AN APPROACH TO THE STUDY OF CYBERNETIC SYSTEMS

BASED ON THE CONSTRUCTION OF MODELS SIMULATING THE CENTRAL NERVOUS SYSTEM

Thesis for the degree of Doctor of Philosophy

by

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SUMMARY

This thesis describes the research that was carried out with a series of engineering models based on the Central Nervous System. The modelling process began with simple hardware simulations of single neurons and their associated synapses, progressed to networks composed of these elemental units, and concluded with a computer simulation of a large, structured neural system. At each stage in this process the current model was critically examined, and both the advantages and disadvantages were assessed in order to specify the direction in which further work was to proceed.

The object of the research is twofold: firstly to construct pragmatic engineering systems by modelling the cybernetic phenomena of self organisation that are ubiquitous in the natural world and yet almost completely absent from the field of engineering, and secondly to use engineering techniques to aid in the task of understanding these phenomena of self organisation, especially with respect to the brain. The concluding model which has resulted from this research is, therefore, not only a useful engineering system which can generalise, select, associate and reproduce a range of sequences, but is also of relevance to the organisation of the brain and could possibly assist the physiologist in his task of interpreting the complex structure of the nervous system.

The thesis begins with two introductory chapters, one to clarify the meaning of Cybernetics, and the other to describe the initial considerations which form the basis of the present cybernetic study. The next four chapters describe the models that were built, and the conclusions are drawn in chapter 7.

ACKNOWLEDGEMENTS

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C H A P T E R 1

THE MEANING OF CYBERNETICS.

THE MEANING OF CYBERNETICS

1.1 Introduction.

The purpose of this introductory chapter is to specify clearly the meaning of Cybernetics. It was deemed necessary because the author has been unable to find a satisfactory definition of Cybernetics anywhere in the existing literature. Weiner's original definition, " The science of control and communication in the animal and machine " seems to embrace the whole of science and is probably responsible for the emergence of pseudo-cybernetic subjects such as 'Psycho-cybernetics', 'Cybernetic Art' and 'Human Cybernetics'. There are more specific definitions such as " The science of the application to engineering of devices and techniques derived from biology " (Ref R.1.2) which state that author's particular interests, but which fail to convey the essence of Cybernetics.

In order to convey this essence, the chapter begins by looking briefly at the historical perspective of Cybernetics and then develops the author's inevitably subjective understanding of its meaning. The chapter concludes by discussing the relationship of Cybernetics to the study of intelligence, as this seems to be one of the central problems for the cybernetician.

1.2 Specialist and Interdisciplinary Science.

In 1959 a catalogue was published listing the sciences then in existence. It contained 1,150 entries . (Ref R.1.35.) This process of progressive specialisation seems to be an inevitable consequence of the rapid expansion of Science, but it means that the horizons of the specialist must become closer and closer. As this happens, communication between the different experts becomes more and more difficult: the specialist has dug an intellectual moat around himself.

By the 1930's it had become obvious that the analysis of the universe into discrete, isolated bits of knowledge was an extremely unsatisfactory state of affairs, and the more enlightened scientists began to consider interdisciplinary studies. This involved a complete change in attitude whereby knowledge began to spread throughout the various disciplines: the natural scientists began to adopt mathematical methods of analysis and the engineer turned to living systems for inspiration. Generally, it began to be appreciated that all the various branches of science can complement each other in a truly symbiotic way.

One of the values of interdisciplinary study is that it produces general theories that are widely applicable; science is plagued with highly specialised ideas that work well within their own restricted reference frame, but are of little value elsewhere. Interdisciplinary science was conceived in order to discover the bridges between the artificially created categories.

To achieve this end, it is essential for the scientist to keep his horizons as broad as possible, for all knowledge is valid and progress is most likely to be made through coherent systems of knowledge which unite rather than fragment.

1.3 Cybernetics.

The emergence of Cybernetics was one of the most important products of the interdisciplinary attitudes that were prevalent during the 1930's and 40's. Advances in control systems and computers were producing behaviour that was sufficiently complex to be interesting to behavioural scientists, and at the same time, physiologists such as McCulloch, Rosenbluth and Walter were beginning to study their subject with techniques taken from engineering. The meeting of these developments came to fruition in two books that were published at the end of the 1940's: Weiner's 'Cybernetics' (Ref R.1.20) , and Shannon and Weaver's 'Mathematical Theory of Communication' (Ref R.1.22). This marked the beginning of the Cybernetic era.

Cybernetics is taken from the Greek 'steersman' and it seems to the present author that the essence of Cybernetics is the study of systems that steer themselves. In alternative language, Cybernetics is the study of self-regulation, problem solving, planning and the attainment of goals. Another definition involves self-organising-systems, but this is just another way of expressing the basic interest in steersmanship.

Thus, the task of the cybernetician is to understand the principles which enable a system to manage its own behaviour, and he will be concerned with the processes of control and communication which are part of this self-organisation. The cybernetician obviously has much to learn from physiology and biology as both can provide examples of cybernetic systems that are partially understood. Engineering is also of assistance as disciplines such as control theory and information theory can furnish the cybernetician with the tools that he needs for his analysis.

And the converse is obviously true: Cybernetics can help to solve some of the problems that concern the physiologist in his search for understanding, and can suggest to the engineer ways in which his machines can be improved so as to incorporate the cybernetic properties which seem to have been previously neglected.

~~This symbi~~osis forms the basis of Cybernetics.

1.4 Cybernetics and Intelligence.

As much of the work in Cybernetics is called either 'Machine Intelligence' or 'Artificial Intelligence', it would seem essential to understand the relationship between Cybernetics and intelligence. However, explicit definitions of intelligence are extremely hard to find, and the meaning of intelligence must inevitably be a matter of opinion.

The relationship between Cybernetics and intelligence can be clarified by regarding them with respect to human behaviour. All humans can solve problems and learn from their experience in order to attain their goals. This behaviour is obviously cybernetic, and the human's capacity to exhibit this behaviour is obviously intelligence. A man's intelligence determines how well he can organise himself and adapt to new situations. Thus in the context of the human, Cybernetics is the study of those factors which enable a man to exhibit intelligence.

If this relationship is generally accepted, then it must also be accepted that all cybernetic systems are also intelligent. In fact, on closer examination, both Cybernetics and intelligence seem to be refering to the same phenomena. Thus, Cybernetics may be regarded as the study of generalised intelligence, and intelligence as the property peculiar to cybernetic systems.

1.5 Conclusion.

In the aforegoing sections, Cybernetics has been described as the study of systems that organise, or steer, themselves in order to attain goals. This steersmanship is the essence of Cybernetics and the job of the cybernetician is to understand the principles that enable a system to manage its own behaviour.

The relationship between Cybernetics and intelligence has been discussed briefly, and it follows that one of the possible methods of investigating the principles that underly the cybernetic, intelligent behaviour of animals could begin with the mechanism that produces this behaviour - the Central Nervous System (C.N.S.). The C.N.S. is the product of two billion years of evolution, and is the most highly organised functional unit available for the cybernetician to study. Thus the search for an understanding of cybernetic systems leads to a study of the structure and behaviour of the C.N.S., for any information which originates from the C.N.S. is likely to provide invaluable assistance to the cybernetician in his task of discovering the principles which underly self organising systems.

It is this approach which is adopted in the present work.

C H A P T E R 2

SOME PRELIMINARY CONSIDERATIONS.

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2.1 Introduction.

This thesis describes a research program that is concerned with the construction of engineering models related to the structure and behaviour of the brain. Chapter 1 has explained why Cybernetics is interested in the brain, and the purpose of the present chapter is to clarify the kind of cybernetic study which has been undertaken.

There is a multitude of methods that are available; each has its merits, and the problem is to select the one that is of most relevance. Throughout this chapter the various approaches are described and discussed, and the reasons for the alternative used in this thesis are presented.

The chapter begins by explaining why the modelling technique has been adopted, and discusses the various ways in which models of the brain may be implemented. Neuron models are then discussed and threshold is introduced. The nomenclature adopted in the thesis is defined, and the chapter ends with a simple neuron model and a preliminary representation of the brain as an assembly of threshold elements.

2.2 The Construction of Models.

A model may be defined as a convenient means of describing those features of a system under investigation which are of most interest to the investigator. A model may be a small scale solid representation, a mathematical equation describing a system, or a computer program.

The widespread use of models is an important method of studying the environment and of communicating the resulting understanding to others. Models are of use in all branches of science, but their greatest use is in interdisciplinary science, where a model can express ideas taken from several disciplines in a single parsimonious form.

A great deal has been written previously on the subject of model making (Refs R.1.3., R.1.5., R.1.8., R.1.32., R.14.1.) and a synopsis of the salient points follows.

1) The construction of a model is a test or demonstration of the designer's understanding of his theory:

"History suggests that a man can create anything he can visualise clearly. The creation of a model is proof of the clarity of the vision. If you understand how a thing works well enough to build your own, then your understanding must be nearly perfect." (Ref R.1.33)
In the author's experience the modelling process inevitably reveals flaws in the original theory. These must be corrected before the model can be completed.

2) Once a model has been constructed, it can be used in a wide range of experiments. This generates an invaluable understanding concerning the possible functions that the model can exhibit, and consequently about the subject that was the source of the model. In this case, the model acts as a <u>thinking tool</u> which enables the research worker to

design his future experiments. It is unlikely that this understanding could be gleaned in any other way.

3) One of the most useful aspects of model making involves the understanding of complex systems. When a system under analysis becomes too complex for a theoretical study to provide a clear understanding, it is possible to build a model of that system, and the construction of and experimentation with the model helps to clarify the structure and behaviour of the original system.
In the work that is to follow, systems are described consisting of interconnected brain cells. Physiology provides no blue-prints, but it does give suggestions and guide lines. When these have been exhausted, the cybernetician has to make his assumptions concerning the structure of these systems and the functions that they may be expected to perform. Generally a theoretical analysis of such a system quickly becomes extremely complex, and it is at this point that the construction of a model becomes of use, since the behaviour of the model provides useful data concerning the structure and functions of the assumed system.

Thus in model making, synthesis and analysis go hand in hand in a symbiotic interaction. When analysis reaches a useful limit, it can be used in the construction of a model. This both tests the existing analysis and helps to define the direction of further work. This method of successive approximations is used throughout the thesis, beginning with an extremely simple model of a single brain cell and concluding with relatively complex plans for an assembly of such cells.

4) Models that are based on an engineering modelling environment occasionally lead to engineering systems of pragmatic value. An example is the artificial kidney machine.

In summary, the usefulness of the modelling technique may be expressed by the following factors:

1) Parsimonious expression of complex data.
2) Test and demonstratation of the designer's understanding.
3) An aid to the understanding of systems which are too complex to be easily understood by a theoretical study.
4) Use as a conceptual, thinking tool.
5) Synthesis of pragmatic hardware.

From this rapid survey it can be seen that there are two broad reasons for the construction of models: the first is the use of models in the process of <u>understanding</u>, and the second is the <u>construction</u> of useful engineering systems. These two go hand in hand, and their interaction is an indication of the importance of the modelling technique.

2.3 Levels of Analysis.

During the last thirty years, there have been innumerable attempts to produce an engineering model which can reproduce intelligent behaviour. These can all be categorised into one of three sections, corresponding to the level of analysis used by the research worker.

Level 1 : The first level is concerned with models of behaviour, and usually involves the use of a large digital computer. It is concerned with the reproduction of intelligent behaviour, without regard for the natural system that exhibits the original behaviour. Level 1 is not interested in physiological structures.
Examples of level 1 models are given in the categorised references under R.5 Computer Programs that Reproduce Intelligent Behaviour. They include the General Problem Solver (Ref R.5.5), a chess playing program (Ref R.5.3), and Natural Language programs (Ref R.5.2). An excellent review of this level is given by Michie (Ref R.5.7).

Level 2 : The second level begins with well known biological phenomena such as association or homeostasis, and involves the construction of models based on these phenomena.
Examples of level 2 models are Associating Machines (Refs R.13.17, R.8.15, R.8.16, R.8.18, R.8.19, R.13.24 , R.13.6, R.13.8, R.13.9), and Ashby's Homeostat (Ref R.11.6).

Level 3 : At the third level of analysis, the Cybernetician focusses his attention on the structure of the brain, and produces models that are based on the elements from which the brain is composed. This approach is reductionist in that it assumes that the behaviour of the brain is a consequence of its components, just as the behaviour of a computer is a consequence of the logic blocks that compose it. Level 3 is concerned

with the explanation of the mechanisms that are responsible for the Cybernetic properties of the brain.
Examples of level 3 models include the majority of hardware neuron models (Refs R.7, R.8, R.9, R.10, R.11, R.12), the work on neural nets both mathematical (R.14), and simulated by digital computer (R.6), and many of the large hardware cybernetic systems listed in R.13.

All of the experimental work that is to be described in this thesis is concerned with level 3 : it begins with a model of the brain's elementary component and builds up networks based on this component. The reasons for this approach are as follows :

1) Level 3 is the only one that is concerned with the machinery of the brain. As the brain is the product of several million years of evolution, it seems reasonable to assume that the engineer has a great deal to learn from its structure.

2) It seems much more sensible to study the brain, which is known to work, rather than to adopt a completely new approach (such as computer programming) which may be inherently unsuitable.

3) By beginning at the most basic level, it should be possible to discover the principles that underly the organisation of simple systems, and to extrapolate these principles in order to gain insight into the behaviour of more complex systems.

2.4 Modelling Environments.

The Cybernetician is faced with a multitude of modelling environments which fall naturally into two categories : hardware and software. Thus each of the three levels mentioned in the previous section may be modelled in two environments. The present work involves both hardware and software models, but the majority of the thesis evolves around hardware simulation. The reasons for this are as follows:

1) A hardware model is an extremely flexible unit : it can quickly be patched into circuits that give an immediate representation of the system under analysis. This flexibility helps the experimenter to develop a working knowledge of the functions which his model can exhibit.

2) Hardware models work in real time and usually with simple spatial mappings. Thus, the analysis can proceed without complex interpretation of results.

3) The highly parallel nature of the nervous system has proved to be difficult to simulate on a digital computer, which is a serial machine.

4) A hardware model may be directly applicable to an engineering process. Recent advances in Integrated circuits suggest that any digital electronic piece of hardware can be made extremely small and relatively inexpensive. Consequently, there is a probability that a hardware cybernetic machine could quickly become an economically viable proposition.

Despite the strength of these arguments, the last model that was produced involved a software simulation. This was found necessary because the system to be modelled was extremely large, and the construction of a hardware simulation would have been an arduous and extremely costly process. In cases such as this, the Cybernetican has no choice but to turn to the computer which, despite its drawbacks, is capable of handling very large systems with relative ease.

2.5 The Use of Threshold.

In any inter-disciplinary subject such as Cybernetics, it is impossible to advance without the assistance of certain concepts that can be applied to the various disciplines that are the basis of the subject. In relation to the study of the brain, an analysis must be made in terms of universal concepts that can then be used in the construction of a model. Thus the concept enables the cybernetician to perform an analysis of physiology and psychology, and then apply this to electrical engineering. The present analysis begins with the concept of threshold, which is universally applicable to any system involving flow.

Threshold is defined as the magnitude that a stimulus must exceed in order to produce an effect. The threshold concept is well known to the electrical engineer as it is the basis of the Schmitt trigger: the input voltage has to exceed a threshold before an output can be produced. The power of the threshold concept lies in its generality. It may be applied to Quantum Mechanics by regarding the quantum jumps in the electron orbitals as the result of a threshold somewhere within the atom. In logic, an AND gate may be thought of as an 'N' input threshold element with a threshold of 'N'. Similarly, an OR gate is a threshold element with a threshold of one. As the threshold varies between one and 'N', the element exhibits the complete range of majority logic phenomena. Even mundane situations can be interpreted in terms of threshold: to open a door the stimulus (pushing the door) must overcome a threshold (friction and inertia) before the effect (open door) is produced.

These examples indicate the power of the threshold concept. Any analysis that is produced in terms of this concept enables the cybernetician to construct a model in any system that itself exhibits a threshold, and this may be electrical, mechanical, chemical, or whatsoever is the most convenient modelling environment.

2.6 Neuron Models and Threshold Units.

This section introduces neuron modelling and must begin with definitions of neuron and synapse.

NEURON : The structural unit of the nervous system. The neuron is a single living cell which is composed of a cell body, and a long, thin 'axon' as shown in Fig 1. There is great variety in the size and shape of different neurons, but they are all basically composed of a cell body and its attached axon.

Fig 1.

SYNAPSE : The region where two neurons come into close contiguity and a signal passes from one to the other.

Fig 2 illustrates three neurons and their synaptic interconnections.

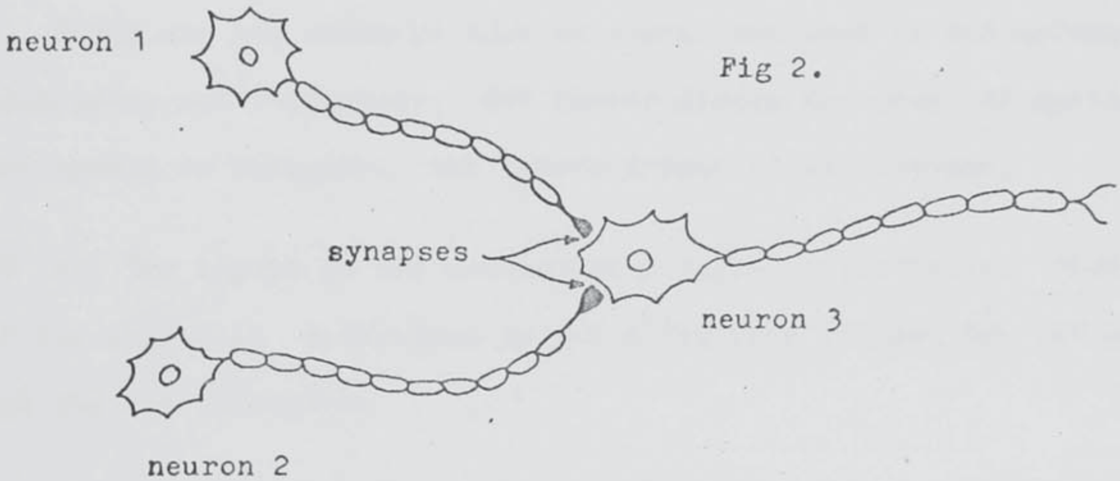


Fig 2.

This may be reduced to a block diagram as shown in Fig 3.

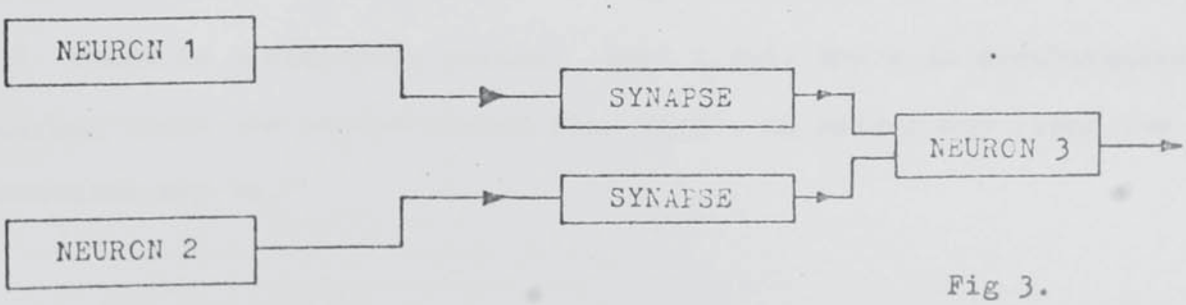


Fig 3.

As can be seen, the neuron and synapse are regarded as separate functional units. Throughout the thesis, the term "neuron-synapse" or "N-S" is used to refer to a single neuron and the synapses at its inputs. Thus, in Fig 3, neuron 3 and the two synapses at its inputs comprise a single N-S element. In this way the properties of the neuron and synapse can be defined without confusion.

Rigorous mathematical analysis of a single N-S has shown that an 8th order non-linear differential equation is required for a complete description of its properties (Ref R.1.18., p631.). This kind of analysis is invaluable in providing the cybernetician with a specification for his models, which is most usefully represented as a list of functional properties as follows:

1) There is a threshold of activation. If the inputs to the N-S cause the excitation level to exceed this threshold, then the neuron will fire, and produce an output of constant size and duration.

2) There are two distinct type of signal produced by the nervous system: excitatory and inhibitory. The former causes the level of excitation in the neuron to increase, the latter causes it to decrease.

3) All the inputs to the neuron are integrated spatially. Thus the effect of the inputs is determined by the difference between the net excitation and the net inhibition.

4) All the inputs are integrated temporally. Thus, a single sub-threshold excitatory input stimulus may be capable of firing the neuron, provided that it is repeatedly presented at a high frequency.

5) There is a refactory period. Once fired, there is a subsequent period during which the neuron cannot fire again, no matter how large the input stimulus may be.

6) The outputs from a neuron can either be all excitatory or all inhibitory. There are no known examples of neurons which produce both excitatory and inhibitory output signals.

7) The response of a neuron habituates. After regular use its output frequency (which is normally determined by the spatial and temporal sum of its inputs) begins to fall, and it becomes progressively more difficult to produce an output.

