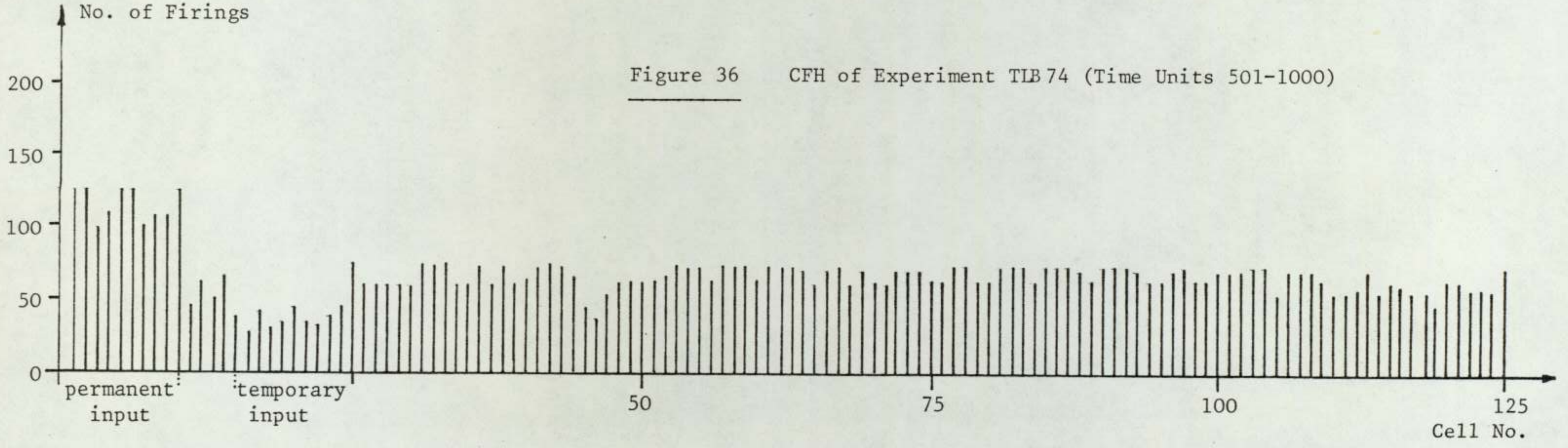


Figure 36 CFH of Experiment TLB 74 (Time Units 501-1000)

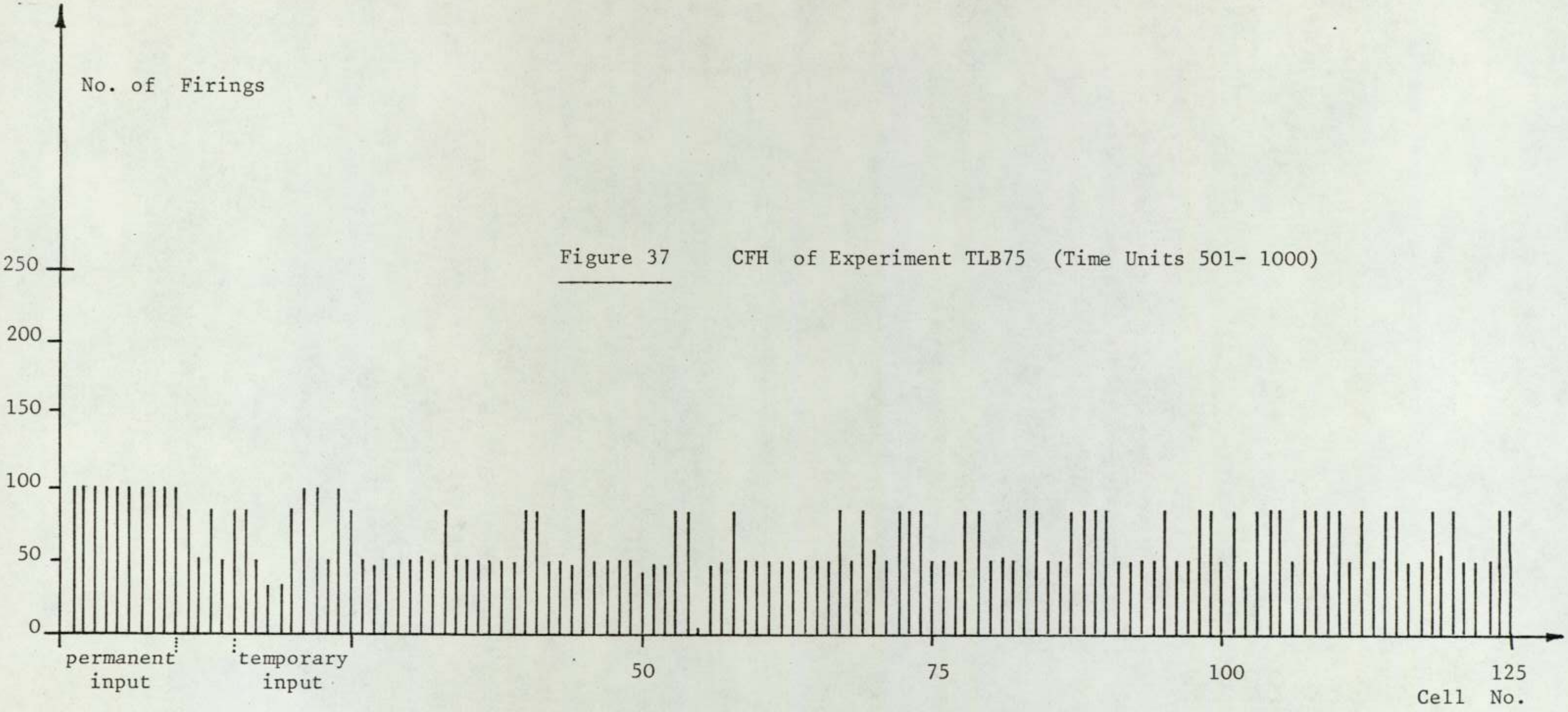


Figure 37 CFH of Experiment TLB75 (Time Units 501- 1000)

Expt. Code	Net No.	Decays	Type	Conn. Mode	MSYN	FACTOR	Adapt Method	X	Y	Input Type	Comment
TL2	25	60	2	Local	512	1/0.1	1	8	1	1	
TL3						5/0.1					
TL4						2/5	2				
TL5							3				
TL6								4		3	
TL7								3			½-Learn
TL8											Full Learn
TL9								4			No Learning
TL10								6			½- Learn
TL11								4			
TL12								5			
TL13					200	20/10	4	4			
TL14						20/20	5				Initial Weight Range = 10
TL16	26				100						
TL17											Rounding Term
TL18								5			
TL19								–			
TL20						10/10					
TL21				3							Toroidal
TL22				3*							Reflecting
TL23											Toroid,init. syn. wt. = 10
TLB1	28						6	6			Modify Excit
TLB2								5			
TLB3								–			No Adaption
TLB4								5			No Adaption
TLB5								–			Split Run
TLB7	29*			2							Random Conns
TLB8	30		1					6			No Adaption
TLB9											Adaption
TLB10								5			
TLB11								7			
TLB12								8			
TLB13				1							
TLB14								7			
TLB15	31	45									
TLB15								8			
TLB17								5			
TLB18	29	60	2					6		1	
TLB19	30		1	2	150					3	
TLB21					105						

Table 1 , page 1

Expt. Code	Net No.	Decays	Type	Conn. Mode	MSYN	FACTOR	Adapt Method	X	Y	Input Type	Comment
TLB22	30	60	1	2	95	10/10	6	6	1	3	
TLB23					100	15					
TLB24					125	10					
TLB25					75						
TLB26					85						
TLB27					100	5					
TLB28						20					
TLB29					90	10					
TLB30					100	8					
TLB31	48	50				10					
TLB32		40									
TLB33		30									
TLB34					50	20					
TLB35		40							2		
TLB36									3		
TLB37									4		
TLB38									5		
TLB39									6		
TLB40								7			
TLB41									5		
TLB42									4		
TLB43									3		
TLB44									2		
TLB45								8			
TLB46									3		
TLB47									4		
TLB48									5		
TLB49									6		
TLB50	67							4	2		
TLB51	68							5			
TLB52	69							6			
TLB53	70							6	3		
TLB54	71							9	2		
TLB55	73							6	2	1/6	ICSIG=20
TLB56	74									4/7	
TLB57	75									5/7	
TLB58	76									1/6	ICSIG=50
TLB59	77										ICSIG=100
TLB60	78							1	1	1/7	ICSIG=20

Table 1,page2

Expt. Code	Net No.	Decays	Type	Conn. Mode	MSYN	FACTOR	Adapt Method	X	Y	Input Type	Comment
TLB65	83	40	1	2	50	20	6	1	2	1/7	ICSIG=50
TLB68	86							6	2	1/6	ICSIG=30
TLB69	87										ICSIG=60
TLB70	88										ICSIG=90
TLB71	89										ICSIG=120
TLB72	94								1	1/7	ICSIG=50 delay=1
TLB73	95										delay=2
TLB74	96										delay=3
TLB75	97										delay=4
TLB76	98										delay=5

Table 1 , page 3

CHAPTER VI

General Conclusions and Further Directions

Introduction

This Chapter collects together the main findings of the Experiments and indicates the areas that appear the most promising for further work. The Conclusions, naturally, only refer to the models of neural networks simulated in this thesis.

List of Conclusions

1. Highly complex behaviour was obtained from simple component units. This was obvious from the first simulation and indicates how difficult it is to predict behaviour without some form of modelling.

2. The type of net simulated with decays of 20-60% and rich interconnections of 5-20 efferent fibres per cell, produces activity which is highly damped and yet, with a constant input, generally stable and oscillatory.

3. The frequency of the activity of the Net is directly proportional to the decay rates of the cells in the net. The frequency resulting was named the Natural Frequency.

4. If cells have different threshold and excitation decays then there is a mixture of frequencies of activity with neither dominating.

5. If the mode of connection is changed (e.g. local bias to random) then the frequency of activity is altered, but the same number of different connections in the same mode has no effect on frequency.

6. Changing from the larger to the smaller net size simulated, can have a slight effect on the frequencies observed. This may be due to a relative increase in edge effects inherent in a smaller net.

7. Periodic input signals to a non-adaptive net do not eradicate the natural frequency of the net, by driving the net at the input frequency.

8. Resonance effects were not observed in these highly damped nets.

9. Non-adaptive nets lose the effect of an input signal very quickly after the signal is removed.

10. The frequency of activity of an adapted net is not related to the frequency of the signal input in a useful way.

11. Cycling in nets' activity levels is only likely in those nets whose cells have a high decay rate and therefore a limited number of states. Consequently, cycling, resulting from adaption, is also only likely in nets with relatively few microstates before adaption.

12. The final activity of an adapted net is highly sensitive to changes in input signal pattern and, therefore, is a unique record of the signal it adapted to.

13. It is likely that different pathways have been formed for each input, which implies that by 'listening' to a subset of the adapted net, the signal produced is likely to be different for different inputs as well.