These are the essential functional properties of the N-S system, the most basic of which is its threshold. Any attempt to produce a model of the N-S must begin by choosing the type of threshold that is to form the basis of the model. In the past an immense number of N-S models has been produced which involve the use of voltage thresholds, magnetic thresholds, mechanical thresholds, logical thresholds, and various forms of mathematical threshold. These models have used modelling environments that range from electrical and mechanical engineering to such fields as opto-electronics and superconductivity. If more information is required, the reader is referred to the categorised references that are given at the end of the thesis, or to one of the reviews that are available (Refs R.1.1., R.1.3., R.1.19., R.14.1.). A comprehensive review of the field of neuron modelling is not given here, as the main result of the author's personal literature search was to re-inforce the hypothesis that threshold is an extremely important parameter in the construction of an N-S model.

In most of the models that were studied the existence of a threshold is self evident, but in others it is not immediately obvious. The SLAM system (Ref R.7.6.) is a digital N-S model in which the connections between the input and output can either be open or closed. This is an extreme case of the threshold phenomenon: an open pathway has a negligble threshold, a closed pathway has an infinite threshold. The vast majority of the N-S models which have been studied have thresholds that lie between these two extremes: pathways are neither fully open nor fully closed, and varying levels of input stimulation are capable of overcoming the threshold and thus propagating the information.

2.6 (a) Development of Neuron Models.

While threshold is a necessary property of any N-S system, it may not be assumed that it is sufficient. The N-S is an extremely complex, highly specialised biological system, and the assumption that it may be modelled by a single threshold element involves a gross oversimplification. Nevertheless, it is with this assumption that the present work begins. The author believes that the most effective modelling philosophy involves initially simple models. As the first approximations prove to be inadequate, further sophistication can be introduced to obviate these inadequacies.

Throughout this process of progressively more complex models, the author regularly turned to the C.N.S. for assistance, for if the models are to have any relevance to the physiology of the nervous system, then this biological knowledge must be fully exploited in the search for a solution to problems which emerge with the models.

This method involves a methodical series of successive approximations, and is of great value in that it involves a gradual aquisition of knowledge.

2.7 Nomenclature.

As the work described in this thesis is interdisciplinary, it is inevitable that the discussion will move rapidly between the various disciplines. It is, therefore, essential to define unambiguously all of the terms which relate to a single discipline. For instance the term "neuron" refers to a biological system and must be distinguished from the electronic models that were constructed to simulate their biological counterparts.

In order to do this as simply as possible, the following convention has been adopted:

neuron	:	biological neuron.
synapse	:	biological synapse.
N-S	:	biological system consisting of a single neuron and the synapses at its input from other neurons.

The engineering systems which were built to simulate the behaviour of these biological elements are referred to as follows:

neuron model	OR	'neuron'
synapse model	OR	'synapse'
N-S model	OR	'N-S'

Thus, from this point onwards, whenever neuron, synapse or N-S appear within single inverted commas ('neuron', 'synapse', 'N-S') it may be assumed that the term refers to an engineering model of a biological system.

2.8 <u>The Decade Counter as a Neuron Model</u>.

The models that are described in this thesis all evolve around the concept of a <u>number threshold</u>. The experimental work began with the oversimplification that any system that exhibits a number threshold can be approximated to a neuron model. The most obvious example of this is a decade counter.

Consider the system illustrated in Fig 4:

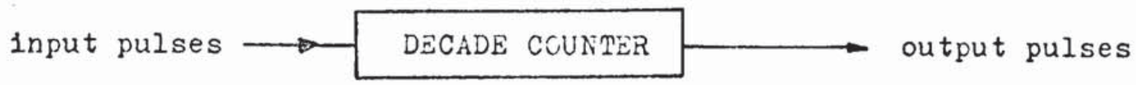


Fig 4.

Ten input pulses must be presented to the system before an output pulse is produced. This behaviour will repeat itself, as shown in Fig 5:

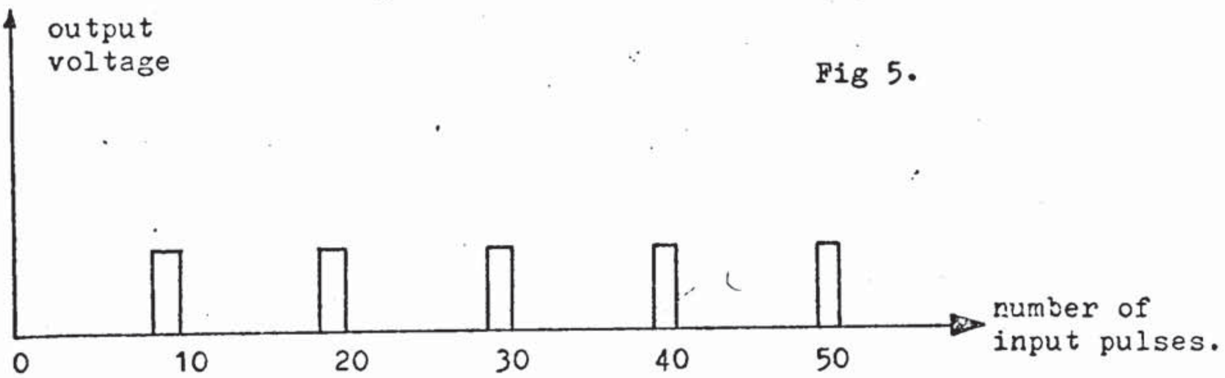


Fig 5.

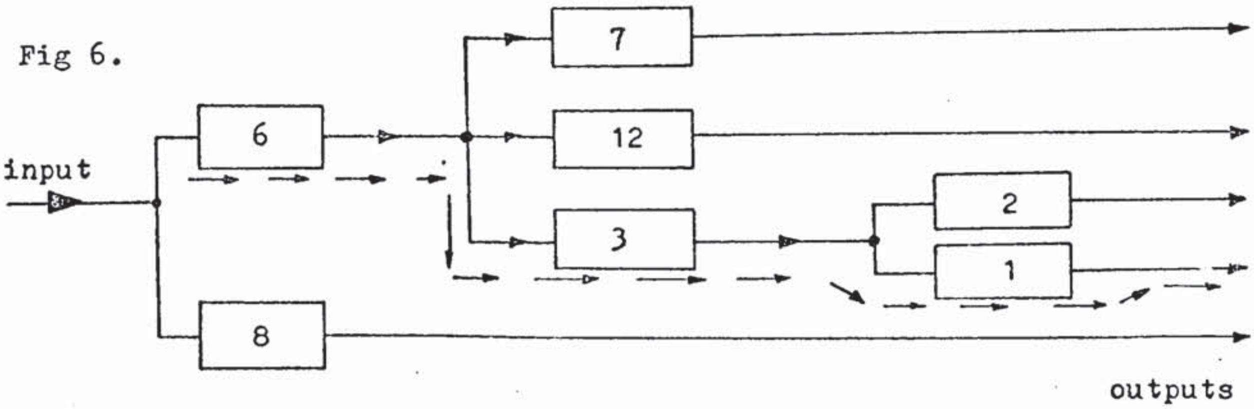
An output pulse is produced every ten imputs, and this is of a constant size. Consequently it may be regarded as having a threshold equivalent to ten input pulses. As the output is produced by a succession of single input pulses, the model also exhibits temporal summation . Further, an output causes the counter to be reset and this means that it possesses a refractory period.

The model does not exhibit spatial summation or habituation, and it is obviously inadequate as an exact N-S model. It does, however, provide a first approximation which is both simple and accessible and thus of pragmatic value.

2.9 The Brain as an Assembly of Threshold Elements.

By assuming that the fundamental property of a N-S is its threshold, the brain may be conceptualised as a system consisting of 10^{10} interconnected threshold elements. Again this is an oversimplification, but it does provide insight into one of the basic properties of any brain-like system : the way that the information flow is determined by the relative threshold values. Fig 6 represents an interconnected system of threshold elements. The value of the threshold (H) is indicated by the number in each of the boxes.

Fig 6.



If an input is presented to the system, the information will flow along the path indicated by the arrows, as it will always flow along the branch which contains the lowest threshold. This is a universal property of threshold systems and has previously been described by Farley and Clark (Ref R.6.1) as follows:

"When the average threshold in an area is raised, activity tends to avoid it, and when the average is lowered, activity tends to be attracted into the area."

Considerations such as this lead to the hypothesis that the brain may be approximated by a network of threshold elements in which the flow of information is determined by two factors: (a) the pattern of interconnections and (b) the relative threshold values of the elements.

2.10 Summary.

This chapter has described the preliminary considerations upon which the rest of the thesis is based. They are as follows:

1) Model making is an extremely powerful approach to the study of the environment.
2) There are three levels of analysis open to the cybernetician who wishes to study the brain. The present work is involved with the third level: N-S modelling and the systems that result from these models.
3) It is assumed that the behaviour of the brain has its basis in neuronal events, and can be explained in terms of signals which by synaptic operation fire neurons.
4) The modelling technique can use either hardware or software modelling environments. Hardware appears to be the more powerful, and thus the present work begins with hardware models.
5) Threshold is a powerful interdisciplinary concept which is of use in modelling the nervous system.
6) The N-S may be modelled by a threshold element, and the decade counter presents a simple, accessible implementation. It also introduces the concept of number threshold.
7) The brain may be approximated as an assembly of threshold elements, in which the information flow is determined by the structure and the relative threshold values of the elements.

C H A P T E R 3

PLASTICITY.

PLASTICITY

3.1 Introduction.

The main purpose of the experimental work undertaken in this research program is to provide an understanding of the processes that underly such phenomena as learning, memory and perception. The author has assumed that these phenomena are the result of neural circuitry, and that by experimentation with models of neuron-like elements, engineering systems may be constructed which produce similar phenomena.

In section 2.6, the fundamental properties of the N-S were defined, but no capacity for change was provided. As all intelligent behaviour involves changes in the behaviour of the organism, it seems safe to assume that somewhere in the machinery that produces this behaviour,changes must also occur. Chapter 3 concerns these changes. It begins by introducing and discussing the two possible types of change that may occur - structural and plastic - and explains why the latter is the more plausible alternative. Previous cybernetic machines that exhibit plastic change are discussed and categorised, and the author's electronic models of plastic change in the N-S are introduced and described. Finally, the author's initial experiments with plastic N-S models are outlined with respect to the explanation of learning, memory, association and simple perceptual phenomena.

3.2 Structural Change and Plastic Change.

All intelligent behaviour involves changes in the behaviour of an organism, and this must be produced by some change in the machinery of that organism which produces the behaviour. It may be of two types:
1) Structural Change: the change in behaviour may be the result of the growth of a new neural circuit, or the severing of an existing one. In engineering terms, structural change involves the re-wiring of a circuit, or the addition of new components.
2) Plastic Change: the behavioural change may be the result of changes in the strength or effectiveness of components within the existing system.

To clarify this dichotomy, consider the system of threshold elements illustrated in Fig 6.* A change in the behaviour of this system may have been produced by a structural change, such as the addition of a new threshold element or the reconnection of some of the existing elements; alternatively a plastic change may have occured, such as the alteration of the value of threshold (H) in one of the elements. Thus, if the behaviour changes so as to give an ouput from output 1, then this may be the result of the addition of high H components in all the other channels (structural change), or of the lowering of the value of threshold from 7 to 2 in that channel (plastic change).

Throughout this thesis it is assumed that plastic change is the mechanism that underlies the meaningful changes in the behaviour of the brain. Physiologists are now reasonably sure that, after the age of about five years, the structure of the human brain is unchanged :

"Nerve impulses are transmitted over definite, restricted paths in the sensory and motor nerves, and in the central nervous system from cell to cell through definite intercellular connections" (Ref R.2.28)

As structural change seems to be out of the question, we are forced to turn to plasticity. Direct evidence of plastic changes in the

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N-S has been accumulating during the last few years, and there is now a considerable body of knowledge in support of the plasticity hypothesis (Refs R.3 'Evidence of Plasticity'). The review of Kandel and Spencer (Ref R.3.1) contains the evidence for plastic change that was available in 1968. It contains 367 references, and leaves the author in no doubt that, within the nervous system of humans and animals, plastic changes do occur, and that this is the mechanism that underlies intelligent behaviour.

Long before plasticity had been demonstrated experimentally, it had been the basis of several theoretical works attempting to show how cellular mechanisms can result in intelligent behaviour. The most famous of these is Hebb's 'Organisation of Behaviour', in which the plasticity hypothesis is clearly stated as follows:

"When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased.' (Ref R.2.1)

The references listed in R.4 'Theories based on the Plasticity Hypothesis', all begin with Hebb's basic assumption and then use it to account for the behaviour of parts of the brain. Although these theories develop along very different lines, they exemplify the power of the plasticity hypothesis in showing how cellular changes can account for the behaviour of an intelligent organism.

The case for plastic change is considerable from both the physiologist and the psychologist's point of view, and it is therefore not surprising that the vast majority of engineering learning systems has exhibited plasticity in one form or another. There have been several computer simulations that change the threshold of the input channels to each 'N-S' element (Refs R.6.5., R.6.6., R.6.7., R.6.10., R.6.11., R.6.12., R.6.20.).

Hardware learning systems have involved plastic changes of several different forms. These include changes in the state of oscillating circuits (Ref R.8.15), in probabilities (Ref R.13.12), in magnetic fluxes (Ref R.13.9), in statistical switches (Ref R.13.3), in bits on a magnetic tape (Ref R.13.17) in motor driven potentiometers (Refs R.13.14., R.11.2) and even in such parameters as the resistance of chemically coated cotton wires (R.10.4) and the state of iron balls in an acid solution (Ref R.10.3). Probably the most practical plastic element is Widrow's memistor (Ref R.10.13), a solid state system which changes its resistance as the result of a control signal.

This very rapid survey of plasticity in physiology, psychology and engineering learning machines should suffice to illustrate the importance of plastic change. The rest of the thesis is concerned with the way in which plastic changes at the cellular level can result in intelligent, behavioural changes.

At the end of Chapter 2, the brain was approximated to an assembly of threshold elements in which the information flow is determined by the relative threshold values. This model can now be extended to embrace the plasticity hypothesis: if the behaviour of the system is determined by the value of the threshold of its components, then the plastic changing of these values produces the intelligent behaviour of that system. In other words, <u>the study of intelligent behaviour is the study of the way in which plastic changes are controlled</u>.

3.3 Internal and External Control of Plastic Change.

During the 1950's and 1960's, a large number of learning machines were developed which use plastic changes that are controlled externally. They may be described generally by Fig 7.

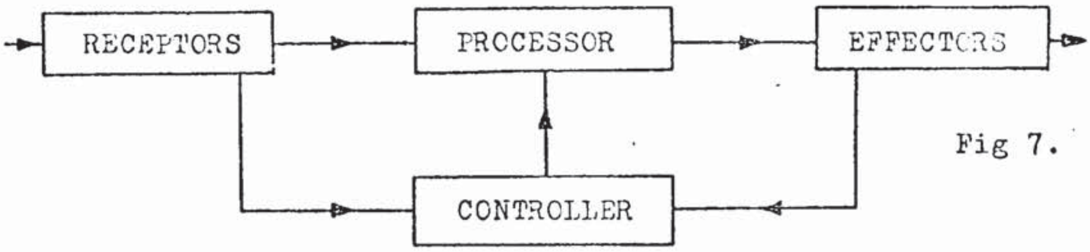


Fig 7.

The operation of these machines is dominated by the 'controller', which is an all-knowing system capable of changing the plastic parameters of the 'processor' so as to give the required system performance. Eventually the processor 'learns' to exhibit the type of behaviour that is demanded by the controller.

An enormous amount of energy has been expended on this type of system; the most famous example is the Perceptron (Ref R.1.8), but there are many others (Ref R.1.34). Generally, they are called "Trainable Pattern Classifying Systems". It is the opinion of the author that this type of system leaves much to be desired as a brain model. The existence of an all-knowledgeable part of the brain can be dismissed, and thus there is no parallel with the structure of the brain. Further the 'learning' process is better described as 'setting up', and the system is only capable of mimicking. These criticisms do not mean that the Perceptron is of no value: it is an engineering system which was designed to recognise patterns and in this it is successful. It cannot, however, offer any assistance in the cybernetic problem that is central to the present research - how does the mechanism of the brain produce intelligent behaviour ?

The alternative to the Perceptron type of system involves plastic changes that are controlled internally. This entails plastic changes in the 'N-S' that are determined automatically by the information at the inputs and output of the 'N-S'. This is exactly the type of plastic change that has been found by the physiologist, (Refs R.3), and that forms the basis of the psychological theories mentioned in the previous section (Refs R.4). Hebb's hypothesis gives the Cybernetician a description of the type of internally controlled plastic change that is of importance in the synthesis of a brain model.

Due to the influence of the Perceptron program on Cybernetics, most plastic changes have been externally controlled. There are, however, a few exceptions to this. The work of Taylor (Refs R.6.20., R.8.17., R.11.2., R.13.13) has involved both hardware and software models based on the internally controlled plasticity idea. He states:

"It has been demonstrated that an increase of transmission with use is a sufficient condition for the learning of visual pattern classification ." (Ref R.8.21., p 166)

Other examples of hardware internally-controlled plastic systems can be found in the work of Steinbuch (Ref R.13.9), Young (Ref R.13.17), and Uttley (Ref R.13.12). All of these change the strength of their component parameters when certain relationships between input and output are fulfilled.

3.4 Models of Plastic Change.

In order to investigate the behaviour of a hardware system of internally controlled plastic elements, it was necessary to design and build a model of plastic change which is capable of exhibiting the features described in Hebb's hypothesis, without being excessively expensive.

Previous models of plastic change were reviewed, and all were found to be unsatisfactory. Three alternatives are apparent. The first involves the charge on a capacitor which represents the threshold of a system component. As that component is used regularly, the charge is changed and thus the threshold is lowered. This approach has been used by Taylor (Ref R.8.21), Uttley (Ref R.13.12) and Wilkins (Ref R.8.19), and is unsatisfactory because the capacitors inevitably leak, and thus all the plastic changes gradually fade away. As the average human is capable of remembering data for several years, a permanent storage of plastic change becomes an essential design feature.

The second approach is to use motor driven potentiometers to store the threshold values. This alternative has been used by Taylor (Ref R.11.2) and in the Perceptron program (Ref R.13.14). Although its functional properties are ideal, the motor driven potentiometer is bulky, expensive and slow. As the author was planning to build systems involving thousands of plastic units, this was obviously out of the question.

The only other possibility was the Memistor (Ref R.10.12), which is ideal in terms of its properties and size, but also very expensive and thus outside the budget of a PhD program.

As all these alternatives proved to be unsuitable, the first priority became the design and construction of a small, inexpensive, internally-controlled, plastic element. During the first year's research, several plastic elements were constructed, all of which used digital

(and thus integrateable) components. In order to explain the behaviour of these models, it is necessary to describe only one of them, as they all evolve around the same basic principles. Details of the six plastic models that were developed, and the reasons for their increasing complexity may be found at the end of the thesis in Appendix 1. (page 159)

Fig 8 illustrates plastic model 4 (PM4), and is shown below:

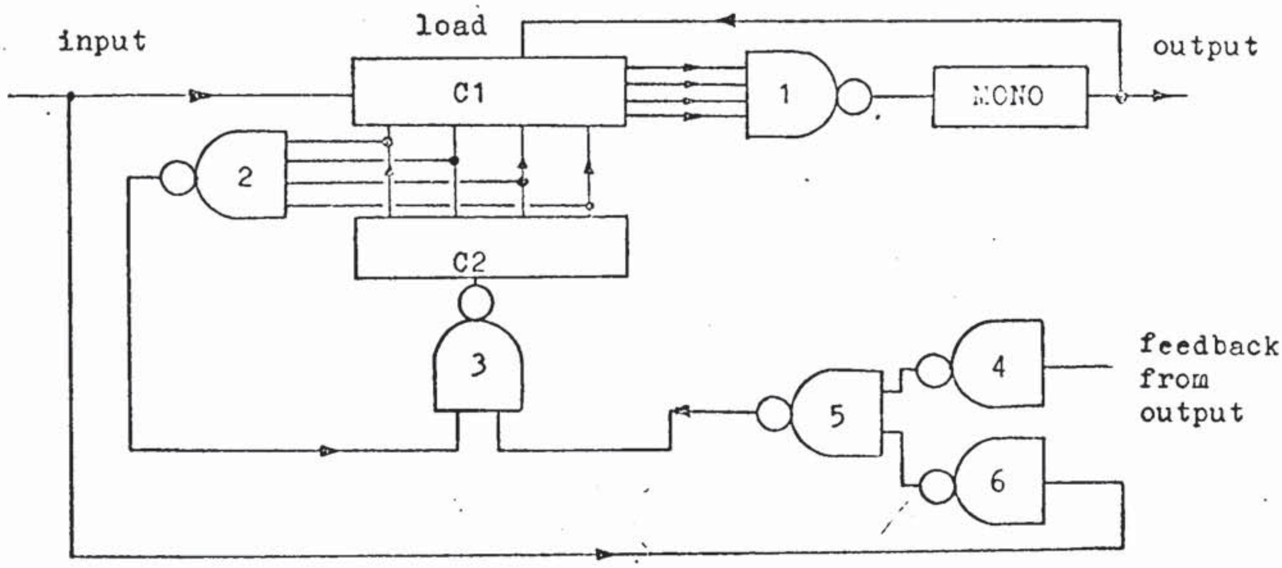


Fig 8.