14. An Associative ability of the net was demonstrated.

15. This ability is extremely sensitive temporally, producing inhibited, or disassociated, areas of the net for conditions not satisfying the conditions for reward.

The aim of this project was to look for interesting machines in the digital models of neural networks. It was hoped to find machines inherently capable of pulse processing functions.

The Adaptive Nets of Chapter 5 satisfied this search. The Non Adaptive nets did not. The area of possible models this Experimental System provides is very large and there was a danger of picking entirely the wrong set of parameters. Indeed, there may still be areas untouched by this project that may yield even more useful machines. However, the Hebbian type algorithm simulated does offer a most promising area to search further. The Key conclusions are 12-15. These conclusions, in combination, provide a possible mechanism for recognising signal patterns. Consider three areas of a net, netlets 1, 2 and 3 of Figure 1. Two signals are required to be matched and they may occur at different times. Their pattern is recorded in netlets 1 and 3. These netlets are made of identical cells and use the same connection mode. After adaption, the final signals pass into netlet two, one signal at one end and one at the other (analogous to the permanent and temporary areas of the Association Experiments). This third area is now adapted and the final level of activity of either area indicates their temporal similarity. This machine therefore employs a memory mechanism and a signal processing mechanism. This idea could be extended to compare unknown signals with standard signals, provided by sets of non-adaptive netlets each having different decay rates.

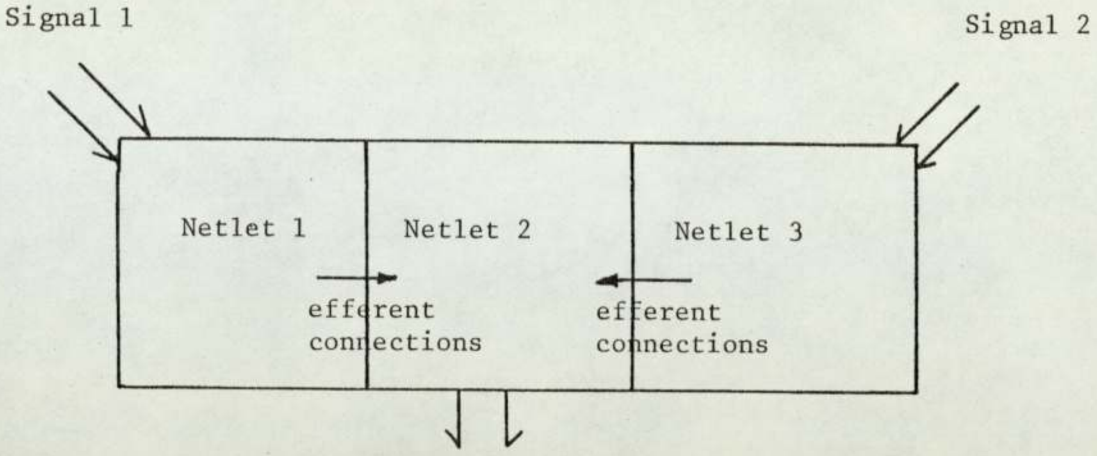


Figure 1

Comparison of Signals by final activity level of adapted Netlet 3

Further Directions

As a result of all the Experiments a possible mechanism for pulse processing has been demonstrated. However, as indicated in the texts of Chapters 4 and 5 there are many areas that could fruitfully be explored in greater detail. A suggested list is:

1. Variations in the Hebbian algorithm to change the conditions necessary for reward, to see if associations can be created more easily and what effect this has on the types of signal 'recognised'.
2. Further analysis on how the associations form, to help the design of adaptive algorithms to solve a required class of problem.
3. Hardware analogues of adaptive nets, perhaps using groups of similar adaptive netlets as building blocks to a larger system.

4. In the search involved in 2, new methods of analysing the formation of underlying connection patterns would be very useful. For examples 3-D displays of the Connection Weight Matrix or the Cell Firing Histogram to illustrate how preferred pathways form. These might provide useful techniques for analysing Natural Neural Nets.

To summarise, with apologies to Sir John Eccles, the task of understanding Neural Nets stagger their own imagination!

APPENDIX A

Spectral Analysis

Introduction

The study of cyclical components in time series analysis is performed using autocorrelation and spectral analysis. As the raw data in this study is from a digital computer simulation, then it is strictly deterministic, unlike a time series which deals with random data fluctuating about a mean value. However, it provides a technique to achieve the data reduction required to analyse the various waveforms produced. The purpose was only to get an indication of the changes in frequency components between different nets. The program to perform the autocorrelation and spectral analysis was taken from "Mathematical Methods for Digital Computers" (1960, ed.A. Ralston and H. S. Wilf, Wiley & Sons, London). This appendix provides a brief description of the program plus the formulae the program implements.

Method

The Spectral Analysis routine, SPEC3, outputs the autocorrelation function r(p), calculated in two similar ways and the autocovariance function W (p) . W(p) is also displayed graphically. In the course of the calculations the raw data is normalised and printed out together with the mean and standard deviation. The data is normalised by first subtracting the mean from each item and then dividing by the standard deviation. The normalisation means the formula for the autocorrelation, $r(p) = \frac{\sum x_i x_{i+p}}{\sum x_i^2}$, $i = 1$ to $N-p$ (1)

(where x_i is the raw data, p is the lag and N is the total number of data items) can be employed. This is an alternative to the usual form

$$r(p) = \frac{(N-p) \sum x_i x_{i+p} - (\sum x_i)(\sum x_{i+p})}{\sqrt{(N-p)\sum (x_i^2) - (\sum x_i)^2} \sqrt{(N-p)\sum (x_{i+p}^2) - (\sum x_{i+p})^2}} \quad (2)$$

which was also used as a check.

The autocovariance function, W(p), was calculated using

$$W(p) = \frac{1}{N-p} \sum_{i=1}^{N-p} x_i x_{i+p} \quad (3)$$

Finally the Raw Estimate of the spectral density or Power Density Function is given by

$$L(p) = W(o) + 2 \sum_{q=1}^{M-1} W(q) \operatorname{Cos} \frac{qp\pi}{M} + W(M) \operatorname{Cos} p\pi \quad (4)$$

Where the W(q) are calculated by (3) and M is the maximum lag.

The Smoothed Power Density Function is calculated using

$$U(p) = 0.23\ L(p-1) + 0.54\ L(p) + 0.23\ L(p+1) \quad (5)$$

Where $L_{-1} = L_1$ and $L_{M+1} = L_{M-1}$

The Raw Spectra and Smoothed Spectra are output graphically and the Smoothed Spectra output again using a logarithmic scale as Jenkins and Watts (1968) suggest, so that the "variation in the spectrum can be accommodated".

The frequency corresponding to each lag (p) value resulting is $f = \frac{p}{2m\Delta t}$ where m is maximum lag, and Δt is the time increment between each data item. (see Blackman and Tukey, 1959).

Using this, an experiment's length could be determined to isolate a particular frequency if one uses the recommendation from Blackman and Tukey that $M < 0.1\,N$. Certain experiments were run to ensure that the rounded values of a particular period fell within one cell of the histogram displayed. This meant the effect could be compared to all other frequency components. This mode of use was employed briefly, the general method being to use a run of 1000 and a maximum lag of 50.