C1 and C2 are two binary counters (0 to 15) which initially both hold zero. As inputs are presented to the system, C1 counts up, and when it holds 15 (binary 1111), an output pulse is produced by the MONO. This is the basic number threshold described in section 2.7.

The output from the MONO sets the 'load' input on C1 to zero volts, causing the contents of C2 to be read into C1. Initially C2 contains zero, and thus 16 input pulses are again required to count up C1 and to fire the MONO.

NAND gates 4,5 and 6 ensure that the contents of C2 is incremented only when there is a co-incidence between the input and output pulses. Practically this means that C2 is incremented when input pulses are presented at a frequency greater than 3·5 Hz. This frequency is dependent on the characteristics of the output pulse from the MONO, and is not of paramount importance in the design.

Thus, when the input frequency is greater than 3·5 Hz, 16 input pulses are needed to fire the cell, and then C2 is incremented. The '1' in C2 is then read into C1 due to the 'load' signal, and thus only 15 pulses are required to produce an output pulse. Thus, the number threshold of the system has decreased.

The process of incrementing C2 continues progressively (thus diminishing the number of input pulses needed to fire the cell) until C2 contains 15. At this point NAND gates 2 and 3 prevent further input to C2, and thus it cannot recirculate. Thus when the cell is used repeatedly or persistantly, its threshold decreases progressively until one input pulse is able to fire the system. This behaviour is illustrated in Fig 9.

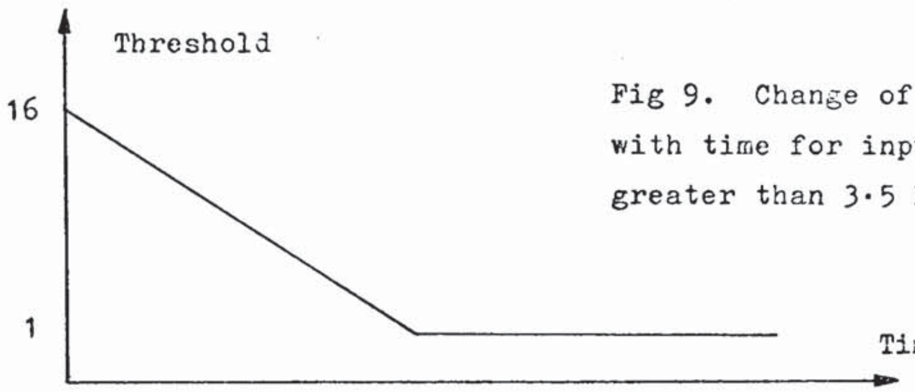


Fig 9. Change of Threshold with time for input frequency greater than 3·5 Hz.

The development of this system occupied several months work. The most severe practical problem that had to be overcome was the construction of a digital system which only changed its behaviour for high frequency input signals. Digital equipment is ideal for the long term retention of data, but inherently unsuitable for the modelling of short term phenomena that must be forgotten within a few seconds. The design of PM4 is unique in that slow input pulses have no effect on its basic property, and yet regular and persistant input pulses lead to progressive threshold lowering, ie to internally controlled plastic change, which is retained for as long as is necessary.

3.5 The Use of the Plastic Model in Simple Networks.

Having completed the design and construction of a satisfactory plastic model, a series of experiments was initiated in order to study its properties both singly and in combination. This section describes the first, simple experiments that were performed.

3.5.1 The Location of the Plastic Element in the 'N-S'.

The model PM4, illustrated in Fig 8, is a single input, single output device, and may therefore be considered as a plastic N-S model with a single input. As the N-S has many inputs, the first undertaking was to design a plastic system with three inputs. The first approximation is shown below in Fig 10.

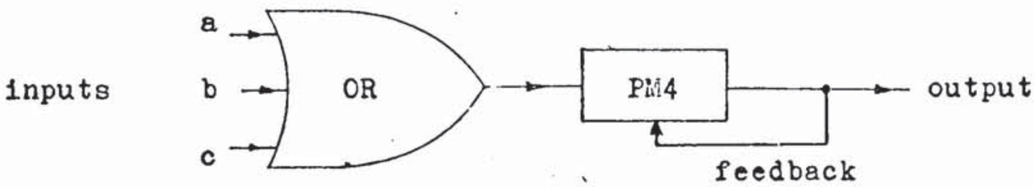


Fig 10.

As soon as the experiments began, it became obvious that this arrangement was unsatisfactory as there was no way of distinguishing the inputs. For example, a regular input to input b caused the threshold of the plastic element to fall as required so that input b produced an output with a single input pulse. However, a single input to either input a or input c also fired the model, and in order to distinguish all the inputs, the plastic element had to be relocated as shown in Fig 11.

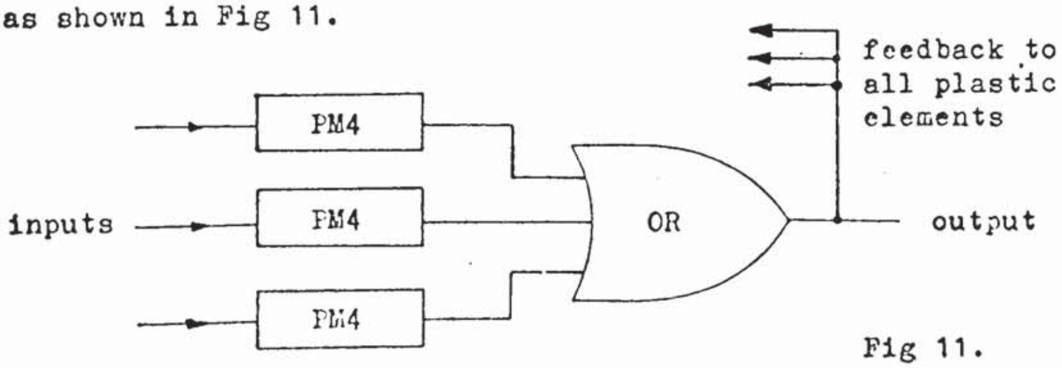


Fig 11.

In all cases, the feedback which controls the plastic changes is taken from the output of the 'N-S' system. Thus in Fig 11 a PM4 element will change its behaviour if it is presented with a pulse train with a frequency greater than 3.5 Hz., and the other two plastic elements will be unaffected since there can be no co-incidence between input and output. Fig 11 is, therefore, a model of a N-S with three inputs in which regular and persistant signals into any one of its input channels cause plastic changes to occur relative to that channel only. Fig 11 describes the organisation of the plastic 'N-S' systems which are the elemental hardware units used in the experiments described in this chapter. The location of the plastic unit at the input means that the model is in agreement with the aforementioned works on physiology and psychology which generally locate the learning phenomena in the N-S at the synapse. In order to be consistant with these works, the lowering of threshold at the synapse will hereafter be considered as an increase in synaptic weighting, and is given the symbol "W".

3.5.2 Association.

To many of the early psychologists, it seemed likely that the phenomenon of association was the basis of the whole of the brain's behaviour, and this view is still prevalent among cyberneticians today. The present author does not hold with this opinion, but the importance of association as an inherent property of neural networks cannot be denied. During the early experiments with plastic N-S models, a possible explanation of this was found: in any single plastic N-S model association is an inherent property. Consider a simple model consisting of two plastic elements ('synaptic' weights W1 and W2) arranged as illustrated in Fig 12.

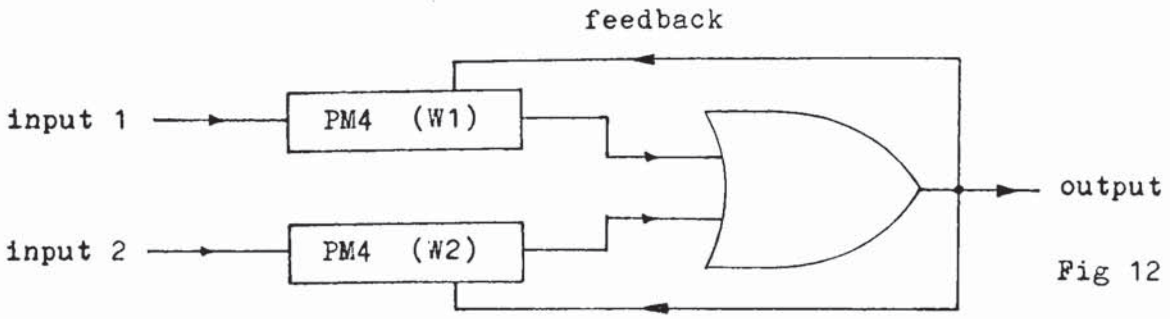


Fig 12

Let us assume that input 1 has been used regularly so that a plastic change has occured in that input channel such that every input pulse into input 1 causes the system to fire. For the purposes of this experiment, input 1 is considered as the "specific stimulus" and the output from the 'N-S' as the "specific effect". Input 2 produces an output only after 16 input pulses and this is considered as the "neutral stimulus".

Now, let us suppose that the neutral stimulus is unable to produce a plastic change in the system due to insufficient excitation frequency. Nothing will happen unless the two inputs are presented <u>co-incidentally</u>. If this occurs, then the input to the plastic element in channel 2 will co-incide with the output from the 'N-S' caused by input 1, and consequently W2 will begin to rise. After 15 co-incidences W2 will be at its upper limit, and a single pulse into channel 2 will fire the system.

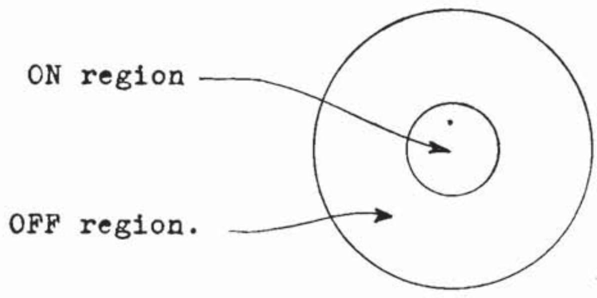
Thus, when the specific stimulus and the neutral stimulus are presented co-incidentally, the system learns to associate so that the neutral stimulus eventually produces the specific effect. The way in which plastic change is controlled (which depends upon a co-incidence between the input to, and the output from the 'N-S') ensures that all the inputs to a plastic N-S model can associate with each other.

3.5.3 A Model of the Visual C.N.S.

The plastic models were then used in a series of experiments based on the structure and function of the visual nervous system. The work was inspired by the experimental evidence of Hubel and Weisel (Refs R.2.24., and R.2.25.) which gives the cybernetician a sound behavioural basis on which to begin. Their work shows conclusively that there are cells in the brain that respond to very specific kinds of visual input stimuli, and to nothing else. The experiments that follow were designed to synthesise a system that teaches itself to exhibit these phenomena from the information that is presented to it. There are no external controllers: any input stimulus modifies the system so that it is more sensitive to further input of that stimulus. This means that the system will only "see" those inputs which have been presented to it regularly, a phenomenon recently reported by Blakemoor and Cooper (Ref R.3.16.).

The first experiment was designed to simulate a system which produces the "spot response" reported by Hubel and Weisel. They found that stimulation of the retina by a small round spot of light in a specific location produced an excitatory response (called the "ON response") in one specific cell, and that stimulation with the light spot around the ON response location produced an inhibitory response (OFF response) in the same cell. This is illustrated below in Fig 13.

Fig 13: Receptive field for ON centre spot response.



A model exhibiting this behaviour was constructed, and is illustrated in Fig 14. It consists of five receptors (R1 to R5), and eight plastic elements with weightings W1 to W8 grouped in three 'N-S' systems each with a single output.

As in the previous models, learning occurs when there is a co-incidence between the input to, and output from the 'N-S'. Thus, if R1 and R2 are both activated at frequencies above 3.5 Hz, AND gate X will produce an output pulse and consequently W1 and W2 will change plastically. Eventually both W1 and W2 will reach their maximum weighting values, and AND gate X will respond every time that a stimulus is presented to both R1 and R2. In a typical experiment, the input frequencies were set at about 5 Hz., and the learning process was completed in a little more than seven minutes.

AND gates Y and Z may be taught in a similar manner: the former learns to respond to an input from R2, R3 and R4, the latter to R3, R4 and R5.

The possibility of learning any particular pattern is dependent on the built-in structure of the network, but the pattern which is actually learnt depends on the experience of the machine.

The three AND gates X', Y', and Z' and their inter-connecting circuitry are a digital implementation of the lateral inhibitory structures which are found throughout the nervous system. In the early experiments the inhibitory system was connected between AND gates X, Y, and Z, but this involved 4-input NAND gates which were found to be unreliable. Consequently the system was built using extra circuitry, as shown in Fig 14.

The inhibitory system ensures that each output responds to a stimulus at the centre of its receptive field, and is inhibited by

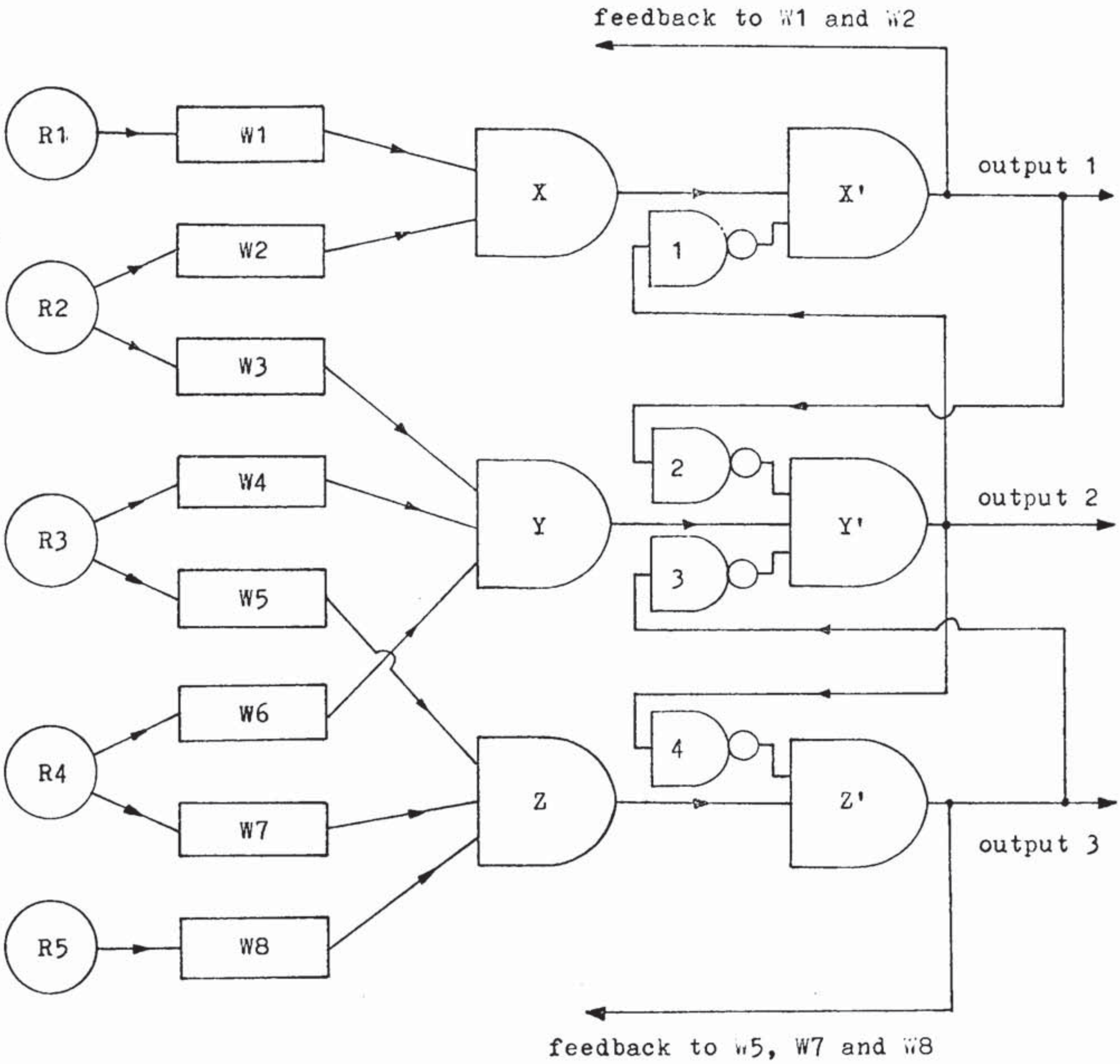


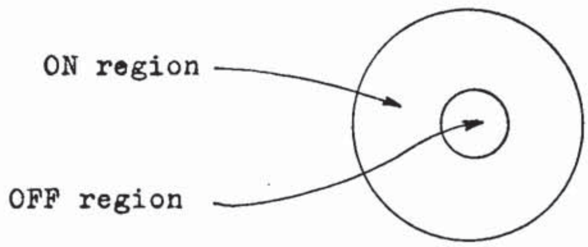
Fig 14: Plastic model which learns to exhibit "spot response" behaviour.

: Output 2 is fedback to W3, W4 and W6.

stimuli around the periphery. Further, it explains how the various receptive fields may overlap: an input due to the stimulation of R3 may either be part of an ON stimulus for AND gate Y (if R2 and R4 are also stimulated) or an OFF stimulus for AND gate Y (if R4 and R5 are stimulated).

Hubel and Weisel also found cells which exhibit the reverse response, which are called "OFF centre cells". The receptive field of an OFF centre cell is illustrated in Fig 15

Fig 15: Receptive field of an OFF centre cell.

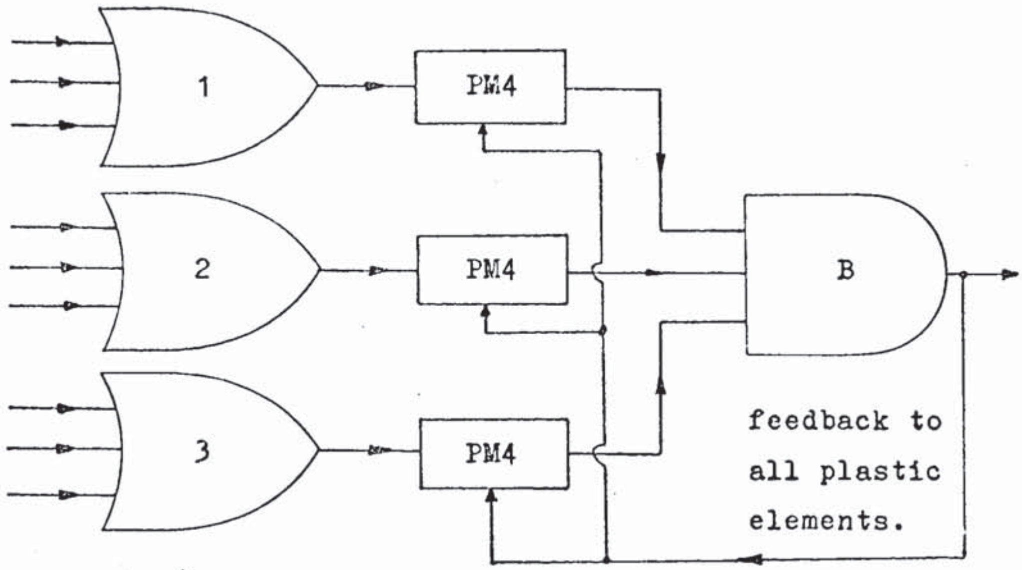


OFF centre cells are inhibited by a stimulus at the centre of their receptive fields and excited by stimulation at the periphery. A system to simulate this behaviour could easily have been constructed by connecting three invertors: the first between X and X', the second between Y and Y', and the third between Z and Z'. Thus stimulation of R2, R3 and R4 would inhibit output 2 and stimulation of R1 and R2 would inhibit output 1 , and thus excite output 2.

It is interesting to note that the system illustrated in Fig 14 exhibits both ON centre and OFF centre characteristics. The AND gates X, Y, and Z exhibit ON centre properties, as has just been described. NAND gate 1 is inhibited when R2, R3 and R4 are stimulated and activated when either R1 and R2, or R4 and R5 are stimulated. It is, therefore, an OFF centre cell.

When cells in the visual cortex are examined, some of them are found to respond to a bar of light in the same way that the cells in the retina respond to spots. The bar response has been assumed to be a consequence of the spot response, and may be modelled as shown below in Fig 16.

from outputs of "spot response" model.



As the output from the spot response model illustrated in Fig 14 allows only one output in three to be active at any one time, a kind of majority logic is needed. Fig 16 illustrates an implementation of this which involves digital components. Each of the three OR gates (1,2 and 3) has three inputs from a single spot response system.

When a bar is presented to the receptors, a number of spot response AND gates will be activated, and these will activate AND gate B. The relevant plastic elements will learn if the stimulus is presented regularly and persistantly, and eventually the system learns to respond to that particular bar.

The bar response cells show similar ON/OFF receptive fields to the spot response cells, and the present model has assumed that the former is a direct consequence of the latter. For example, consider nine receptors arranged as shown in Fig 17.

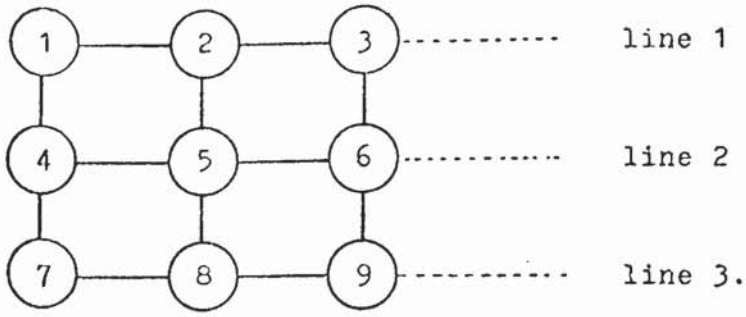


Fig 17.

The lateral inhibition system ensures that every cell at the spot response level inhibits its immediate neighbours. Thus, if line 2 is activated then the inhibition at the spot response level will ensure that lines 1 and 3 are inhibited.

The model shows that the spot response may be regarded as a functional element which ensures that every bar, no matter what its orientation, will exhibit the necessary on/off behaviour without the addition of further neural circuitry.

The last effect to be modelled was the moving bar response. Certain cells in the cortex respond to a bar of light moving in one direction, but not in the opposite direction. A model exhibiting this behaviour is illustrated in Fig 18.

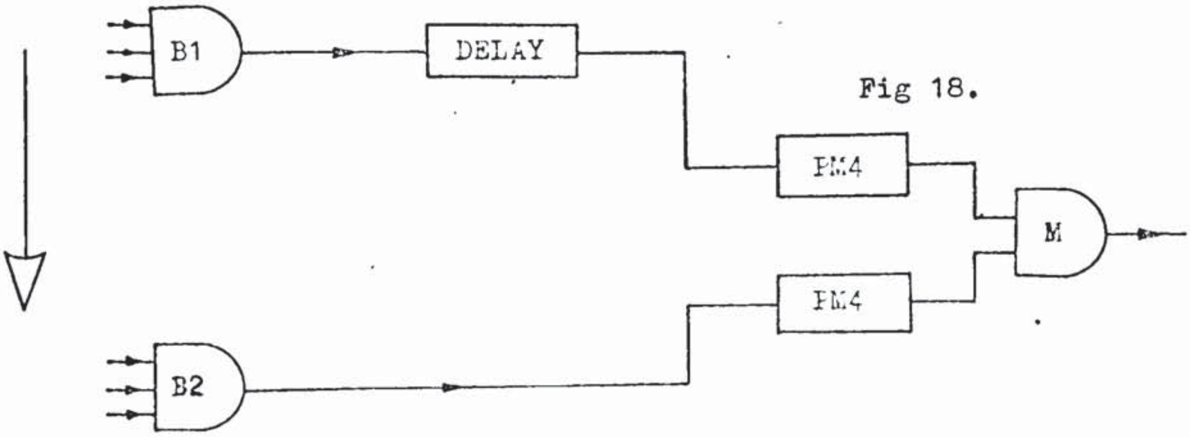


Fig 18.

A bar moving in the direction indicated will produce an output from B1 followed by an output from B2. If the time difference between these signals is similar to the delay in the system, then the two signals will co-incide, the two 'synapses' illustrated will change plastically, and the gate M responds to the moving bar.

The experimental system built to illustrate this effect took several minutes to complete the learning process, and it had to be assumed that the output from B1 and B2 was in the form of a short burst of pulses. At the completion of the process of teaching the system, the gate M responded to a bar moving in the downward direction, but not to a bar moving in the upwards direction. The system had learnt, therefore, to be <u>direction sensitive</u>.

All of these experiments illustrate how an input stimulus can itself teach the visual system to learn to respond preferentially to that stimulus in the future. It is likely that a large system could be built from these prototypes, and that given a comprehensive classification system, its behaviour would be non trivial.

3.5.4 Learning and Memory.

Learning and memory are both terms that are closely connected to the concept of plastic change. Intelligence involves changes in behaviour, and this is assumed to be the result of controlled plastic changes. Learning, the process by which intelligent behaviour is attained, may be regarded as the process by which plastic changes are produced. Similarly, memory becomes the endurance of the plastic changes that are produced as the result of the learning process.

The Cybernetician is in an invaluable position as his language is limited neither to physiology nor psychology. Thus, learning and memory (two psychological terms) may be re-thought in purely physiological concepts , in order to gain a greater understanding. From this point of view, the model of plastic change is an extremely useful aid to analysis: it shows that learning and memory are two properties that are inherent in any plastic system. The former refers to the way in which plastic changes occur, the latter to their endurance.

3.5.5 Assessment of the work on Simple Neural Networks.

The work described in this section involved the construction of networks of neuron and synapse models, which were designed in order to do a particular job. In the case of the visual system, the function of the system was defined, and then the model was constructed using the 'neural' elements. In this way it is very easy to construct a simple simulation of basic properties of the C.N.S. This work was not radically different from that of Uttley (Ref R.1.18., p 123) and others, although it did begin from a different perspective.

The difficulty with this kind of approach becomes apparent when an attempt is made to extend the scope of the model to perform non-trivial learning or classification tasks. It quickly becomes apparent that as the power of the system rises arithmetically, the amount of necessary apparatus increases geometrically. In the case of Uttley's systems mentioned above, the relationship between the number of inputs (I) and the number of 'neurons' (N) is given by :

$$N = 2^I$$

This is obviously an absurd situation, for if all the brain's 10^{10} cells are used, then for complete classification only 33 inputs are permissable.

In order to resolve this problem, it must be realised that the behaviour of any cybernetic system is determined by the interaction of two factors:

(a) The hardwired, inherited <u>structure</u> , ie the built-in interconnection pattern and the basic properties of the elements.

(b) The changes that occur in the properties of these elements as a result of the learning process.

All learning machines are affected by both these factors, and the difficulty arises in the choice of balance. The systems described in 3.5, and the early work of Uttley, Taylor and others are all dominated by the first factor: their structure. These 'structure-dominant-systems' (S.D.S) exhibit properties that are largely determined by the interconnection pattern of the elements, and the effect of the learning process - the second factor - is generally to select the relevant sub-systems from the alternatives presented. This is certainly true of the work described in this section, as reference to 3.5.3 will clarify.

The main drawback to the S.D.S is the extension of simple networks to large, powerful, cybernetic machines. Another serious problem involves reliability: as the behaviour of the system is dominated by the built in interconnection pattern, any change in this pattern (due to, say, the death of one of the neurons) will interfere with, and possibly eradicate, one of the essential properties of the system. It is possible that the learning process will be able to find another identical circuit which performs the same function, but this requires a great deal of 'back-up' in order to ensure that the system can withstand damage. It is possible that S.D.Ss do exist in the peripheral areas of the C.N.S., for the severing of nerve fibres in the visual region of animals does lead to the loss of specific functions, and these can only be re-learnt with great difficulty. But the majority of the brain, especially the cerebral cortex, shows an astonishing resistance to damage and decay, and it must therefore be concluded that the in-built structure is of secondry importance. Somehow, the interconncection pattern provides a foundation which, although obviously involved in the resulting behaviour of the system, allows the learning process to play a significant or even a dominant role.

In order to discover the way in which this kind of system is organised, it is necessary to abandon all intentions of designing a system with a specific structure which is to do a specific job. The most obvious alternative is a system with random interconnections, for if the built in structure is random, then the learning process must perform the self-organisation and thus dominate the properties of the system.

It was at this point that the work with plastic elements changed its emphasis from structure dominant systems, and began to experiment with randomly interconnected networks.

3.6 Conclusion.

In this chapter, internally controlled plastic change has been introduced as the cellular mechanism most likely to underly the cybernetic behaviour of the brain. The physiological and psychological evidence for this assumption has been discussed briefly, and previous attempts to construct hardware models of plastic change have been mentioned. The author's digital implementations of the internally controlled plastic phenomenon have been described, and used in a series of experiments that show the following:

1) In the model the plastic element is most suitably located at the inputs to the 'N-S' system. This corresponds to the physiological evidence that learning involves some sort of change in synaptic efficiency. (See Refs R.3 "Evidence of Plasticity" , page 188)

2) Association is inherent in a plastic N-S model with two or more inputs which is organised so that the plastic changes are determined by a co-incidence between input and output signals.

3) The plastic models may be used to construct a learning machine which exhibits several properties analagous to phenomena observed in the visual nervous system of animals.

4) Learning and memory are inherent in any plastic system.

These experiments also acted as a proving ground for the models: their reliability was tested and found to be highly satisfactory. During the two months of the experimental period, very little time was lost in the repair and adjustment of the models. They were plugged in and used immediately.

The models of plastic change are, consequently, useful from three points of view: to the engineer they are simple, reliable and relatively inexpensive, to the physiologist they are suitable for the modelling of biological systems, and to the psychologist they suggest explanations of psychological phenomena.

At the theoretical level, this chapter has reduced the study of the brain to the study of internally controlled plastic change at the cellular level, and has found that although structure dominant systems are satisfactory in the production of small systems of 'neurons' and 'synapses', they are completely impractical where large, non-trivial N-S models are concerned.

The work that follows is, therefore, based upon the plasticity hypothesis, but progresses from structure dominant systems to randomly interconnected networks.

C H A P T E R 4

HOMEOSTASIS.

HOMEOSTASIS

4.1 Introduction.

In 1948, an article appeared in the journal 'Electronic Engineering' called 'Design for a Brain'. (Ref R.11.6) It described a system called the Homeostat, which was presented as the basis for a complete model of the brain : "The making of a synthetic brain requires now little more than time and labour. " Today, Ashby's claims look outrageous, for the Homeostat was nothing more than a system with several negative feedback paths that was, not surprisingly, extremely stable. To Ashby, this negative feedback seemed to endow his Homeostat with life-like properties.

The deficiency of the Homeostat is that it is completely non-plastic and thus incapable of any kind of learning or memory. It has subsequently been described as a 'floundering machine', and todays Cyberneticians seem to have totally abandoned the Homeostat as a model of the brain. Nevertheless, it is still true that homeostasis (or complete stability) is a very necessary property of any brain-like system, and this is one of the central themes of the thesis.

The need for homeostasis emerged as the 'N-S' systems under investigation progressed from the simple,structured circuits described in 3.5 to nets with a high degree of interconnectivity. The initial experiments showed that in richly interconnected nets of 'N-S' elements instability arises, and the introduction of homeostasis became an essential undertaking. As the experiments proceeded, it became apparent that homeostasis not only overcomes the problems of saturation and instability, but that it also plays a large part in the information processing properties of the net.

The various stages of this experimental process are described in this chapter.

4.2 Instability in a Small Net of 'N-S' Elements.

With the conclusion of the work on structure dominant systems described in the previous chapter, work began on simple, randomly connected networks of plastic 'N-S' elements. The construction of the first few systems showed that even simple models tended to be inherently unstable. Consider the following system:

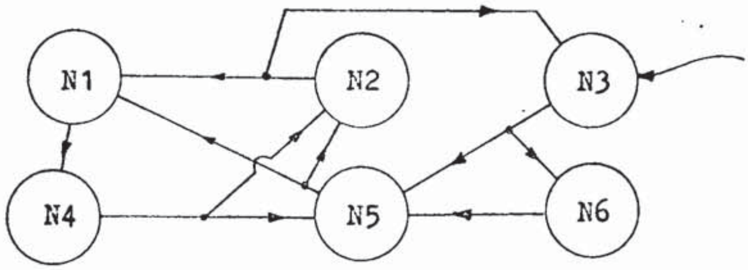


Fig 19

Each circle represents a 'N-S' of the kind described in the previous chapter. Thus N1 consists of an OR gate with two PM4 models at its inputs; the feedback which controls the plastic changes is similar to that defined in Fig 11.

If an input is presented to N3 at a frequency greater than 3.5 Hz., plastic changes will occur in the PM4 models between N3 and N5 and between N3 and N6. As this process continues, every plastic element in the net is affected, and eventually they all reach their upper limit. This means that an input to N3 (or to any other'N-S') will cause all the 'N-S' elements in the net to be activated, and this activity will recirculate in several loops within the network. The net has, consequently, become completely saturated and it cannot possess any information processing qualities whatsoever.

This problem does not arise in structure dominant systems, since the flow of information is resticted by the structure of the system. As soon as a network of neuron-like elements becomes <u>richly inter-connected</u>, loops are created and the system becomes potentially unstable.

4.3 Homeostasis in Physiology and Engineering Science.

As the essence of this thesis is the simulation of the C.N.S., it must be accepted that any problem has a solution somewhere within the the original system that is to be modelled : the brain 'works' and so contains all the answers to the problems arising in the model.

The difference between the net illustrated in Fig 19 and the C.N.S. is that the net contains excitatory connections only, while in the C.N.S. they are both excitatory and inhibitory. These two influences interact, and the result is homeostasis : "If it were not for inhibition, it is likely that excitation would spread in a uncontrollable manner through the complex network of interconnecting neurons composing the nervous system. As a result, the organism would be in a state of convulsive activity. " (Ref R.2.7., p23)

Thus, it becomes obvious that the solution to the instability problem involves the introduction of some influence that <u>opposes</u> the spread of activity. From the physiologist's point of view, the net is unstable as it lacks inhibition.

The engineering solution to the problem of instability is the introduction of some sort of negative feedback. As the activity in the net increases, it is measured, and then fed back so as to decrease this activity. Since the invention of Watt's mechanical speed regulator , negative feedback has provided the engineer with the means of introducing homeostasis, and there is no reason to prevent this principle from being applied to the net.

Essentially, the physiological and engineering methods of making the net homeostatic are the same. As activity spreads, it must be limited in some way, and this may be regarded as 'inhibition' or 'negative feedback' depending on the language of the discipline.

4.4 Homeostasis in Previous Cybernetic Systems.

The majority of cybernetic systems that have simulated neural networks have involved highly structured systems of the type described in 2.5. In these, the total amount of equipment may be active at one time without forcing the system to become unstable. These highly structured systems may be regarded as interesting cybernetically, but they bear no relationship to any part of the brain which is rich in neuron to neuron interconnections.

As soon as the level of complexity approaches that found in the brain, instability arises and the networks can only be full-on, or full-off. Much of the early work described by Beurle (Ref R.6.3) Farley and Clarke (Ref R.6.1) and Ashby (Ref R.14.18) found exactly this phenomenon, but offered no solution. All these involved large, richly interconnected nets of 'neurons' which contained excitatory 'synapses' only.

Further mathematical analysis revealed that a large net containing both excitatory and inhibitory 'synapses' could be stable (Griffiths, Ref R.14.11), and Smith and Davidson have demonstrated that a computer simulation of a large, random network of neuron-like elements can exhibit homeostasis, when both excitatory and inhibitory 'synapses' are used. (Ref R.6.2). More recent mathematical analysis by Amari shows that a similar arrangement of 'neurons' and 'synapses' can not only be mono-stable, bi-stable or tri-stable but also astable with a stable oscillation (Ref R.14.12). Thus, the introduction of inhibitory 'synapses' has been shown to cure the instability problem.

However, other methods of introducing homeostasis are available. In the work of Rochester et al (Ref R.6.5) , homeostasis was maintained by limiting the value of the sum of the 'synaptic' weightings to a fixed maximum. When this value was reached, any new learning that took place resulted in specific changes in 'synaptic' weightings (due to the learning process) at the expense of other, previously taught weightings. This kind of parasitic learning is also to be found in the work of Von der Malsburg (Ref R.6.11); his program uses internally controlled plastic change, similar to the type used in the present author's models , but the sum of the 'synaptic' weights at any one 'neuron' cannot exceed a fixed maximum.

" This last step could correspond to the idea that the total synaptic strength converging on one neuron is limited by the dendritic surface available. It means that some weightings are increased at the expense of others. "

Both Rochester and Von der Malsburg found that the parasitic learning theoram produced a homeostatic system. The third method of introducing stability is illustrated by Uttley's mathematical 'Informon' (Ref R.14.9) which uses negative feedback. This is implemented by the introduction of a negative constant in the equation for the strength of neuron to neuron interconnections.

4.5 The Homeostatic Principle.

In the last two sections, homeostasis has been considered from the physiological viewpoint, as an engineering problem, and it has been discussed in the light of previous models that have involved richly interconnected nets of 'neurons'. From these considerations the principle of homeostasis may be extracted. It is as follows:

"As activity spreads within a richly interconnected net of 'neurons', some antagonistic influence must oppose this activity in such a way that the number of 'neurons' active at any one time cannot exceed a fixed maximum."

This definition gives the Cybernetician a further design feature which must be incorporated into any model which attempts to simulate the workings of the brain.

4.6 Implementation of a Plastic N-S Model for a Homeostatic System.

In order to introduce homeostasis into the net, a N-S model had to be designed which was susceptible to both excitatory and inhibitory influences. The most obvious method of achieving this is to construct a model which emulates the neuron more exactly, in that excitatory and inhibitory inputs summate spatially. A model of this kind was constructed (see PM6 in Appendix 1), but it was found to be complicated, expensive and impractical in that it needed much time to adjust the operating conditions.

Because of the highly satisfactory performance of the digital models used in the previous experiments, the author decided to continue with number thresholds and to exploit the count up/count down facility that is available in some of the more sophisticated binary counters. It was assumed that the excitatory influence (count up) could be opposed by an inhibitory influence (count down) in order to maintain homeostasis. This concept resulted in PM5, illustrated in Fig 20.

The model is basically similar to PM4, in that input pulses count up C1 (Texas SN74193 up/down binary counter) and fire the MONO when C1 holds a count of 15. The SN74193 counters have a "max/min" output pin which is activated when the counter holds either 15 in the count up mode, or zero in the count down mode. This simplified the design, as PM4 had to include additional gating to perform this function. Plastic change occurs in the same manner as in PM4 : when there is a co-incidence between the input and the output from the 'neuron' the contents of C2 is incremented and the weighting of the model increases. The 'neuron' refered to in Fig 20 is an OR gate. The division of the 'N-S' into a plastic 'synapse' and a 'neuron' is in keeping with the definitions of neuron, synapse and N-S given in section 2.6. (page 16)

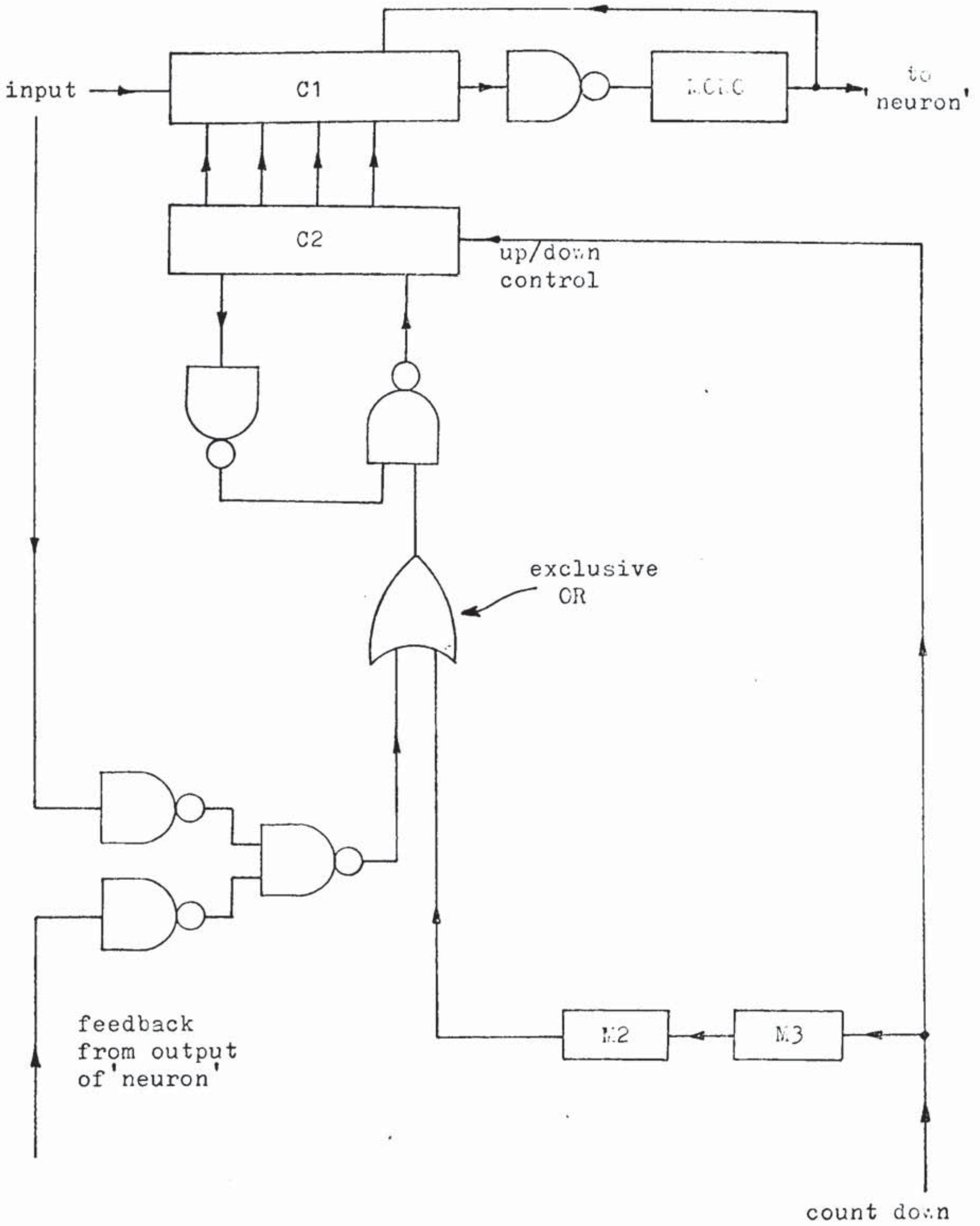


Fig 20: Plastic 'synapse' suitable for a
homeostatic system.