APPENDIX B

```
C               ******************
C               * NET SUBROUTINE *
C               ******************
C
       SUBROUTINE NET
C
       INTEGER COUNT, PTR, EOFLAG, CUNIT, WTINDX, WTIM, TBASE,
      XREWARD, PDEV, FIBLOK, BLOKNO, FIDBAS, FILPTR, TINDEX, CONBAS, FILCN
      XT, ABLOCK, CONPTR, INDEX, TIM, WEIGHT, TBP, REWARD, CNPTR, BLKCNT, UTI
      XM, TOP, BOTTOM, HOWM, CONLST( 460 ), DBFLAG, Z,
      XFILIST( 460 ), THIST, OPNBLK, S, SPNPTR, INP( 40, 40 ), OPTR
      X, GENOPT, SBP, FLENTH
C
       DIMENSION NBAV( 2 ), NNWV( 2 )
C
       COMMON IP( 500 ), NIB( 7360 )/A/ISPPTR( 14 ), IR( 50 ), LEARN( 50 ),
      XISERVO( 50 ), IOBUFF( 1600 ), ISPON( 1000 )/D/IWT( 20 ), ICONNS( 20 )
C
       EQUIVALENCE ( IP( 4 ), THIST ), ( IP( 422 ), NIDBAS ), ( IP( 423 ), NBAV( 1 )),
      X( IP( 425 ), NNWV( 1 )), ( IP( 427 ), NLENTH ), ( IP( 428 ), NBUFSZ ), ( IP( 429 ),
      XOPNBLK ), ( IP( 430 ), NUNIT ), ( IP( 431 ), CUNIT ), ( IP( 432 ), CONBAS ),
      X( IP( 434 ), CONPTR ), ( IR( 1 ), NWV ), ( IR( 2 ), NN ), ( IP( 437 ), FILPTR )
      X, ( IP( 438 ), FIDBAS ), ( IP( 8 ), LBP ), ( IP( 409 ), NTYPE ), ( IP( 408 ), PTR )
      X, ( IR( 5 ), PDEV ), ( IP( 421 ), NIN ), ( IOBUFF( 1 ), CONLST( 1 )),
      X( IOBUFF( 461 ), FILIST( 1 )), ( IP( 419 ), TIM ), ( IP( 413 ), LEVEL )
      X, ( IP( 390 ), NOP1 ), ( IP( 391 ), MN1 ), ( IP( 389 ), CSEED )
      X, ( IP( 387 ), COUNT ), ( IP( 386 ), EOFLAG ), ( IP( 385 ), ABLOCK )
      X, ( IP( 384 ), WTINDX ), ( IP( 383 ), WTIM ), ( IP( 382 ), TBASE )
      X, ( IP( 381 ), BLOKNO ), ( IP( 380 ), TINDEX ), ( IP( 379 ), FILCNT )
      X, ( IP( 378 ), INDEX ), ( IP( 377 ), WEIGHT ), ( IP( 376 ), REWARD )
      X, ( IP( 375 ), CNPTR ), ( IP( 374 ), BLKCNT ), ( IP( 373 ), UTIM )
      X, ( IP( 372 ), TOP ), ( IP( 371 ), BOTTOM ), ( IP( 370 ), HOWM )
      X, ( IP( 369 ), S ), ( IP( 368 ), DBFLAG ), ( IP( 367 ), LP )
      X, ( IP( 366 ), IRP ), ( INP( 1, 1 ), IOBUFF( 1 )), ( IP( 392 ), FIBLOK )
      X, ( IP( 1 ), M ), ( IP( 2 ), N ), ( IP( 3 ), Z ), ( IP( 7 ), SBP )
      X, ( IP( 150 ), NINFO ), ( IP( 151 ), IBLOK ), ( IP( 152 ), IFBLOK )
      X, ( IP( 153 ), NUM ), ( IP( 154 ), NPTR ), ( IP( 155 ), NBLOCK )
      X, ( IP( 156 ), IN ), ( IP( 157 ), NCONT ), ( IP( 158 ), NDBLOK )
      X, ( IP( 159 ), ININFO ), ( IP( 160 ), NCNPTR ), ( IP( 161 ), OPTR )
      X, ( IP( 162 ), IFLAG ), ( IP( 163 ), I ), ( IP( 164 ), NINDEX )
      X, ( IP( 420 ), FLENTH ), ( IP( 220 ), GENOPT )
C
C      START OF PROGRAM
C
       NINFO=1
       EOFLAG=0
       DBFLAG=0
        ININFO=NIDBAS+( NINFO-1 )*16
C
C      READ BLOCK NINFO OF NEURON INFO
C
       CALL RCYL( NBAV( 1 ), NBAV( 2 ), ININFO )
       LP=1
       IRP=1
C
```

```
C
 1     IF(INP(LP,IRP))2,3,2
 2     CALL EXCITE
 3     IRP=IRP+1
       IF(IRP-M)1,1,333
 333   IRP=1
       LP=LP+1
       IF(LP-N)1,1,3345
 3345  FIBLOK=1
 3346  FORMAT(' REWARD = ',I7,' IN = ',I7)
       BLOKNO=1
       IBLOK=BLOKNO+CONBAS-1
C
C      READ FIRST BLOCK OF CONLST
C
       CALL RREC(CONPTR,NWV,NN,IBLOK,PDEV,30000)
 7     IFBLOK=FIDBAS+FIBLOK-1
C
C      READ FIRST BLOCK OF FILIST
C
       CALL RREC(FILPTR,NWV,NN,IFBLOK,PDEV,30000)
       FILCNT=1
C
C      COUNT THE NUMBER OF NEURONS IN BUFFER
C
 11    IF(FILIST(FILCNT))9,8,9
 9     FILCNT=FILCNT +1
       IF(FILCNT-FLENTH)11,8,8
 8     COUNT=1
       PTR=1
C
C      HAS THIS ENTRY BEEN USED BEFORE
C
 40    IF(FILIST(PTR))5 12   EOFLAG=1
       GO TO 60
C
C      CALCULATE ABLOCK FOR FILIST(PTR)
C
 119   NUM=FILIST(PTR)
       ABLOCK=((NUM-1)/CUNIT)+1
C
C      IS INFO IN CURRENT CONLIST
C
       IF(ABLOCK-BLOKNO)50,13,50
C
C     HAVE WE REQUIRED ADIFFERENT BLOCK YET
C
 50    IF(DBFLAG-1)501,502,501
 501   NPTR=PTR
       NABLOK=ABLOCK
       DBFLAG=1
 502    PTR=PTR+1
       IF(PTR-FLENTH)40,40,60
C
```

```
C     HAVE ALL NEURONS IN BUFFER BEEN ACCOUNTED FOR
C
 60   IF(COUNT-FILCNT)14,15,14
C
C     NO REQUIRE ANOTHER CONLST BLOCK
C
 14   CALL WREC(CONPTR,NWV,NN,IBLOK,PDEV,30000)
      BLOKNO=NABLOK
C
C    SETTINGS FOR FIRST DIFFERENCE
C
      ABLOCK=NABLOK
      PTR=NPTR
      NUM=FILIST(PTR)
      DEFLAG=0
      IBLOK=BLOKNO+CONBAS-1
      CALL RREC(CONPTR,NWV,NN,IBLOK,PDEV,30000)
      GO TO 13
 15   IF(EOFLAG-1)18,19,18
 18   FIBLOK=FIBLOK+1
      GO TO 7
C
C      EXAMINE THE CONLST BLOCK AND MAKE LEARNING CHANGES
C
 13   WTINDX=1
      NCON=1
      INDEX=(NUM-CUNIT*(ABLOCK-1)-1)*21+1
C
C    ISOLATE NEURON TYPE
C
      NTYPE=0
      IF(CONLST(INDEX).GE.0)GO TO 131
      CALL GCTIM(CONLST(INDEX),WTIM)
      NTYPE=1
      GO TO 21
C
C    HAVE THE WEIGHTS BEEN ALTERED ALREADY
C
  131 WTIM=CONLST(INDEX)
 21   IN=INDEX +NCON
C
C    EOF TEST (BIT1)
C
      IF(CONLST(IN))23,22,22
 23   NCON=NCON-1
      GO TO 235
 22   IWT(WTINDX)=CONLST(IN)
      WTINDX=WTINDX+1
      NCON=NCON+1
      IF(NCON-20)21,21,23
C    GENERATE THE CONNECTIONS
C
 235  CALL RCTIM(CONLST(INDEX),TIM)
      CALL GEN1(NCON,NUM)
      CNPTR=1
```

```
      NCONT=NCON
 28   IF(ICONNS(CNPTR))30,29,30
 30   NBLOCK=((ICONNS(CNPTR)-1)/NUNIT)+1
C
C     IS REQUIRED NEURON INFORMATION IN CORE
C
      IF(NBLOCK-NINFO)291,31,291
C
C     NO IF NO MORE FROM CORE GET ANOTHER NINFO BLOCK IN
C
 291  IF(NDEFLG-1)292,29,292
 292  NDBLOK=NBLOCK
      NDEFLG=1
      NCNPTR=CNPTR
 29   CNPTR=CNPTR+1
      IF(CNPTR-NCON)28,28,32
 32   CALL WCYL(NBAV(1),NBAV(2),ININFO)
      NINFO=NDBLOK
      ININFO=NIDEAS+(NINFO-1)*16
      CALL RCYL(NBAV(1),NBAV(2),ININFO)
      NDEFLG=0
      CNPTR=NCNPTR
C
C     CALCULATE INDEX TO INFO AND UPDATE
C
 31   NINDEX=(ICONNS(CNPTR)-(NINFO-1)*NUNIT-1)*4+1
      CALL UPDATE(NINDEX,CNPTR,NTYPE)
      ICONNS(CNPTR)=0
      NCONT=NCONT-1
C
C     FINISHED THE AFFECT FOR THIS NEURON
C
      IF(NCONT)28,33,28
C
C      MARK USED
C
C    MARK USED
C
 33   FILIST(PTR)=-1
      COUNT=COUNT+1
      GO TO 502
C
C     EFFECT STAGE
C     CLEAN OUTPUT BUFFER (FILIST AND OP)
C
 19   DO 34 J=461,1600
      IOBUFF(J)=0
 34   CONTINUE
      BLKCNT=0
C
C    WRITE CURRENT CONLST BLOCK BACK
C    TO DISK
C
      CALL WREC(CONPTR,NWV,NN,IBLOK,PDEV,30000)
      OPTR=0
```

```
      LEVEL=0
      PTR=1
      NUM=1
      FIBLOK=1
 35   NINDEX=1
C
C     ISOLATE UPDATE TIME OF CURRENT NEURON
C
 42   CALL GTNTIM(NINDEX,UTIM)
C
C      IF TIME =0  IT MEANS EOF
C
      IF(UTIM)362,36,362
C
C     HAS IT BEEN AFFECTED
C
 362  IF (UTIM-TIM)361,37,361
C
C     YES, SO WILL IT FIRE
C
 37   IFLAG=0
      CALL QFIR(IFLAG,NINDEX)
      IF(IFLAG)363,363,361
 363   CALL ADFIL(NUM,FIBLOK)
C
C     ARE WE DEALING WITH AN OUTPUT SLICE
C
      IF(NUM-NOP1)361,38,38
 361  NINDEX=NINDEX+4
      NUM=NUM+1
      GO TO 41
C
C      ENTER VALUE IN OUTPUT BUFFER
C
 38   CALL ADOP(NUM - (NOP1-1))
      GO TO 361
C
C     FINISHED WITH BUFFER OR NOT
C
 41   IF (NINDEX-NBUFSZ)42,42,36
C
C     IS THERE A SPON OPTION
C
 36   CALL SSWTCH(14,S)
      GO TO (44,43),S
C
C     ARE THERE ANY SPONS IN THIS BLOCK
C
 44   IF (ISPPTR(NINFO))45,43,45
 45   TOP=ISPPTR(NINFO)
      BOTTOM=ISPPTR(NINFO+1)
      IF(BOTTOM)451,452,452
 451  BOTTOM=-BOTTOM
  452 HOWM=BOTTOM-TOP
      I=1
```

```
C
C        HANDLING THE SPONTANEOUS NEURONS
C
 46     IN1=TOP+I-1
        NUM=ISPON(IN1)
        NINDEX=NUM-(NINFO-1)*NUNIT
        NINDEX=(NINDEX-1)*4+1
C
C      HAS IT ALREADY
C      BENN ALTERED
C
        CALL GTNTIM(NINDEX,UTIM)
        IF(UTIM -TIM)48,49,49
 48     IFLAG=0
        CALL SPNFIR(IFLAG,NINDEX)
        IF(IFLAG)491,491,49
 491     CALL ADFIL(NUM,FIBLOK)
C
C       IS IT AN OUTPUT NEURON
C
        IF(NUM-NOP1)49,51,51
 51     CALL ADOP(NUM-(NOP1-1))
 49     I=I+1
        IF(I-HOWM)46,46,43
C
C       IF FINISHED WITH SPONS FOR THIS BLOCK WRITE BACK
C
 43     CALL WCYL(NBAV(1),NBAV(2),ININFO)
        NINFO=NINFO+1
C
C       CHOOSE NEXT NINFOBLOCK
C
        IF(NINFO.GT.NLENTH)NINFO=1
        ININFO=NIDBAS+(NINFO-1)*16