The "count down" signal activates two monostables (M2 and M3) so that while the up/down control is held at 5 volts (count down) a pulse is fed into C2 thus decrementing its contents. This count down signal overides the other influences, so that the "inhibition" can prevent the system from becoming unstable, no matter how strong the excitation may be.

The development of PM5 was a purely engineering process that resulted from the need to construct a plastic element which is susceptible to two opposing influences. Two methods of opposing the spread of activation were apparent: the first involved counting down C1, the second counting down C2. A series of experiments was initiated to test these alternatives and it was found that the former required regular pulses of approximately 10 Hz. to maintain homeostasis whereas the latter required the input of a single pulse whenever activation exceeded an acceptable level. PM5 was, therefore, constructed using the second alternative, as the lower frequency made it simpler to use in the experiments.

If the model is interpreted in physiological terms, it can be seen that the count down pulse is akin to "forgetting" since C2 contains the record of the permanent plastic changes (or "memory") of the model. Homeostasis is therefore maintained by the balance between the forces that spread activation (inputs and plasticity) and those that oppose it (forgetting). Physiologically this is very unlikely as it suggests that the activity of the brain brings about its own forgetting processes. It does however bear some correspondance to the parasitic type of learning mentioned in section 4.4.

4.7 A Small Net with Plasticity and Homeostasis.

The completion of PM5 enabled the author to construct a small homeostatic net consisting of nine 'neurons' (4-input OR gates) and the necssary plastic 'synapses'.

As the work was concerned with the principles of operation of a plastic, homeostatic system it did not seem necessary to begin with a large system and consequently the net was designed as a 3 by 3 matrix. Twelve PM5 elements were constructed and added to the system as 'neuron' to 'neuron' interconnections were made. Small indicator bulbs were used to monitor the activity of the 'neurons'.

Homeostasis was introduced in accordance with the principle derived in 4.5: excitation was allowed to spread freely until four 'neurons' were active - once this level of activation was exceeded, count-down pulses were sent to every 'synapse' thus keeping the number of active 'neurons' at four. A control system for producing this behaviour was developed (see Appendix 2), but it was found to be unnecessary: the number of count-down pulses required to maintain homeostasis was so small that it was found to be perfectly adequate to introduce them by hand.

In this way the net was constructed with plasticity, the property of the synapse that leads to learning, memory and all meaningful changes in the behaviour of an intelligent system, and homeostasis which is essential in the obviation of saturation and instability.

4.8 Properties of the Net.

In this section the behaviour of the net is described and, where applicable, it is interpreted in psychological language. In order to simplify the description, the diagrams only show the positions of the 'neurons' and their interconnections: it should be assumed that every 'neuron' to 'neuron' interconnection is made via a plastic 'synapse'.

4.8.1 Simple Experiments with 'Neural' Pathways.

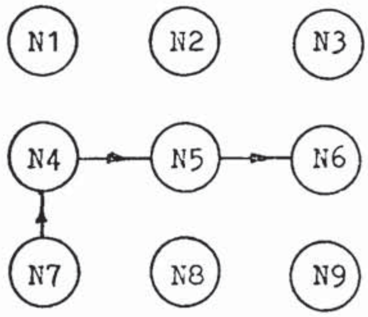


Fig 21.

If connections are made as shown in Fig 21, an input into N7 will give an output after 16 pulses, and so on along the pathway. Thus 16^4 pulses into N7 will be required to get an output from N6. However, if the input is of a high frequency, all the 'synapses' in the chain will 'learn' until one pulse into N7 will cause a signal to travel the length of the chain and fire all the 'neurons' that compose it. This illustrates the way that pathways can become established by regular use.

If two pathways are connected as shown in Fig 22, the system can explain how an 'N-S' network can change its behaviour as the result of the signals at its input.

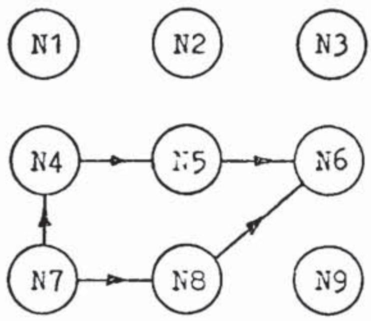


Fig 22.

Let us assume that initially inputs are presented to N7 and N5. The pathway N7-N4-N5-N6 will establish itself, and as this involves four 'neurons' the other pathway (N7-N8-N6) will be suppressed by the homeostasis of the net.

However, if the input changes so that N7 alone is active, the system begins to change its behaviour. As soon as N8 is activated by N7 the homeostasis of the net causes a count-down pulse to be sent to all the 'synapses' in the net. This means that the 'synaptic' weights in the chain N7-N4-N5-N6 are reduced from 1 to $\frac{1}{2}$, and thus a small ammont of time is taken for this pathway to re-establish itself. During this time, the 'synapse' between N7 and N8 can change its plastic parameter fractionally, and as the experiment continues , it becomes apparent that <u>the shorter pathway is establishing itself at the expense of the original longer one</u>. This illustrates the self-maximising property of the system, whereby the most efficient way of conducting information is established, and the old, inefficient ways are lost.

4.8.2 <u>Experiments with a Richly Interconnected Net.</u>

In all the experiments that follow, the net is wired up in such a manner that excitation can spread throughout the net in an unimpeded manner. The actual connections that were used are shown in Fig 23, but this is not critical: any pattern of interconnections would produce similar results as long as the information can flow with relative ease.

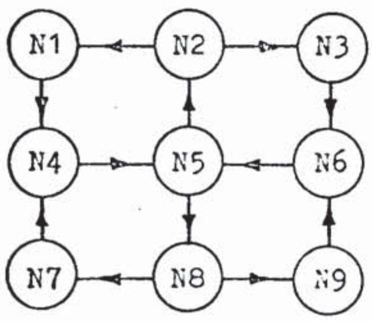


Fig 23.

Inputs were presented to N1, N2, N4, and N5. The 'synapses' connecting these 'neurons' all changed their weightings until a signal could reverberate in the loop connecting the four 'neurons'. This process may be regarded as the establishment of a memory trace, and the activation of any part of the loop will cause the original stimulus (N1, N2, N4 and N5) to be repeated or 'recalled' or 'remembered'.

If a large stimulus is presented to this system (for example an input to every 'neuron') , then homeostasis causes count-down pulses to affect the system until only four 'neurons' are active. The 'neurons' that actually stay active are those which are the most susceptible to activity, that is, those 'neurons' that have been activated most regularly in the past (N1, N2, N4, and N5). This illustrates the principle described in 2.8 : activation is attracted to the area with the highest 'synaptic' weighting, or lowest threshold.

Thus, the combination of a plastic N-S model with a homeostatic system means that a limited number of 'neurons' can be active at one time, and that activation area is determined by the previous inputs , or 'experience' of the system. This type of behaviour is <u>selection</u>: of the nine input signals, only four are sensed by the machine. It is a possible explanation of why the human organism only retains a tiny proportion of the incident information that is presented to it.

If the system is then presented with a small stimulus - for example an input to N1 and N2 - then activity spreads within the net until four 'neurons' are active. Again these will be N1, N2, N4 and N5 as these have previously occured most regularly. This is <u>elaboration</u> : the system has taken a small input signal and extended it, in the same way that the brain can elaborate an 8 to an 8 .

At this point, it can be seen that the homeostatic nature of the system (which keeps the number of active 'neurons' at a fixed maximum) is responsible for both selection and elaboration: if the input stimulus is smaller than this maximum it is elaborated, if it is larger some of it is inhibited and thus selection occurs.

All the 'synaptic' weights were then reset to their original level (ie the net was made to 'forget' everything it had learnt) . It was then re-trained with the pattern shown in Fig 24. The relevant 'synaptic' weights changed, and this became the dominant pattern on the net.

Fig 24

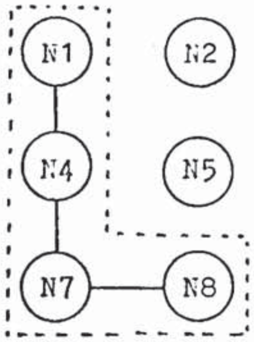
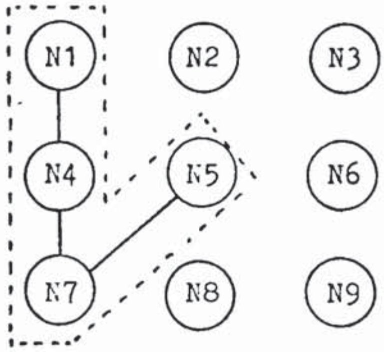


Fig 25



This pattern can be elaborated and selected in the same way as the pattern in the previous example, and if the net is presented with an input as shown in Fig 25, then the high 'synaptic' weights will attract the activation, and the net gives as an output the pattern shown in Fig 24. Any input pattern that is similar to the training pattern causes the system to process this information and to respond with the training pattern. Thus the training or 'experience' of the net determines the way in which it processes information: it can only 'see' in terms of the previous sensory inputs.

To the psychologist this type of behaviour is known as <u>generalisation</u>. Fig 24 is basically an 'L' pattern, and all the test patterns variations of the L. Thus all these inputs were 'generalised' by the net.

If the testing of the net with an input as shown in Fig 25 is continued for a long period, then the plastic nature of the net causes the 'synaptic' weighting pattern to re-organise itself so that the test pattern (Fig 25) becomes the dominant feature on the net. When this happens, all the various 'L' inputs cause the system to respond with an output identical to Fig 25. Thus the net is continuously up-dating its structure to respond to that stimulus which has occured most regularly in its immediate history.

The previous experiments have all involved one training pattern that has become dominant on the 'neural' network. In order to study the behaviour of the system when trained with two different patterns, the 'synaptic' weights were reset and the net was presented first with pattern 1 (illustrated in Fig 26) and secondly with pattern 2.

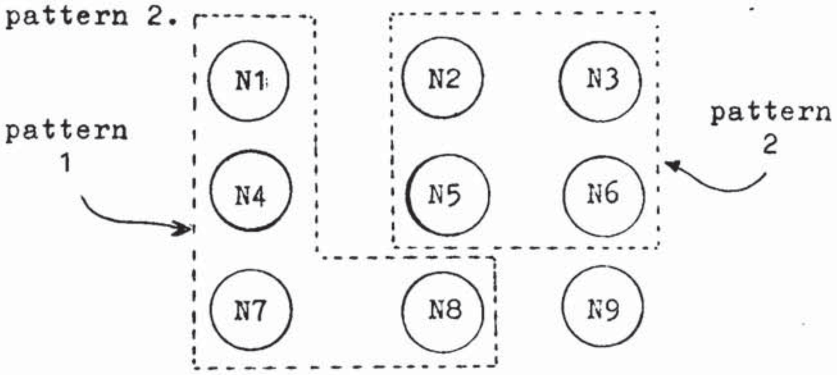


Fig 26

As each pattern consists of four active'neurons', and the patterns do not overlap, it is possible to train the system to retain both patterns. Incoming information is interpreted, therefore, as either one or the other, but not as both due to the homeostasis of the net. This phenomenon may have some bearing on the psychological problem of ambiguous figures such as Wittgensteins's rabbit-duck figure shown in Fig 27. If it is assumed that the rabbit is represented by one assembly of active neurons and that the duck is represented by a second, separate assembly, then a mechanism similar to that illustrated above may operate in the brain. The slight variations in the input stimulus are probably due to shifts in attention as the figure is scanned, and the variation could lead to either the activation of the neural assembly representing the duck or the activation of the neural assembly representing the rabbit but not to both if it is assumed that the homeostasis of the brain limits the number of neurons which can be active at any one time.

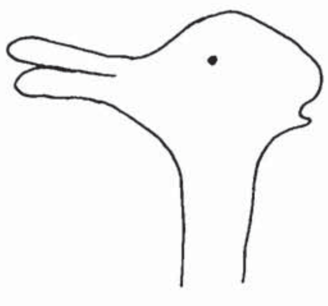


Fig 27

4.9 Assessment of the Work on the Net.

In all the experiments that have just been described, the phenomena that have been exhibited are the result of a randomly interconnected system of neuron and synapse models which exhibits both plasticity and homeostasis. In this respect, the work with the net has been of great value for it has shown that a relatively simple system can produce interesting behaviour when organised in the manner described.

The most obvious limitation is that of size, and a study was subsequently carried out in order to investigate the possibility of extending the physical size of the net . It was hoped that a larger net, organised along similar principles to the 3 by 3 matrix, would be able to exhibit some of the more interesting properties of a brain model, such as the reproduction of sequences. Unfortunately this is not possible without a great deal of new circuitry and extensive re-organisation.

The main problem is that the net can only sustain a pattern of activity when all the PM5 elements involved in that pattern are at their highest weighting value. As soon as the count down signals begin to influence the net, all activity ceases. In the experiments that were performed this is of little importance as the input signals quickly re-establish the weighting values, thus allowing the trace to re-appear. This factor becomes critically important in the implementation of sequential behaviour: for one pattern to follow another it must be assumed that many patterns are potentially stable, so that activity may pass from one to the next in an associated series. The net, in its present form, is completely unable to do this because it has no spatial summation (except of a probabilistic nature) which would allow several inputs through low weighting 'synapses' to fire the 'neuron', and thus maintain the activity. This problem is exacerbated by the large change in 'synaptic' weighting from 1 to ½ which is caused by the count down signal. Although this has been useful in the net in limiting the spread of activation, it makes it extremely difficult to maintain activity with weightings of less than the maximum. Further, the 'N-S' elements have no fatigue so that any established pattern of activity will continue to dominate the net until new input stimuli are presented.

The other major flaw in the design of the net concerns its structure. At the initiation of the experiments with random nets, it had become necessary to progress from the structure dominant systems described in Chapter 3, and the random interconnection pattern was the most obvious alternative. However, as the work began on the extension of the net, the inadequacies of a random system began to emerge. It was found that structure had to be introduced in order to ensure that every input stimuls produced an effect on a large number of 'N-S' elements, and that information was able to flow freely throughout the system.

It became essential, therefore,to find an interconnection pattern which avoids the inadequacies of a structure dominant system without being completely random. Somehow it had to order the flow of information through the system without becoming rigid and inflexible. The learning behaviour had to exert the dominant influence, and yet the structure had to provide a foundation to direct this influence. These considerations led to a more detailed study of the brain in an attempt to discover the kind of structure that it uses, and eventually to the Block organisation described in the following chapter.

With these considerations in mind, the net appears to be an extremely inadequate approximation of a non structure dominant cybernetic system. The elemental units suffer from a) absence of spatial summation b) an unsatisfactory relationship between changes in 'synaptic' weighting values and c) absence of fatigue, and the interconnection pattern needs to incorporate some degree of order so as to direct the flow of information more precisely.

However, the net has provided the author with invaluable experience in experimentation with a plastic, homeostatic system and the criticism which has emerged is useful in that it defines the direction in which the work can proceed. The net has shown that plasticity and homeostasis are able to play a major part in cybernetic processes, but that they must be complemented by more accurate simulation of the properties of the N-S, and by an interconnection pattern which is organised and yet non structure dominant.

4.10 Summary.

The concept of homeostasis has been introduced, and has been shown to be an essential property of any richly interconnected system of neuron-like elements. Homeostasis is necessary in order to prevent saturation and instability.

A small plastic, homeostatic network has been described which is organised by the information that is presented to it. The net exhibits such phenomena as elaboration, selection and generalisation due to the way in which incoming information is processed in terms of the information that has been previously presented to the net. All of these properties are the result of two factors:

(a) Plasticity at the 'synapse' which creates areas of low threshold correseponding to persistently activated input stimuli.

(b) Homeostasis , which ensures that no more than a certain number of 'neurons' can be active at any one time. Homeostasis was introduced to overcome the saturation problem, and has been shown to play an essential role in the processing of information.

The inability of the net to produce more complex phenomena such as the reproduction of sequences and a distributed memory trace are the result of three deficiences: the elemental units are capable of neither spatial summation nor fatigue, and the structure bears no resemblance to the structure of the brain.

The net has demonstrated the importance of plasticity and homeostasis, and has pointed the direction for further work.

C H A P T E R 5

THE BLOCK.

STRUCTURE AND BASIC MECHANISMS.

THE BLOCK.

5.1 Introduction.

The work that has been described in the preceeding chapters is important in that it has derived certain principles that have a significant effect on the synthesis of a brain-like system. Chapter 3 has discussed the importance of plasticity and Chapter 4 has explained why homeostasis is necessary. These two chapters are stages in the study of cybernetic, intelligent phenomena that eventually culminated in the Block system.

The design of the Block system resulted from a growing conviction that the concept of the brain as a randomly interconnected system , which organises itself as the result of its experience is wrong. The vast majority of physiological research seems to suggest that the structure of the brain is highly organised before the learning process begins to effect it:

" At no stage in development are the neurons of the brain connected together as a random network. " (Ref R.2.4., p147.)

This conviction called for a complete revision of the author's structural design parameters for a brain-like system, in order to incorporate this very specific organisation. The result was the Block: a plastic, homeostatic system which is based on the neural circuitry which is evident in the brain. The Block was able to draw together several problems that had emerged during the course of the work, and to open new areas of research that had previously been outside the scope of the Ph.D program.

5.2 Design Requirements for a Large Cybernetic System.

The work on the small net left the author with a firm conviction that the construction of a large cybernetic system is a feasible proposition, and that the way to achieve this is to look more closely at the structure of the brain. Plasticity and homeostasis have been shown to be essential features, and the deficiencies of the net have pointed the direction for further work. Consequently, it is possible to list the design requirements that are needed by a large cybernetic system.

1) It should be composed of internally-controlled plastic synapse models. The learning principle, which specifies the way in which the plastic change is controlled, must be found experimentally.

2) The system must be homeostatic: no more than a fixed number of 'neurons' may be active at any one time.

3) The 'N-S' elements must have all the properties described in section 2.5. This extends the models used in the net by the addition of fatigue and spatial integration.

4) The structure of the system must be more closely related to the structure of the brain. The construction of random nets of 'neurons' ignores a wealth of information that shows that a high degree of organisation may be found in both the cerebellum and the cerebrum.

5) The system should exhibit a distributed memory trace. The net has a localised memory trace, and can therefore offer the cybernetician no explanation as to the function of a distributed trace. The author's respect for the efficiency of the brain's machinery led him to believe that a distibuted memory trace would not be found unless there is a sound, functional reason.

5.3 The Block as an Intermediate Level Building Brick.

The design requirements specified in the previous section acted as a springboard for the work on the Block that is described in this chapter. In the preliminary stages, it became apparent that the task of building an artificial brain from artificial neurons is unrealistically ambitious. The situation is analagous to the construction of a computer directly from transistors without any prior knowledge of electronic logic, counting circuits or shift registers. What seems to be needed is some system which acts as an intermediary between the neuron model and the system representing the brain: a model of the neuro-physiological equivalent of, say, a shift register.

The Block is such an intermediary. It is composed of plastic elements of the type used throughout this thesis, and its structure is homeostatic and based upon the organisation of the brain. It is not, however, a complete brain model, but a 'building brick' from which such a model could be constructed.

As the Block is itself a component part, it was not expected to exhibit any remarkable phenomena, but to provide a conceptual tool which could help to explain one possible way in which the brain might be organised. It was only after the Block had been simulated, that it became apparent that a single Block was capable of performing a wide range of tasks which are generally associated with intelligence: in particular, it could learn, remember and reproduce a number of temporal sequences.

5.4 Columns of Neurons as Functional Units.

The structure of the Block is based on the assumption that columns of neurons exist in the cortex, arranged orthogonally to its surface as shown in Fig 28.

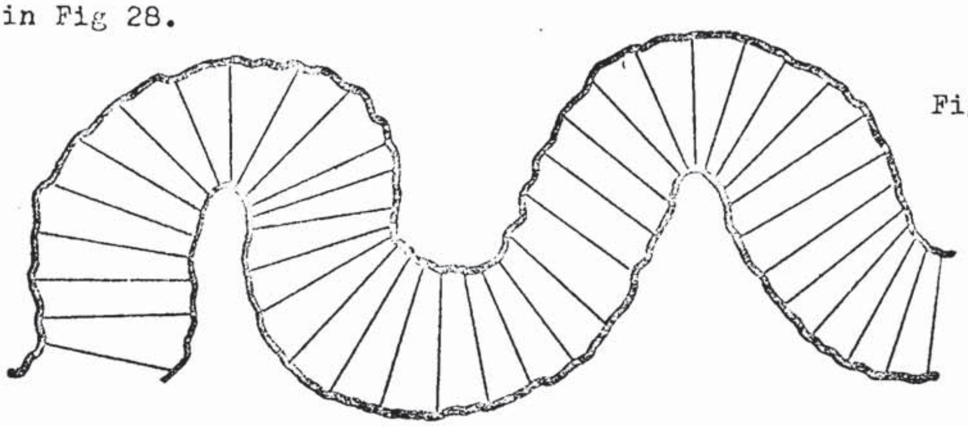


Fig 28

There is a wealth of information in support of this assumption, and a brief description follows.