        BLKCNT=BLKCNT+1
        IF(BLKCNT-NLENTH)53,54,54
 53     CALL RCYL(NBAV(1),NBAV(2),ININFO)
        GO TO 35
 54     FILIST(PTR)=0
C
C      WRITE BACK FINAL FILIST BLOCK
C
        IFBLOK=FIDBAS+FIBLOK-1
        CALL WREC(FILPTR,NWV,NN,IFBLOK,PDEV,30000)
        LEVEL=LEVEL+PTR-1
        CALL SSWTCH(8,I)
        GO TO (541,542),I
 542    IF(TIM.LE.500)CALL HEBB
 541    RETURN
        END
        SUBROUTINE ADFIL(NUM,FILBLK)
C
C        SUBROUTINE TO ADD A NEW ELEMENT TO THE DISK FILE FILIST
C
        INTEGER FILIST(460),PTR,FILBLK,FLENTH,FIDBAS
```

```
     X,PDEV,FILPTR
      COMMON IP(500),NIB(7360)/A/ISP(14),IR(50),IEZ(100),
     XIOBUFF(1600),ISPON(1000)
C
      EQUIVALENCE (IOBUFF(461),FILIST(1)),(IP(420),FLENTH),(
     XIP(438),FIDBAS),(IP(437),FILPTR),(IR(1),NWV),(IR(2),NN)
     X,(IR(5),PDEV),(IP(413),LEVEL),(IP(408),PTR)
C
C     START
C
      FILIST(PTR)=NUM
      PTR=PTR+1
      IF(PTR-FLENTH)1,1,2
 2    IFBLOK=FIDBAS+FILBLK-1
      CALL WREC(FILPTR,NWV,NN,IFBLOK,PDEV,30000)
      PTR=1
      LEVEL=LEVEL+460
      FILBLK=FILBLK+1
 1    RETURN
      END
```

```
C              **************
C              * EVALUATION *
C              **************
C
C      SWITCH DETAILS
C
C      1: CONTINUATION (NO IP READ), FLICK CONTROL (ON STARTS),
C         RUN NUMBER OUTPUT ON TTY
C      2: MULTIPLE RUN
C      3: LINE PRINTER DUMP OF NIB
C      4: EXCITATION GRAPH
C      5: THRESHOLD GRAPH
C      6: FIRING GRAPH
C      7: FIRING PATTERN DISPLAY
C      8: LEARN INHIBIT
C      9: WEIGHTS ANALYSIS DUMP
C      10:TELETYPE PRINTOUT INHIBIT
C      11:TRACE
C      12:TRACE
C      13:INDIVIDUAL ELEMENTS
C      14:SPONTANEOUS ELEMENTS (NOW REMOVED)
C      15:INHIBIT RAW DATA GRAPHS
C      16:TERMINATE NET RUN
C
C
       INTEGER Z,SD(4,20),AS,HM,TIM,SDO(4,20),HMO,ASO,DIFF,
      XSBP,CLENTH,VOL,LBP,FIDBAS,SPNBAS,SPNPTR,
      XTHIST,ARC,SUL,S,PRMPTR,PRMBAS,SIGNAL,FILPTR
      X,SPD,SPW,FILIST(460),PDEV,S2,OUT,FETBLK,FET
      X,SUBAS,AP1,BP1,CONBAS,NETN(20),NETR(20)
C
       COMMON IP(500),NIB(7360)
      X/SAVE/IB(460)
      X/CON/INC(25,3)
      X/GR/GBUF(230)
      X/D/IWT(20),ICONNS(20)
      X/RUN/JETTOT(2,200),IFIR(200),INEX(5,200),IOUFIR(5,100)
      X,ISER(200),LER(200),INDELE(5,100),INDELT(5,200)
      X/A/ ISPPTR(14),IR(50),LEARN(50)
      X,ISERVO(50),IOBUFF(1600),ISPON(1000)
C
       DIMENSION INEXM(5),NBPTR(5),IJ(4),INDELM(5)
      X,MARK(3000),IEX1(1000),IEX2(1000),IEX3(1000)
C
       EQUIVALENCE (IP(1),M),(IP(2),N),(IP(3),Z),(IP(10),AS)
      X,(IP(11),HM),(IP(230),ASO),(SD(1,1),IP(32))
      X,(IP(422),NIDBAS),(IP(432),CONBAS),(IP(231),HMO)
      X,(IP(437),FILPTR),(IP(252),SDO(1,1)),(IP(406),VOL),(IP(407)
      X,MT),(IP(419),TIM),(IP(7),SBP),(IP(8),LBP),(IP(442),NETNO),
      X(IR(4),PRMPTR),(IR(3),PRMBAS),(IR(1),NWV),(IR(2),NN),
      X(IR(5),PDEV),(IP(414),SIGNAL),(IP(9),MNZ),(IP(410),MEAN)
      X,(IOBUFF(461),FILIST(1)),(IP(438),FIDBAS),(IP(416),SPNBAS)
      X,(IP(417),SPNPTR),(IP(413),LEVEL),(IP(170),IEXMAX),
      X(IP(171),ITHMAX),(IP(172),IFMAX)
      X,(IP(357),INEXM(1)),(IP(352),INDELM(1))
```

```
     X,(IP(344),NBL),(IP(173),INELNO),(NBPTR(1),IP(340))
     X,(IJ(1),FILIST(1)),(IP(195),LTIM)
     X,(IP(180),FETBLK),(IP(182),FET)
     X,(IP(218),NARCHB),(NMRUNS,IP(219)),(NETN(1),IP(197))
     X,(IP(223),SUBAS),(IP(222),ARC),(IP(221),SUL),(IP(415),CLENTH)
     X,(MARK(1),INEX(1,1)),(IEX1(1),MARK(1)),(IEX2(1),MARK(1001))
     X,(IEX3(1),MARK(2001))
C
C
C
C      START
C
C       READ DOWN PARAMETER BLOCK
C
      OUT=4
      CALL TRAP
C
      CALL SSWTCH(1,S)
      GO TO(12,1).S
 1    PRMPTR=24907
C
C     SET UP RELATIVE CONNECTION TABLE
C
      CALL GENC
      NWV=448
      NN=1
      PDEV=0
      WRITE(1,192)
 192  FORMAT(' INPUT PARAMETER BLOCK ADDRESS (I6) ')
 193  FORMAT(I6)
      PRMBAS=539
      CALL RREC(PRMPTR,NWV,NN,PRMBAS,PDEV,30000)
      NRRUNS=NMRUNS
      DO 194 I=1,NRRUNS
      NETR(I)=NETN(I)