The earliest account of a columnar organisation was given by Lorente de No (Ref R.2.23). His diagrams reveal a complex vertical organisation which is essentially the same as Fig 28. Since that time, several other physiological studies of the cortex have drawn attention to its columnar oganisation; the work of Scholl (R.2.15), Szentagothai (R.15.2), Bailey and Bonin (R.15.3), Schriebel and Schriebel (R.15.16) and Ariens Kappers (R.15.4) is particularly relevant.

In 1957, Mountcastle published a paper describing the effect of various tactile stimuli on the somatic sensory cortex of the cat (R.15.5). In a rigorous series of experiments he found that the neurons within a vertical column all respond to the same tactile input stimulus. He concluded "The neurons which lie in narrow vertical columns... make up an elementary unit of organisation."

The work of Hubel and Weisel (R.2.24., R.2.25) provides the visual equivalent of Mountcastle's work. In the visual cortex, neurons are arranged in columns, and within one column all the neurons respond to one specific type of visual stimulus.

The same phenomenon can be found in the auditory cortex. Columns of neurons having the same 'best frequencies' (those for which the response threshold is lowest) have been noted by Hind et al (R.15.6), Parker (R.15.7), Gerstein and Kiang (R.15.8), Oonishi and Katsuki (R.15.9) and Abeles and Goldstein (R.15.10). The work of Evans (R.15.11) draws attention to the fact that in the auditory cortex, the function of the columns is not as clear cut as in the somato sensory and visual cortex.

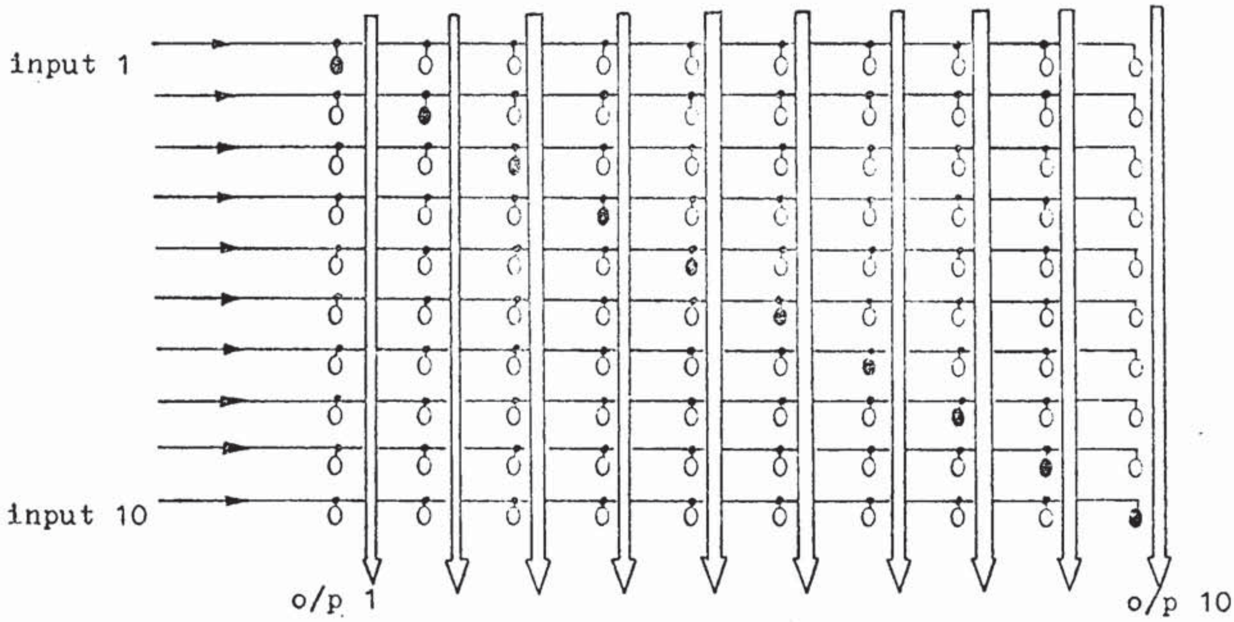
Experiments on the motor cortex by Landgren et al (R.15.12), Weldt et al (R.15.13) and Asanuma (R.15.15) reveal that the columnar structure is also an intgral part of the structure of the motor cortex. The stimulation of any one of the cells within a column of the motor cortex leads to the activation of one particular muscle. These columns may be mapped in exactly the same way as those within the sensory cortex.

The existence of columns was also noted by Sperry (R.15.14). His investigations show that the horizontal spread of activity through the cortex is unnecessary for very fine pattern discrimination, and also for normal motor activity. He concluded: "It follows that rather small vertical columns of the cortex are capable of integrated activity of a high order ".

As a result of this information, the author has been led to assume that columns of neurons exist in the sensory and motor cortex, and that each column acts as a single functional unit. It is with this assumption that the Block model begins.

5.5 Input and Output Configurations.

The Block was designed to be a fairly general model of a small part of the brain, and in choosing the input and output configurations, a study of both the cerebrum and the cerebellum was made. The result is shown below in Fig 29:



O - plastic 'synapse'
● - non-plastic 'synapse'.

The vertical lines represent the columns discussed in the previous section. The inputs are arranged in a matrix, a form which is suggested very definitely by the parallel fibres in the cerebellum, and also by the large dendritic trees on the afferent nerve fibres in the cerebrum.

Each column has inputs of two distinct types: the general, associatory inputs which pass through a plastic 'synapse', and one specific input which passes through a non-plastic 'synapse'. This kind of arrangement can be found in the cerebellum where each Purkinje cell is excited by both the mossy fibres (multiple, general inputs) and the climbing fibre which synapses onto one particular Purkinje cell and provides a specific input.

The outputs are arranged as shown in Fig 29, and to ensure that the work is consistant with the physiology of the C.N.S. , and the conclusions of Chapter 4, only one output can be active at one time. This feature was included in order to account for the powerful systems of lateral inhibition which exist in the cortex due to the basket-type stellate inter-neurons, and in the cerebellum due to the basket and Golgi cells. In both cases the effect is the same:

"It is a general principle of operation of the nervous system that, when groups of cells are activated, they try to sharpen their effectiveness by inhibiting the other groups in the surround. But of course these other groups are doing the same. Thus there is reciprocal inhibition with a continual fight for dominance. " Ref R.2.4., p 114.

Having described the input and output configurations, it seems essential to examine the structure of other cybernetic machines comparatively. The most obvious parallel is between the Block and the previous matrix learning systems described by Steinbuch, Young and Longuet-Higgins (Refs R.13.9., R.13.17., R.1.26.). Although these have both specific and general inputs, a plastic learning element at every cross point in the matrix, and similar output structure, there is an essential difference: in the Block only one output can be active at one time. Previous systems have allowed many outputs to be active at one time, thus ignoring the homeostasis of the brain. There is also a difference in conception: the Block is essentially a model of a physiological system whereas the previous matrix systems were designed in order to reproduce certain behaviour patterns. Thus they belong to different classes of Cybernetic systems as defined in 2.3.

There are also parallels with the work of W.K.Taylor. His systems (Refs R.1.36., R.8.17., R.11.2., R.13.13.) use a matrix-like input configuration which contains specific and general inputs, and involved a divisions into columns. Further, the outputs passed through a 'maximum amplitude filter', so that only one output could be active at one time. Apart from small differences in the matrix, there are several basic differences between the present work and Taylor's machine:

1) Taylor's columns involve a rigidly defined structure, with specific feed-back paths which are essential for the learning process. The Block does not involve such assumptions about structure and learning paths.

2) Taylor's matrix is involved in the input region only: it contains no learning elements. The Block contains a learning element at every cross point in the matrix.

3) There is only one plastic learning element in each of Taylor's columns. Most of the 'synapses' must be non-plastic as they are involved in perfoming specific functions. The Block does not assume the 'synapses' are divided in this way.

4) Taylor's model uses 'good' and 'bad' information in its training phase. The Block is not concerned with good/bad training : it remembers all the information which is presented to it in the same way.

5) Taylor's theories involve both a maximum amplitude filter and a large number of inhibitory 'synapses'. Recent physiological evidence suggests that the function of the inhibitory synapses is actually to perform the functions of a maximum amplitude filter and that it is incorrect to assume that there are surplus inhibitory neurons available for other information processing tasks.

In conclusion, the Block can be seen to contain elements of several previous cybernetic systems, but the way in which these elements are combined is believed to be unique. It is this combination that gives the Block the range of properties that are described in the following pages.

5.6 Properties of the Columns.

Each Block is composed of a number of columns, each of which processes information in exactly the same way. The properties of the columns are assumed to be the same as the neurons that compose them. They are as follows:

1) Spatial summation: the output from a column is affected by the spatial sum of its inputs. The more inputs that are active, the more likely it is for an output to be produced.

2) Temporal summation: the output from a column is also affected by the temporal sum of its inputs. The more regularly an input occurs, the more likely it is to produce an output.

3) Threshold: for an output to be produced, the spatial and temporal sum of its inputs must exceed the threshold of the column.

4) Habituation: no column can produce an output indefinately. It will tire, habituate, or adapt. This habituation gradually decreases as the column recovers.

5) Input weighting: the effect that an input can produce is determined by a weighting factor. If the weighting is large, the effect is large : if the weighting is small, the effect is small. Physiologically, this weighting is produced by the synapse.

In the practical work to be described, a Block is assumed to be composed of ten such columns. This number was chosen arbitrarily in order to begin the experimental work.

5.7 The Learning Theorem.

Having defined the structure of the Block, and the properties of the columns that compose it, it remains to specify the type of internally controlled plastic change that is to produce the learning behaviour.

As in the previous models, learning is assumed to occur at the 'synapse'. At the beginning of the experimental period, the author used a learning theorem similar to that used in the hardware models, but this was found to be unsatisfactory. A number of alternatives was considered, until it became clear that the long lasting changes in 'synaptic' weighting must occur as defined by the following learning theorem:

" PLASTIC CHANGE TAKES PLACE AT A 'SYNAPSE' IF TWO CONDITIONS ARE BOTH SATISFIED: FIRSTLY THE COLUMN ON WHICH THE 'SYNAPSE' IS LOCATED MUST BE PRODUCING AN OUTPUT SIGNAL, AND SECONDLY THE INPUT TO THAT 'SYNAPSE' MUST HAVE BEEN RECENTLY ACTIVATED. "

This learning theorem is a more general case of that used in the hardware models. In the Block, plastic changes occur as in the small net but also for the case in which the 'neurons' fire and an input has been recently activated.

In physiological terms, the learning theorem requires that the release of transmitter substance across the synaptic gap leaves the post synaptic membrane in an excited state for a short time, and that if a column fires while the membrane is in this state, then it becomes more sensitive to further input of transmitter substance.

The learning theorem used by the Block system is believed to be unique, and is, therefore, another factor in comparing the Block with other cybernetic systems.

5.8 The Modelling Environment for the Block.

In order to construct a Block system, the author first designed and built a hardware plastic N-S model which was capable of performing all of the functions specified in section 5.6. The resulting circuit (PM6, see Appendix 1) was so complex that it became imperative to find some other modelling environment for the Block. Not only did the complexity of the hardware models make the construction of a Block an extremely arduous task, but it also made the system prohibitively expensive since each 'synapse' would have cost over £5 in components alone, and a hundred of these were needed for a single Block.

Hardware modelling was therefore abandoned, and the author's attention turned to the digital computer. As the structure of the Block is rigidly defined, the software simulation proved to be a relatively simple task: the program was written in Fortran and is included in Appendix 3. Essentially, the program runs down each column and performs the calculations necessary to evaluate the total spatial and temporal sum of all its inputs. It then compares these values and gives an output from the column whose spatial and temporal sum is the greatest value, assuming it is above the threshold of the column. As only one column can produce an output, the program automatically introduces homeostasis: only 10% of the total number of 'neurons' can be active at any one time. The program then retraces its steps and up-dates the values of 'synaptic' weighting that are specified by the learning theorem. Thus internally controlled plastic change is introduced. Finally the program checks how often the active column has fired in the immediate past and, if this is above a certain value, the threshold of that column is raised in order to make it more difficult to fire. This implements the fatigue phenomenon.

The software modelling environment is suitable in the case of the simulation of a single Block because unit to unit interconnections are not needed. This means that the problems with flexibility mentioned in section 2.4 are not relevant.

5.9 The Non Learning Behaviour of the Simulation Program.

The simulated Block consists of ten columns each with ten inputs: the system has 100 'synapses' arranged in a ten by ten matrix. In order to implement the input configuration described in section 5.5 , the initial state of the 'synaptic' weightings is that shown in Fig 30. As the threshold of each column is initially set at 20, any input will result in an output from the appropriate column.

20	1	1	1	1	1	1	1	1	1
1	20	1	1	1	1	1	1	1	1
1	1	20	1	1	1	1	1	1	1
1	1	1	20	1	1	1	1	1	1
1	1	1	1	20	1	1	1	1	1
1	1	1	1	1	20	1	1	1	1
1	1	1	1	1	1	20	1	1	1
1	1	1	1	1	1	1	20	1	1
1	1	1	1	1	1	1	1	20	1
1	1	1	1	1	1	1	1	1	20

Fig 30.

Hereafter, figures such as this will be referred to as a "W matrix".

All the processing within the Block is performed numerically. Temporal summation is achieved by introducing a factor called "STW" (short term weighting). Every time that a 'synapse' is activated, its value of STW , which is initially set at zero, increases exponentially towards 20. When the 'synapse' is inactive, STW falls exponentially back to zero. Thus as a 'synapse' is used repeatedly, its short term effectiveness increases.

The inputs to the Block are presented via the teletype, and can be either on or off. On is represented by a 1 : off by a 0. An input of 1111111111 indicates that all the input lines are active, as shown in Fig 31(a). An input of of 1100000011 indicates that the first and last two input lines are active, as shown in Fig 31(b).

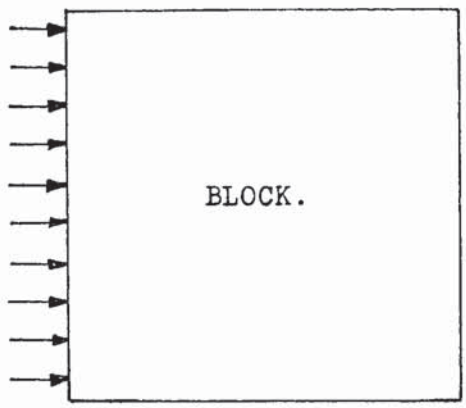


Fig 31(a)
Input represented by 1111111111

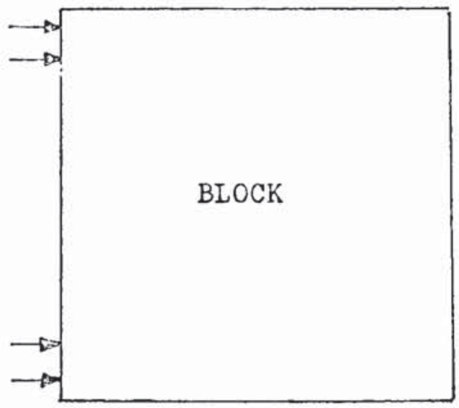


Fig 31(b)
Input represented by 1100000011

(An arrow represents an active input stimulus.)

The program includes an option to print out the W matrix. Each iteration of the program begins with the operater typing in either 1 or 77. 1 indicates that the W matrix is not required and that the following line will contain the information regarding the inputs to the Block. 77 indicates that the W matrix is required : the computer then prints out the W matrix and then waits for the information concerning the next input to the Block.

The computer indicates an output in the form:

6, 24

This means that column 6 has fired, and that the spatial and temporal sum of its input is 24 units above the threshold of the column. This figure of 24 is called DIFF.

5.10 Illustration of Basic Behaviour.

Fig 32 shows the values of DIFF for tests with one, two, three, four and five spatial inputs to column 5. These are plotted in Fig 32(a)

Number of spatial i/ps.	Value of DIFF for successive temporal inputs.						
1	12	15	16	16	16	11	6
2	25	32	35	36	37	33	29
3	38	49	54	56	58	55	52
4	51	66	73	76	79	77	75
5	64	83	92	96	100	99	98

Fig 32.

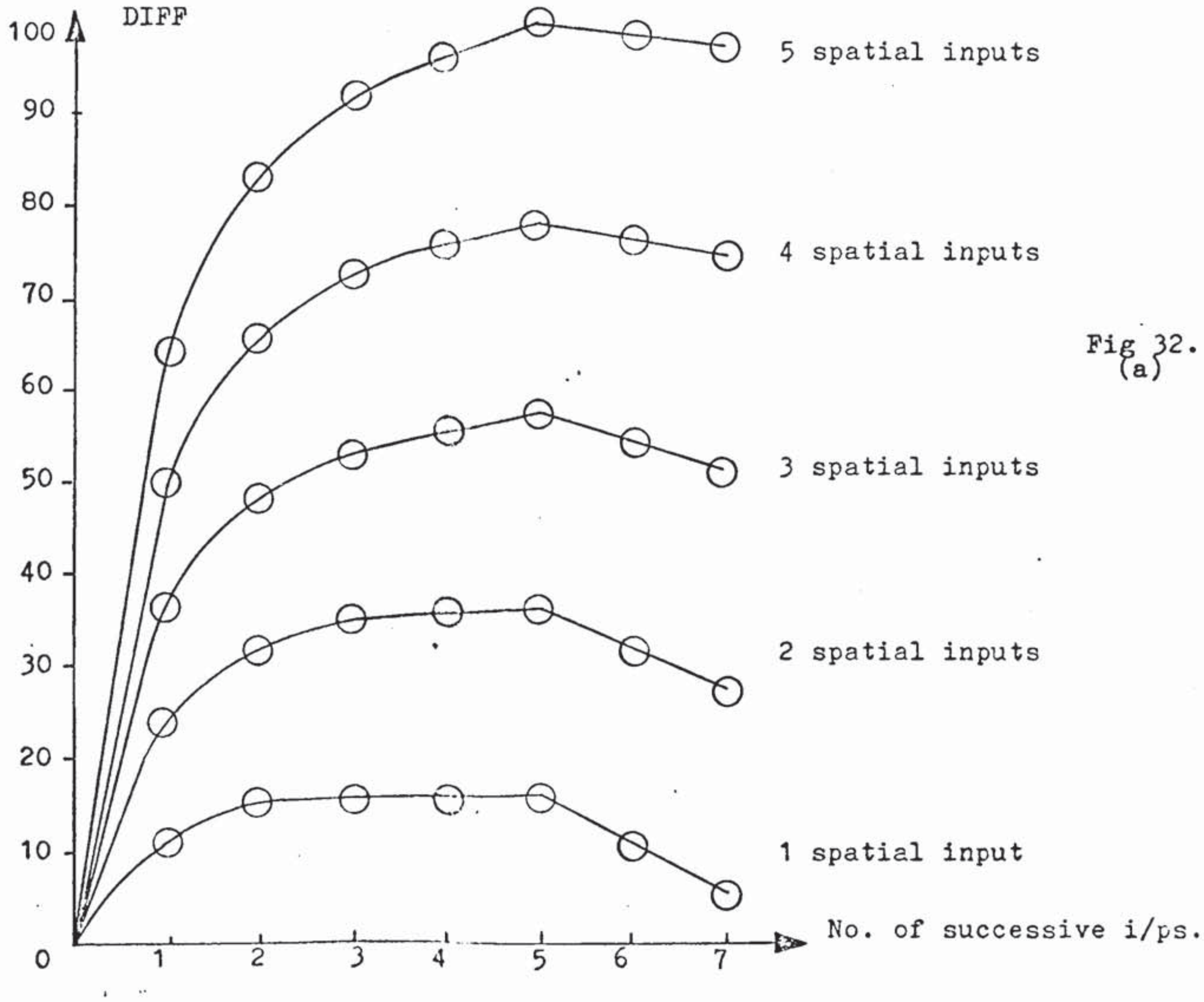


Fig 32. (a)

As can be seen, the column exhibits both spatial and temporal summation of an exponential nature. The column begins to tire after five firings. This graph may be regarded as the set of 'characteristic curves' for a column.

5.11 Example of Learning Process.

The Block was presented with three successive inputs of 1111 (an input to the first four input-lines) and three outputs from column 4 were produced. The computer print-out recording this process and the resulting W matrix are shown in Fig 33.

```
1
1111

  4,51
1
1111
  4,66
1
1111
  4,73

77
 20  1  1  4  1  1  1  1  1  1
  1 20  1  4  1  1  1  1  1  1
  1  1 20  4  1  1  1  1  1  1
  1  1  1 20  1  1  1  1  1  1
  1  1  1  1 20  1  1  1  1  1
  1  1  1  1  1 20  1  1  1  1
  1  1  1  1  1  1 20  1  1  1
  1  1  1  1  1  1  1 20  1  1
  1  1  1  1  1  1  1  1 20  1
  1  1  1  1  1  1  1  1  1 20
```

Fig 33.

'Synaptic' weight updating occurs when a column gives an output, and when an input to that column is in a state of activation. Thus, in the present case, the first four 'synapses' on column 4 are updated by one unit three times. The fourth 'synapse' was initially set to 20 and as this is the maximum permitted by the program, the learning process can have no effect on it.

5.12 Generalisation.

The Block was trained with an input of 1111, which produces an output from column 4. If the Block has the ability to generalise, then it must produce the same output (ie from column 4) for inputs similar to the training pattern. Fig 34 shows the training , the resulting W matrix, and the testing of the Block.

1111	4, 51
1111	4, 66
1111	4, 73
1111	4, 79
1111	4, 82
1111	4, 80
1111	4, 78

20	1	1	9	1	1	1	1	1	1
1	20	1	9	1	1	1	1	1	1
1	1	20	9	1	1	1	1	1	1
1	1	1	20	1	1	1	1	1	1
1	1	1	1	20	1	1	1	1	1
1	1	1	1	1	20	1	1	1	1
1	1	1	1	1	1	20	1	1	1
1	1	1	1	1	1	1	20	1	1
1	1	1	1	1	1	1	1	20	1
1	1	1	1	1	1	1	1	1	20

111	4, 42
0111	4, 70
00111	4, 70
1011	4, 82
0011	4, 64
1010	3, 50

Fig 34. The first column represents the input to the program : the second the output.

As can be seen the W matrix is up-dated as a result of the learning theorem in the same way as in the previous example. After the training , the Block was given an input of zero for a short time to ensure that all the short term effects (habituation and temporal summation) had returned to their base level. The Block was then tested, and can be seen to generalise: the first five inputs were similar to the training pattern and were generalised to give an output from column 4. The sixth test pattern was not sufficiently similar and was not generalised.

The way in which this behaviour is produced may be understood by looking at the spatial summation of the inputs on the ten columns. For instance when an input of 111 is presented to a Block described by the W matrix shown in Fig 34, the ten spatial sums are as follows:

22, 22, 22, 27, 3, 3, 3, 3, 3, 3.

The program selects the column which has the greatest spatial and temporal sum relative to the column's threshold, and as the spatial summation is the dominant factor in the present example, it gives an output from column 4.

It is obvious from this discussion that the more often the training pattern is presented, the greater the probability that the system will generalise , and give an output from column 4. Thus after twelve presentations the input 101 will create a spatial sum of 24, and will be generalised as a 1111.

With the program in its present form there is a serious drawback to this situation, for after a long training period with one input, the relevant W values will reach their maximum value of 20, and an input to any of the first input lines will produce an output from column 4. To overcome this, it would be necessary to introduce a long term forgetting factor which causes W to ebb away exponentially. This factor has not been included in the program as the purpose of the work is to study the effect of various learning processes, and problems such as long term saturation may be obviated by a balanced input program.

5.13 Generalisation Using Two Different Input Patterns.

The Block was trained with two different input patterns (1111 and 110011) in an attempt to ascertain how the system would react when presented with 11, the common part of the two patterns. Fig 35 shows part of the print-out concerned with this experiment.

11	6, 41
1111	4, 98
1111	4,106
1111	4,110
11	4, 66

20	2	1	16	1	14	1	1	1	4
1	20	1	16	1	14	1	1	1	4
1	1	20	16	1	4	1	1	1	2
1	1	1	20	1	2	1	1	1	2
1	1	1	1	20	13	1	1	1	3
1	1	1	1	1	20	1	1	1	3
1	1	1	1	1	2	20	1	1	1
1	1	1	1	1	1	1	20	1	1
1	1	1	1	1	1	1	1	20	1
1	1	1	1	1	1	1	1	1	20

Fig 35.

110011	6, 112
110011	6, 117
110011	6, 117
11	6, 72

As can be seen, the Block initially generalised 11 to be an input of 110011 and gave an output from column 6. After further input of 1111 the Block changes this behaviour and an input of 11 causes an output from column 4. Further input of 110011 causes the Block to revert to its original behaviour, and 11 is generalised to give an output from column 6.

This illustrates the way in which the Block is continuously up-dating its behaviour in order to select that input that has occured most regularly in its immediate history.

5.14 Association.

Due to the way in which the 'synaptic' weights change, the Block may be looked upon as exhibiting association. For example, if the system is presented with an input pattern of 101, then the first 'synapse' on column 3 will be up-dated. When the value of W for this 'synapse' reaches 20, then an input of 100 will cause an output from column 3, instead of from column 1 as is usually the case. In psychological terms the experiment may be interpreted as follows: input 001 is the specific stimulus which produces an output from column 3, the specific effect. The input 100 is the neutral stimulus. Co-incidental presentation of these two stimuli (in the 101 pattern) causes the neutral stimulus 100 to produce the specific effect - output from column 3. Thus the two patterns have become associated.

This type of association, which is only another way of interpreting the generalisation experiments, is of interest but it begs the central problem. The importance of association is in the linking together of two input stimuli that follow each other closely in time. For example, let us suppose that the Block is presented with an input of 1111 and then an input of 0000001111. Further, let us assume that these two stimuli represent the sight of a book and the sound of the word 'book', respectively. In the experience of the system, these two stimuli are going to occur together regularly, and the Block must be capable of learning to link them together. The following experiment shows how this result was achieved.

1111 and 0000001111 were presented sequentially as shown in Fig 36.

1111	4, 51
0000001111	10, 83
1111	4, 94
0000001111	10,102
1111	4,105
0000001111	10,105
1111	4,108
0000001111	10,108

Fig 36

Training proceeded in this manner; the resulting W matrix is shown in Fig 37.

region 1 region 3

20	1	1	12	1	1	1	1	1	11
1	20	1	12	1	1	1	1	1	11
1	1	20	12	1	1	1	1	1	11
1	1	1	20	1	1	1	1	1	11
1	1	1	1	20	1	1	1	1	1
1	1	1	1	1	20	1	1	1	1
1	1	1	10	1	1	20	1	1	12
1	1	1	10	1	1	1	20	1	12
1	1	1	10	1	1	1	1	20	12
1	1	1	10	1	1	1	1	1	20

region 4 region 2

Fig 37.

Four distinct regions of 'synaptic' facilitation are apparent. Regions 1 and 2 are caused by the basic learning behaviour in exactly the same way as that described in the generalisation experiments. But what of regions 3 and 4 ? How do they occur and what is their function ? Let us begin with region 3. When 1111 is presented to the Block, it leaves a short term memory effect on the first four 'synapses' of all ten columns. Column 4 then fires and the Ws in region 1 are up-dated. The input then changes to 0000001111 and this causes column 10 to fire. Now, when column 10 fires, the system interrogates the 'synapses' within this column and up-dates those which have been <u>recently</u> activated. This means the last four (region 2) and also the first four since they are still in an excited state due to the previous input of 1111.

Thus, the combination of the short term memory trace left behind by the 1111 input, together with the firing of column 10 by the 0000001111 input, causes the 'synapses' in region 3 to be up-dated. Similarly, the high W values in region 4 are produced by the short term trace left by the 0000001111 input and the firing of column 4 by an input of 1111.

The function of these two regions is to create a connection between the two input patterns. To illustrate this connection, the system is presented with successive inputs of 1111, as shown in Fig 38.

1111	4, 84
1111	4, 99
1111	4,106
1111	4,109
1111	4,112
1111	4,110
1111	4,108
1111	4,106
1111	4,104
1111	4,102
1111	4, 99
1111	4, 94
1111	4, 89
1111	4, 84
1111	4, 79
1111	4, 74
1111	10, 73

Fig 38.

As can be seen, the 1111 input causes an output from column 4 as expected. After five such inputs, column 4 begins to tire and a short time later this tiring reaches such a high level that column 4 becomes very difficult to fire. At this point, the system changes its behaviour and responds to the 1111 input with an output from column 10. It is column 10 that is chosen because of the high W values in region 3. Thus region 3 acts as a connection between the two inputs.

In terms of the previous analogy, the system perceives the image of the book, holds it for a short time and then shifts its activation to the sound 'book'. Thus, the sight and sound have become associated due to their near co-incidental presentation.

This experiment illustrates how a temporal pattern can be mapped as a spatial pattern on an array of learning elements. It also explains how the spatial pattern can be referenced in order to retrieve the original temporal pattern.

For the Block to associate in the manner just described, there must be at least one feed-back path, so that the output can activate its own inputs. During the experimental period with the digital computer, this feed-back was performed by the computer operator who typed back the input 1111 whenever column 4 gave an output.

Fig 39 illustrates the minimum internal feedback needed by the Block in order to exhibit the association phenomena just described.

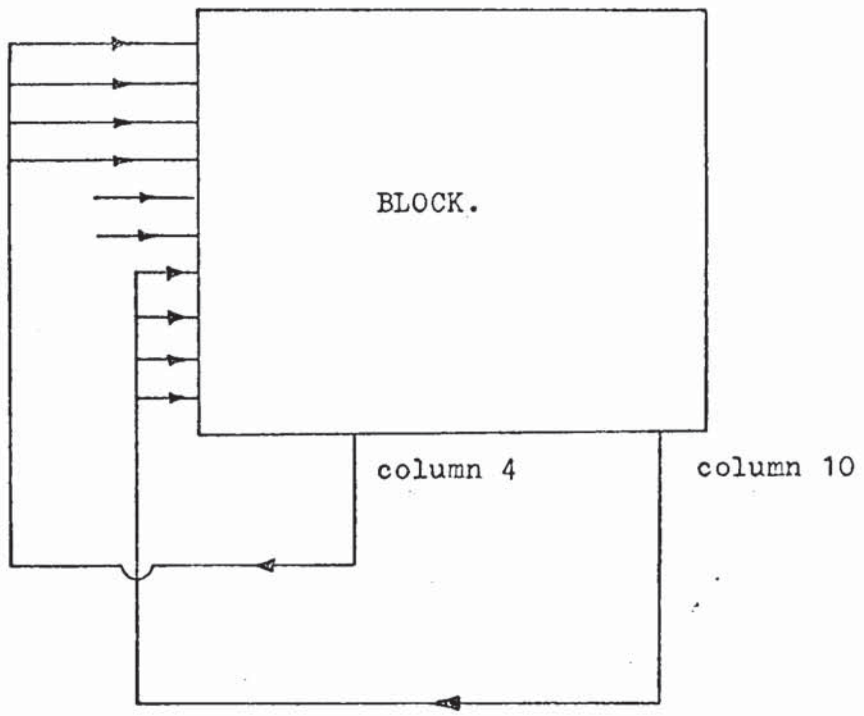


Fig 39.

Physiological studies of the brain suggest that feedback paths such as this are common:

" Measurement of dendritic and axon terminal fields suggest that there are innumerable possibilities for closed feedback paths involving cortical neurons. Even more such loops must be possible if thalamic and other neurons participate. " (Ref R.2.16)

The structure of the Block, in conjunction with this feedback system, thus explains how two patterns may become associated.

5.15 Directional Association.

During the work on the association experiments, it became apparent that each association was directional. If an input A is followed by an input B, then an association is set up from A to B but not in the reverse direction. For the association to move in the reverse direction (ie from B to A) the reverse sequence must be shown to the Block. To test this, the Block was trained with a set of inputs as shown in Fig 40. The resulting W matrix is also shown

1111	4, 51
0000001111	10, 83
00	10, 72
00	10, 65
1111	4, 57
0000001111	10, 94

Fig 40

20	1	1	12	1	1	1	1	1	11
1	20	1	12	1	1	1	1	1	11
1	1	20	12	1	1	1	1	1	11
1	1	1	20	1	1	1	1	1	11
1	1	1	1	20	1	1	1	1	1
1	1	1	1	1	20	1	1	1	1
1	1	1	1	1	1	20	1	1	11
1	1	1	1	1	1	1	20	1	11
1	1	1	1	1	1	1	1	20	11
1	1	1	1	1	1	1	1	1	20

region 3

As can be seen, region 3 has been formed, thus allowing the system to associate 0000001111 with 1111, but as region 4 has not been formed, it cannot associate 1111 with 0000001111.

Most simple associations are bi-directional as the training proceeds A,B,A,B,... allowing both regions to be formed.

5.16 Reproduction of Sequences.

In his classic paper to the Hixon Symposium in 1951, Lashley stressed the importance of serial order in behaviour:

"Reproductive memory appears, almost invariably, as a temporal sequence, either as a succession of words or acts." (Ref R.2.21.) All important behaviour involves time sequences, the most obvious example being language. Even visual perception of static objects seems to involve the integration of sequences of visual features (Ref R.2.17). Thoughts follow one another in sequences: actions are performed by a sequence of control signals from the motor cortex.

Early approaches to sequence recognition and reproduction by Uttley and Taylor (Refs R.1.18., p123. and R.1.36.) used circuits which fall into the 'structure dominant' class discussed in section 3.5.5. Uttley's system used delays, and was capable of recognising any sequence involving two inputs. To do this, 16 'neural' elements were needed and to increase the power of the system, this figure must rise geometrically. For example , if Uttley's theories were used to recognise any sequence of 16 inputs, then 10^{10} neural elements - the entire human brain - would be needed.

Work with the Block program has shown that the 10 by 10 matrix is capable of learning any sequence of up to eight elements. These elements may either be single inputs or combinations of inputs. Generally the sequence must contain non-repetitive elements, although later experiments have shown that the Block can learn a class of sequences in which the same elements appear twice.

The power of the Block is due to the fact that its behaviour is not dominated by its structure: it was not designed specifically to remember sequences, but to simulate the machinery of the C.N.S. The properties of the Block which emerged during the experimental period are all the result of a generalised structure and the changes due to the learning theorem . The range of properties which have resulted from these factors gives the author an indication that the premises on which the simulation is based may be similar to the basic organisation of the nervous system.

The following example illustrates the Block's capacity to learn, remember and reproduce a sequence.

The simplest sequence to be presented involved four input stimuli as shown in Fig 41:

0001	4, 12
000001	6, 20
00000001	8, 25
0000000001	10, 29

Fig 41.

This sequence was presented to the Block several times. The W matrix that resulted is shown in Fig 42:

20	1	1	1	1	1	1	1	1	1
1	20	1	1	1	1	1	1	1	1
1	1	20	1	1	1	1	1	1	1
1	1	1	20	1	5	1	1	1	1
1	1	1	1	20	1	1	1	1	1
1	1	1	1	1	20	1	5	1	1
1	1	1	1	1	1	20	1	1	1
1	1	1	1	1	1	1	20	1	5
1	1	1	1	1	1	1	1	20	1
1	1	1	5	1	1	1	1	1	20

Fig 42.

As can be seen, the sequence has caused four 'synapses' to up-date their long term weighting values. The mechanics of this are identical to that described in the association section: when two inputs follow each other, the learning theorem causes a 'synaptic' weight increase to occur on specific regions defined by the inputs.

In order to reproduce the sequence, the same type of feed-back is required as that shown in Fig 39. As each input pattern consists of only one active input line, this would involve each output from the Block being fed back to its corresponding input. Thus column 1 would activate input line 1, and so on. In practice this was again performed by the computer operator, who typed the input to the program which corresponded to the previous output. The results from this test are shown in Fig 43.

0001	4, 28
0001	4, 25
0001	4, 22
0001	4, 20
0001	4, 13
0001	4, 7
0001	6, 1
000001	6, 23
000001	6, 23
000001	6, 21
000001	6, 20
000001	6, 13
000001	6, 7
000001	8, 2
00000001	8, 23
00000001	8, 23
00000001	8, 21
00000001	8, 13
00000001	8, 7
00000001	10, 2
0000000001	10, 23
0000000001	10, 23
0000000001	10, 21
0000000001	10, 20
0000000001	10, 13
0000000001	10, 7
0000000001	10, 2
0000000001	4, 1
0001	4, 23
0001	4, 23
0001	4, 21

Fig 43.

As can be seen, the entire sequence is reproduced. The first input causes column 4 to fire; this tires and the output shifts to column 6 because of the plastic change that occured at the fourth 'synapse' on column 6. This changes the input to 000001, maintaining an output from column 6 until it too tires. An output from column 8 results, then column 10, and finally back to column 4.

The sequence is composed of four directional associations: column 4 to column 6, column 6 to column 8, column 8 to column 10, and column 10 to column 4. The regions of 'synaptic' facilitation corresponding to these directional associations are clearly visible on the W matrix shown in Fig 42.

This example describes the basic mechanism whereby the Block creates areas of 'synaptic' facilitation in specific locations on the W matrix to represent a sequence, and how it is then able to use the spatial pattern of facilitated 'synapses' in order to reproduce the original sequence.

5.16(a) <u>Effect of Errors in Sequence Training</u>.

As the Block is able to generalise its inputs, it follows that a large range of mistakes within a sequence will also be generalised, and will not, therefore, interfere with the Block's capacity to reproduce the basic temporal pattern that is being presented. Further, as the Block works with majority logic, an occasional mistake in the training sequence will have a negligible effect on its behaviour.

To demonstate the Block's behaviour when faced with imperfect inputs, a simple training sequence was presented as follows:

0001	4, 12	
000001	6, 20	Fig 44
00000001	8, 25	

This was presented regularly, and occasional errors were added. For example 1001 was input instead of 0001, both of which produce an output from column 4 and do not therefore interfere with the basic sequence. One incorrect sequence was presented (0001, 00001, 000001) causing the outputs to respond with 4, 5, 6,...

The resulting W matrix is shown below:

20	1	1	1	1	2	1	1	1	1
1	20	1	1	1	1	1	2	1	1
1	1	20	1	1	2	1	1	1	1
1	1	1	20	2	11	1	1	1	1
1	1	1	1	20	1	1	1	1	1
1	1	1	1	1	20	1	12	1	1
1	1	1	1	1	1	20	1	1	1
1	1	1	12	1	1	1	20	1	1
1	1	1	1	1	1	1	1	20	1
1	1	1	1	1	1	1	1	1	20

Fig 45

The effect of the basic training pattern can be seen in the three W values of 11, 12, and 12, as can the affect of the errors in the several W values of 2. Obviously the behavior of the Block is going to be dominated by the highest W values, and the subsequent tests on the system demonstrated that the basic training sequence may be reproduced without any noticeable interference from the erroneous inputs.

5.17 Spurious Outputs.

During several of the tests on generalisation and association, the Block exhibited an extremely interesting phenomenon: repeated input of a single stimulus eventually led to the production of totally unrelated outputs. Fig46 illustrates this; the data was produced during the experiments concerned with generalisation described in section 5.13.

1111	10, 78
1111	10, 83
1111	10, 88
1111	10, 93
1111	10, 91
1111	10, 89
1111	10, 83
1111	4, 80
1111	10, 79
1111	4, 76
1111	10, 75
1111	4, 72
1111	10, 71
1111	4, 68
1111	10, 67
1111	3, 67
1111	3, 70
1111	3, 73

Fig 46.

As can be seen, outputs occur from columns 10 and 4 as expected until both of these become tired, when column 3 fires. At first this phenomenon was a little disturbing, and the validity of the program was questioned, but it became apparent that a similar result has been reported by Lilly during experiments with tape loops (Ref R.2.29., p 72.) If a subject is told to listen to a tape loop of a repeated word, his initial perception of that word soon tires, and as many as thirty different words may be heard at different times throughout the experiment. This is just the type of behaviour that was encountered in the experiments shown in Fig 46.

A more detailed description of this phenomenon may be found in Ref. R.2.30.

5.18 Conclusion.

The work presented in this chapter provides an introduction to the Block organisation. Its origins have been described in terms of the principles that have been derived from the aforementioned work on hardware cybernetic systems, and the physiological data on the cortex which has emerged during the last few years. The Block structure has been described, and a qualitative description of its properties has been given. It has been shown to be capable of generalisation, association and of learning, remembering and reproducing a sequence. All of these phenomena can be explained directly by observing the changes in the 'synaptic' weights of the system, and thus the Block provides an explanation of how a plastic system may be modified by input stimuli and how these modifications in internal organisation can result in behavioural changes.

The simplicity of the basic organisation, and the power of the resulting behaviour suggest that the Block is of importance in the study of the way in which neurons and synapses interact so as to produce systems which can exhibit the kind of phenomena that are termed "intelligent". In order to pursue this line of study, a thorough analysis was performed so as to produce more precise data concerning the properties of the Block. This data is described in the following chapter.

C H A P T E R 6

SEQUENTIAL PROPERTIES OF THE BLOCK

SEQUENTIAL PROPERTIES OF THE BLOCK

6.1 Introduction.

The previous chapter has described the structure and basic behaviour of the Block. The present chapter describes the experiments which were performed in order to give a more thorough evaluation of the performance of the Block. The work is restricted to sequential properties, since the ability to reproduce sequences is by far the most interesting aspect of the performance of the Block.

The proceedure adopted in the experiments is identical to that described in the previous chapter, but before the work is described it seems essential to clarify two points:

a) The reproduction of a sèquence depends on the experimenter for feedback. He initiates the sequence by presenting the Block with one of the elements of the sequence (not necessarily the first element of the "training set"), and the Block responds with the corresponding output. This informs the experimenter that he must present the Block with an input corresponding to the previous output, and as this process continues the sequence is reproduced. Thus, after defining the point of entry into the sequence, the experimenter is under the control of the Block in order to provide the necessary feedback. It would be possible to introduce a feedback loop into the program and thus enable the Block to reproduce sequences without help from the experimenter. This has not been found necessary in the experimental work, since the experiments generally must be performed slowly and the information in the W matrix needs regular attention.

b) The mechanism which ensures that no column may fire for an extended period of time involves raising the threshold of any column which fires more than five times, thus making it progressively more difficult to fire. Throughout this chapter this phenomenon is refered to as "tiring" or "habituation", and columns are referred to as "tired" or "habituated".