 194  CONTINUE
      NETIN=1
      GO TO 2001
 2000 NETIN=NETIN+1
      IF(NETIN.GT.NRRUNS)GO TO 2005
      IPAR=NIDBAS-(NETR(NETIN)+5)
      CALL RREC(PRMPTR,NWV,NN,IPAR,PDEV,30000)
      SUBAS=ISU+(ARC+SUL)
      NARCHB=NARCHS+(ARC+SUL)
C
C     RECOVER INITIAL SET UP DATA
C
      AP1=MNZ*4/NWV+1
      DO 2002 I=1,AP1
      NT=NIDBAS+I-1
      NF=SUBAS+I-1
      CALL RREC(FILPTR,NWV,NN,NF,PDEV,30000)
      CALL WREC(FILPTR,NWV,NN,NT,PDEV,30000)
 2002 CONTINUE
      DO 2003 I=1,CLENTH
```

```
      NCT=CONBAS+I-1
      NCF=SUBAS+AP1+I-1
      CALL RREC(FILPTR,NWV,NN,NCF,PDEV,30000)
      CALL WREC(FILPTR,NWV,NN,NCT,PDEV,30000)
 2003 CONTINUE
 2001 NINFO=0
      DO 95 I=1,1000
      IEX1(I)=0
      IEX2(I)=0
      IEX3(I)=0
 95   CONTINUE
      JETTOT(1,1)=0
      JETTOT(2,1)=0
      IFIR(1)=0
      CALL SSWTCH(4,I1)
      GO TO(91,92),I1
 92   CALL SSWTCH(5,I1)
      GO TO(91,93),I1
 93   CALL SSWTCH(6,I1)
      GO TO(91,94),I1
 91   CALL GRAFIN
C
C     SET A BLOCK TO ZERO FOR TIME 1
C
 94   DO 1772 I=1,8
      ISPON(I)=0
 1772 CONTINUE
      SBP=2
      LBP=2
      DO 22 I=1,50
      ISERVO(I)=0
      LEARN(I)=0
 22   CONTINUE
      FET=9
      FETBLK=1
C     SET UP LONG RUN DISK FILE POINTERS
C
C     ZEROISE ALL + FILE SIZE
C
      DO 221 I=1,5
      NBPTR(I)=0
 221  CONTINUE
      CALL SSWTCH(4,IJ(1))
      CALL SSWTCH(5,IJ(2))
      CALL SSWTCH(6,IJ(3))
      CALL SSWTCH(13,IJ(4))
      DO 222 I=1,3
      IF(IJ(I).NE.1)GO TO 222
      NBL=NBL+1
      NBPTR(I)=NBL-1
 222  CONTINUE
      IF(IJ(4).NE.1)GO TO 223
      NBPTR(4)=NBL
      NBL=NBL+2*INBLNO
C
```

```
C     PUT EOF IN
C
 223  FILIST(1)=0
      CALL WREC(FILPTR,NWV,NN,FIDBAS,PDEV,30000)
C     DISPLAY NETNO
 200  FORMAT(//' NET NUMBER ',I3//)
 199  TIM=1
      CALL SSWTCH(3,IS)
      GO TO(298,2),IS
 298  CALL NINLP
 2    I=1
C
C     CLEAN IO BUFFER
C
      DO 888 J=1,1600
      IOBUFF(J)=0
 888  CONTINUE
C
C     GENERATE INPUT SIGNAL
C     BASED ON TYPE
C
 3    ISD=SD(1,I)
 41   GO TO (42,43,44,45,46,47,48),ISD
 42    CALL GN1SIG
      GO TO 49
 43   CALL GN2SIG
      GO TO 49
 44   CALL GN4SIG
      GO TO 49
 45   CALL GN5SIG
      GO TO 49
 46   CALL GN6SIG
      GO TO 49
 47    CALL GN7SIG
      GO TO 49
 48   CALL GN8SIG
 49   IST=SD(3,I)
      GO TO(491,492),IST
 491  CALL GENSPR(I)
      GO TO 499
 492  CALL GEN2SP(I)
 499  I=I+1
      IF(I.GT.HM)GO TO 5
      IF(AS.EQ.1)GO TO 41
      GO TO 3
 5    TIM=TIM+1
      CALL SSWTCH(1,I1)
      GO TO(51,52),I1
 51   WRITE(1,53)NETIN,NETR(NETIN)
 53   FORMAT(1H ,' RUN  ',I3,'   NET   ',I3)
 52   CALL NET
      CALL FEATUR
 10   CALL SSWTCH(4,I4)
      CALL SSWTCH(5,I5)
      GO TO (15,16),I4
```

```
 16   GO TO(15,17),I5
 15   CALL GRFTOT
 17   CALL SSWTCH(6,I6)
      GO TO(18,19),I6
 18   CALL FILEV
 19   CALL SSWTCH(3,IS)
      GO TO (297,296),IS
 297  CALL NINLP
 296  CALL SSWTCH(7,I7)
      GO TO(20,21),I7
 20   CALL PATTRN
 21   CALL SSWTCH(9,I9)
      GO TO(396,397),I9
 396  CALL WTDUMP
C
C     TERMINATE OPTION
C
 397  ITIM=MOD(TIM,200)
      IF(ITIM.EQ.0)CALL SAVTIM
 771  IF(TIM.GE.LTIM)GO TO 11
      CALL SSWTCH(16,S)
      GO TO (11,12),S
 12   CALL SSWTCH(10,LS)
      GO TO(2,1022),LS
 1022 WRITE(1,101)TIM
 101  FORMAT(1H ,I3)
      GO TO 2
 11   ITIM=MOD(TIM,200)
      IF(ITIM.NE.0)CALL SAVTIM
C
C    SAVE USED PARAMETER BLOCK IN FILIST DISK FILE
C    FOR BACK UP PROG IF LP FAILS
C
      CALL WREC(PRMPTR,NWV,NN,FIDBAS,FDEV,30000)
      CALL SSWTCH(2,IS)
      GO TO(2004,2005),IS
 2005 CALL FLICK
      CALL RESUL1(DIFF)
      CALL STOP
C
 2004 ISU=SUBAS
      NARCHS=NARCHB
      CALL ARCHIV
      GO TO 2000
      END
```

Appendix C : References

Introduction

The authors included are all those who are specifically mentioned in the text plus those whose work was felt to be relevant and recommended reading for those readers new to the field.

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