6.2 Sequences with Non-repetitive Elements.

This section describes the work that was carried out with sequences in which each element is used only once within a single iteration. This class of sequence includes A B C D, D E C A, and E A D B C for example, but not A B A C or D B B C A. (Each capital letter represents one element of the sequence.)

6.2.1 Single Spatial Inputs.

The simplest class of sequence involves non-repetitive elements in which each element is composed of a single spatial input to one of the inputs to the Block. An example is given below:

0001	4, 12	
0010	3, 20	Fig 47
1000	1, 25	
0100	2, 29	

The nature of the input stimulus enables a shorthand notation to be adopted: the sequence illustrated in Fig 47 may be described completely as a "4 3 1 2" sequence. This is only possible when all the elements are composed of single spatial inputs: with more complex sequences, both the inputs and outputs must be specified for a complete description.

Minimum Training Period. For a sequence of this type to be reproduced, it must be presented to the Block at least four times. Experiments with only three presentations have shown that although the Block is able to make the relevant changes in weightings in the W matrix, it is unable to reproduce the sequence, since there is insufficient strength in the weightings to initiate the necessary directional associations.

The mechanisms involved in sequence reproduction have been fully described in the previous chapter. In the testing mode, a single input is presented and is stable until it tires. As can be seen in Fig 43, an input of 0001 causes column 4 to fire and its DIFF value falls progressively from 28. After six presentations the activation shifts to column 6, as it has a greater DIFF value due to the updated W values created in the training program. If the sequence is presented only three times, the Block is unable to shift the activation as the value of DIFF on all the columns falls to zero, and there is, consequently, no information to enable the sequence to be reproduced.

Maximum Length of Sequence. During the experiments with single spatial element sequences, it became apparent that although short sequences could be reproduced easily, the longer ones were unable to make any effect on the W matrix. A typical experiment involved ten single spatial elements presented non-repetitively: the Block was trained for an extended period of twenty presentations, and still there was no change in the W matrix. In order to explain this phenomenon, it became necessary to examine the STW values, since it was obvious that the columns were firing and thus the only other variable relevant to the learning behaviour of the Block - STW - had to be examined.

Consequently, the program was modified to print out the value of STW of the first input line. This was found to be sufficient as in sequential phenomena, the STW values all follow the same pattern.

Consider the data pertaining to the presentation of a four element sequence:

Input	:	1000	0100	0010	0001	1000	0100
Output	:	1	2	3	4	1	2
STW	:	8.4	5.88	4.116	2.881	9.207	6.445

Fig 48.

The STW value of the 'synapses' stimulated by channel 1 rises to 8.4 when channel 1 is activated. It then decays exponentially to 2.881 as the other inputs are presented and rises to 9.207 with the second input to channel 1. The second presentation of 0100 causes column 2 to fire, and at this critical time the STW of the 'synapses' at the top of each column is 6.445. Thus, the first 'synapse' on column 2 is updated as a) that column is active and b) the STW value of 6.445 shows that its input has been recently activated. The "recently activated" condition is defined by a STW value of 6 and over.

The other 'synapses' are updated in a similar manner.

In a sequence composed of eight elements the value of STW pertaining to the 'synapses' on the top row of the W matrix change as follows:

8.4 5.88 4.116 2.881 2.107 1.412 0.988 0.692 8.594 6.016

Again at the critical time the value of STW is just above 6 (6.016) and thus the relevant 'synapses' are updated and the sequence is reproduced.

In a sequence composed of nine elements, the following values of STW were obtained:

8.4 5.88 4.116 2.881 2.017 1.412 0.988 0.692 0.484 8.536 5.975

As the value of STW is 5.975 at the critical time, the program concludes that there are no inputs which have been "recently activated" and, consequently, no long term learning results.

From these experiments it may be concluded that sequences of eight or less elements of this type may be reproduced, whereas those with nine or more elements are unable to affect the W matrix and are therefore, incapable of being reproduced.

<u>Experiments with 4 element Sequences.</u> In order to define the range of sequences of this type which can be reproduced by the Block, a series of experiments was undertaken. Each experiment began by resetting the Block variables, so that its past experience did not interfere with the new sequence. Thus we are concerned with the <u>range of possible sequences</u> which can be reproduced by the Block, and not at present with its capacity for simultaneously remembering many sequences.

The first set of experiments involved the first four input channels only. There are 24 different combinations, but only six different sequences since a 1 2 3 4 sequence which repeats contains 2 3 4 1, 3 4 1 2, 4 1 2 3. The six sets are illustrated below:

1234, 2341, 3412, 4123.
4321, 3214, 2143, 1423.
1342, 3421, 4213, 2134.
1243, 3421, 4213, 2134.
1324, 2431, 4312, 3124
1423, 4231, 2314, 3142.

Fig 49.

The shorthand notation is the same as that defined with respect to Fig 47.

After four presentations - the minimum training period - each of these sequences was reproduced by the Block, given any one of its elements.

The next set of experiments was designed to test the inputs which had been previously ignored. Thus four-element sequences were presented as follows :

5 6 7 8	1 8 3 6	2 6 4 9
9 8 7 6	4 7 1 10	10 1 9 2

3 6 4 9	6 1 9 4	9 2 3 7
10 4 1 6	3 2 1 5	1 3 5 7
8 6 4 2	1 8 6 10	9 5 1 8

These sequences were chosen so as to ensure that all ten inputs were used in at least one of the experiments. Again, after four or more presentations, every one of these permutations was reproduced by the Block.

Experiments with N-element Sequences. Further experiments were undertaken in order to investigate sequences with more than four elements. Examples are given below in Fig 50.

1 2 3 4 5 6 7 8
10 9 8 7 6 5 4 3
3 8 5 9 6 2 1
10 1 7 3 9
1 8 4 2 6 10
9 1 8 2 7 3 6 5

Fig 50.

As the experiments proceeded it became obvious that regardless of the order in which any "N" single spatial inputs were combined into a sequence, there would always be N 'synapses' to make the relevant connections and thus, after four or more presentations, to enable the sequence to be reproduced. All sequences of this type, without exception, were reproduced, provided they had less than nine elements.

It should be stressed that after each experiment, the Block variables were reset, so that each sequence was presented to an "uneducated" Block.

Calculation for N-element Sequences. From the experiments which have just been described, it may be assumed with a fair degree of certainty that a single Block can reproduce all sequences which are a) composed of single spatial-input elements, b) eight or less elements in length, c) presented more than three times and d) composed from non-repetitive elements.

For an "N" element sequence and a ten input Block, the number of possible sequences is given by:

$$\frac{10!}{(10-N)!} \quad \frac{1}{N}$$

This equation gives the following results:

Length of Sequence	Number Reproducible
2 elements	45
3 "	240
4 "	1260
5 "	6048
6 "	25200
7 "	86400
8 "	226800

This calculation shows that theoretically the Block can reproduce a total of 345,993 different sequences of this type. This figure is indicative of the range of sequences which are reproducible, and has no relevance to the capacity of the Block to work with more than one sequence at a time.

Although only a small proportion of these sequences have actually been tested, a representitive sample has , as far as possible, been used and on every occassion the sequence has been reproduced with equal facility.

6.2.2. Complex Spatial Inputs.

This section describes the experiments which were performed with sequences composed of many-input elements.

6.2.2 (a) Non-overlapping Input Elements.

The following sequence was presented to the Block:

1111	4,	51	
000011	6,	57	Fig 51.
0000001111	10,	87	

The first element involves the first four inputs, the second involves the fifth and sixth inputs, and the third involves the last four. Thus there is no overlap (due to two or more of the elements using the same inputs) within the sequence. After several presentations, the following W matrix resulted:

20	1	1	7	1	6	1	1	1	1
1	20	1	7	1	6	1	1	1	1
1	1	20	7	1	6	1	1	1	1
1	1	1	20	1	6	1	1	1	1
1	1	1	1	20	7	1	1	1	6
1	1	1	1	1	20	1	1	1	6
1	1	1	5	1	1	20	1	1	7
1	1	1	5	1	1	1	20	1	7
1	1	1	5	1	1	1	1	20	7
1	1	1	5	1	1	1	1	1	20

Fig 52.

The W values of 7 are the result of the static learning process defined in section 5.11. The W values of 6 and 5 are the result of the sequential presentation of the three elements of the sequence, and provide the link between these elements. As can be seen, there are groups of high W values to interconnect the sequence rather than a single high W value, as in the previous section. This does not affect the Block's ability to reproduce the sequence: a test on the above sequence showed that after ten presentations it could be reproduced by the Block.

Experiments were then carried out with further sequences of this type. Examples are given below:

111	1100110011	10101
000111	0011000000	01010
0000000111	0000001100	0000011111
11	1100000011	111
0011	00101	00011
000011	000101	00000111
0000001111	00000011	0000000011

Fig 53

As the experiments continued, it became obvious that as long as there is no overlap, a Block is capable of reproducing any sequence of up to eight elements regardless of their spatial format, provided that they are presented often enough.

Minimum Training Period. Complex spatial input element sequences require a longer training period than the simple sequences described in the previous section. Consider the following sequence:

11
0011
000011

Fig 54

After seven presentations to the Block, the following W matrix was produced:

20	7	1	6	1	1	1	1	1	1
1	20	1	6	1	1	1	1	1	1
1	1	20	7	1	6	1	1	1	1
1	1	1	20	1	6	1	1	1	1
1	5	1	1	20	7	1	1	1	1
1	5	1	1	1	20	1	1	1	1
1	1	1	1	1	1	20	1	1	1
1	1	1	1	1	1	1	20	1	1
1	1	1	1	1	1	1	1	20	1
1	1	1	1	1	1	1	1	1	20

Fig 55.

Testing the system began with an input of 11 which activated column 2. The feedback maintained the activity of column 2 until it tired, at which point the activation shifted to whichever of the other columns was most excited by the 11 input. This was not column 4 as expected (sum of W values on first two input lines = 12) but column 1 (sum of W values on first two input lines = 21).

The sequence was presented a further six times, so that the relevant W values had increased to 12 and the sum of the W values on the first two inputs to column 4 had increased to 24. This meant that the directional association from column 2 to column 4 was stronger than that from column 2 to column 1 and the subsequent testing of the Block showed that the original sequence was reproduced correctly.

Further experiments revealed the following results:

No. of Inputs in Element.	Minimum Training Period.	Resulting Sum of Relevant W values.
2	11	22
3	8	24
4	6	24
5	6	30
6	5	30

Fig 56.

The explanation of this is as follows: a complex spatial-input element activates several input channels, and will consequently have a significant effect on all those columns in which a non-plastic 'synapse' (W = 20) is stimulated. Thus, the directional associations which implement the reproduction of the sequence must be correspondingly stronger, in order to attract the activation away from these columns.

Calculation for Two Element Sequence: Complex Spatial Inputs.

Consider a two-element sequence consisting of the first "N" inputs to the Block followed by the last "10-N" inputs. The first element may be permuted in 2^N different ways, although one of these may be ignored as it is composed from N "0"signals , or no input. Thus the number of different sequences of this type is given by:

$$(2^N-1)\ (2^{(10-N)}-1)$$

This equation gives the following results:

N	Number of Different Sequences
1	511
2	765
3	889
4	945
5	961
6	945
7	889
8	765
9	511

This calculation shows that 7,191 different sequences of this type may be presented to the Block, and the experiments which have been concerned with a small but representitive sample of these suggest that they are all reproducible by the Block organisation.

6.2.2 (b) Overlapping Input Elements.

This section describes sequences which are composed from non-repetitive elements, in which the same input stimulus is used in two or more of the elements. An example is given below:

111	3, 38	
11	2, 39	Fig 57
1	1, 31	

After five presentations, the following W matrix was produced:

20	6	6	1	1	1	1	1	1	1
6	20	6	1	1	1	1	1	1	1
1	5	20	1	1	1	1	1	1	1
1	1	1	20	1	1	1	1	1	1
1	1	1	1	20	1	1	1	1	1
1	1	1	1	1	20	1	1	1	1
1	1	1	1	1	1	20	1	1	1
1	1	1	1	1	1	1	20	1	1
1	1	1	1	1	1	1	1	20	1
1	1	1	1	1	1	1	1	1	20

Fig 58

Testing the system began with an input of 111. Column 3 was activated, and this remained stable for eight iterations. It then tired, and the activity passed to column 2 as expected. This was followed by column 1, but when this tired the activity moved not to column 3 (the beginning of the sequence) but to column 2. As can be seen from the W matrix an input of 1 stimulates column 1 most strongly, and then column 2 and column 3 equally. Thus, the critical factor in this situation is the <u>tiring value</u> corresponding to each of these columns. In the present example, column 3 was more tired than column 2, and thus the activity passed to column 2.

This example illustrates the kind of problem which emerges when overlapping patterns are used as the elements in a sequence. It cannot be obviated by longer training periods, since both the directional associations (from column 1 to column 2, and from column 1 to column 3) will become stronger at the same rate.

The same three elements were then used in the reverse order, and the following results were obtained:

1	1, 12	Fig 59
11	2, 28	
111	2, 46	

The third input does not produce an output from the third column, as the Block "generalises", and gives an output from column 2. As the system "sees" the second and third inputs as the same, it is incapable of combining then into a sequence. This situation will obviously be true for many other sequences of this type: where there is a high degree of overlap, the inputs will be similar, and there is a high probability that they will produce the same output.

The difficulties with this kind prompted a set of experiments to test three-element sequences of this type. The results are shown below:

Input Sequence	W matrix (relevant 9 values)	Output Sequence
111 11 1	20 6 6 6 20 6 1 5 20	3,2,1,2
1 01 011	20 6 1 7 20 7 6 1 20	1,2,3,2,
1 01 011	20 14 1 15 20 15 14 1 20	1,2,3,1,2,1,
1 01 111	20 11 12 10 20 12 9 2 20	3,1,2,3,1,2,3
101 01 1	20 8 9 8 20 1 1 8 20	1,3,1
101 01 1	20 17 18 17 20 1 1 17 20	3,2,1,3,2,1,3
1 01 101	20 6 7 1 20 6 5 1 20	1,3

1	20 7 7	
11	6 20 7	1,3
011	5 1 20	
011	20 1 8	
01	10 20 10	1,3,2,3
1	1 9 20	
001	20 9 9	
11	8 20 1	3,2,1,2
1	2 8 20	
1	20 8 8	
11	1 20 7	1,3
001	6 1 20	
111	20 4 5	
01	5 20 5	3,2,1,3,2,1,3
1	1 4 20	

Fig 60

As can be seen, the relevant'synapses' were updated in all cases, and yet the Block was only able to reproduce a fraction of the permutations. The reasons behind this low success rate may be clarified by closer examination of one of these experiments. Consider the following sequence:

100	1,12
01	2,20
011	3,33

Fig 61

After seven presentations, the following W matrix resulted:

20	6	1
7	20	7
6	1	20

Fig 62 W matrix
(relevant 9 values only)

On testing, the Block reproduced the first three elements, but was unable to make the connection from element three (011) back to the beginning of the sequence (100). This is because the directional association due to the second and third 'synapses' on column 2 (combined value 21) is greater than the relevant 'synapses'on column 1 (combined value 13).

This is analagous to the situation described in section 6.2.2 (a): the complex input pattern activates two input channels, and thus has a significant effect on column 2, as its non-plastic 'synapse' (W = 20) is activated. In order to obviate this problem, a longer training set is required. Consequently, the training was resumed until the relevant W values reached 14, and subsequent testing showed that the Block is able to make the connection from element 3 back to the beginning of the sequence. The test showed that the pattern is reproduced correctly, but only for the first five iterations. A complete examination revealed the following order of columnar outputs:

1,2,3,1,2,1,2,3,1,2,1,2,3.

It will be noted that confusion arises after column 2 tires. On the first occasion activation passes to column 3, on the second to column 1, the third to column 3 and the fourth to column 1. This may be explained by examination of the W matrix. Column 2 is activated by an input of 01. When it tires there are two equal directional associations to influence the Block a) to column 1 and b) to column 3. These are determined by the high W values at the second 'synapse' on columns 1 and 3. As the directional associations are equal, the effect of tiring is critical: if activation passes from column 2 to column 3 on the first occasion it will pass from column 2 to column 1 on the next occasion since column 3 is more tired.

Thus, the mechanisms which enable the simple sequences discussed in sections 6.2.1 and 6.2.2 (a) to be reproduced are insufficient for the reproduction of sequences composed of overlapping input elements.

Calculation for Three Element Sequence(three inputs only). Three inputs to the Block may be combined in eight different permutations. One of these (000) may be ignored. Thus there are $7 \times 7 \times 7$ different three element sequences of this kind which may be presented to the Block. (343 possible permutations.)

If those sequences which contain two or more identical inputs are ignored (eg 111, 111, 111.), then the total of 343 falls to 294 (343 - 49). for non-repetitive elements.
Further, all those sequences may be ignored which contain elements which the Block "generalises" to give the same output. For example 001, 011, 101, and 111 all give an output from column 3 and cannot therefore be combined into a sequence. This lowers the number of possible sequences to only sixteen. They are as follows:

1	001	1	001	1	011	1	011
01	01	11	11	01	01	11	11
001	1	001	1	011	1	011	1

1	101	1	101	1	111	1	111
01	01	11	11	01	01	11	11
101	1	101	1	111	1	111	1

Fig 63.

These sixteen permutations were all tested, and only five were found to be reproducible by the Block. Thus out of a theoretical value of 294 possible sequences only 5 can be reproduced by the Block.

6.2.3 Summary.

The sequences which have been described in this section involve non-repetitive elements consisting of both single and complex input configurations. The experiments have all been designed to investigate the range of sequences which are reproducible by the Block organisation. Thus, each experiment began by resetting all the Block variables to their original level, and the sequence was then presented to an "uneducated" Block. In all the experiments the computer operator provided the feedback needed to reproduce the sequence by typing in the input corresponding to the output given by the Block.

The first section involved single spatial inputs, and as far as can be ascertained from the limited sample that was tested, the Block is able to reproduce any sequence that is:

a) composed from single spatial-input elements,

b) eight or less elements in length,

c) composed from non-repetitive elements, and

d) presented four or more times.

The Block exhibited a similar capacity to reproduce complex, but non-overlapping input element sequences. These were found to need a longer minimum training period, but over an extensive experimental period, the Block was able to reproduce every sequence which was presented to it regularly. Again, a small but representitive sample suggests that the Block is able to reproduce every sequence of this type.

A major problem was encountered with overlapping input element sequences. A comprehensive experimental program checked every permutation of triple-input three-element sequences and has shown that only five out of a possible 294 sequences may be reproduced. The reasons behind this failure have been discussed, and it may be concluded that the Block is inherently unsuitable for reproducing sequences composed of elements which exhibit a high degree of overlap.

6.3 Sequences with Repetitive Elements.

This section involves sequences which use the same element more than once in a single iteration. An example is shown below:

11	2, 25	
00011	5, 41	Fig 64
11	2, 46	
0000011	7, 55	

As can be seen, the 11 input is presented twice in a single iteration of the sequence. After several presentations, the following W matrix was produced:

20	20	1	1	13	1	14	1	1	1
1	20	1	1	13	1	14	1	1	1
1	1	20	1	1	1	1	1	1	1
1	13	1	20	13	1	2	1	1	1
1	14	1	1	20	1	2	1	1	1
1	12	1	1	1	20	14	1	1	1
1	12	1	1	1	1	20	1	1	1
1	1	1	1	1	1	1	20	1	1
1	1	1	1	1	1	1	1	20	1
1	1	1	1	1	1	1	1	1	20

Fig 65

The difficulty with this sequence is that the learning process produces two directional associations which both start from column 2. Thus when column 2 tires, the activation is directed towards column 5 and towards column 7. The test on the system was carried out in the same way as in the previous section: a single element was presented to the Block and thereafter the computer operator provided the feedback by typing the next input to the program which corresponded to the previous output. The results are shown below:

11	2, 64
11	2, 65
11	2, 62
11	2, 60
11	2, 51
11	5, 44
00011	5, 68
00011	5, 66
00011	5, 62
00011	5, 58

Fig 66.

00011	5, 51
00011	5, 44
00011	2, 42
11	2, 64
11	2, 65
11	2, 62
11	2, 60
11	2, 51
11	7, 47
0000011	7, 68
0000011	7, 66
0000011	7, 62
0000011	7, 58
0000011	7, 51
0000011	7, 44
0000011	2, 43
11	2, 64
11	2, 65

Fig 66 (contd.)

As can be seen the complete sequence is reproduced correctly. The explanation of this is as follows: after column 5 has fired seven times, the activity shifts to column 2, leaving column 5 habituated. After column 2 tires, the activity is directed towards both column 5 and column 7, but as column 5 is still habituated the activity shifts to column 7. Column 7 then fires seven times, becomes tired, and the activty shifts back to column 2. Column 2 fires five times, tires, and the activity moves to column 5, since column 7 is habituated.

In other words, the activity moves from column 2 to whichever of column 5 or column 7 is the <u>least</u> habituated.

Further experiments were performed to find the range of repetitive element sequences which are reproducible by the Block organisation. Examples are illustrated below:

11	111	11
0011	00011	11
11	00011	00011
0011	111	00011
11	111	11
0011	00011	11
00001111		00011
		00011

Fig 67.

The three sequences illustrated in Fig 67 were each presented to an "uneducated" Block and subsequent testing revealed that in all cases the Block could not reproduce them. The experiments have shown that the Block is able to repond to changes in input stimulation, but has no mechanism to respond to a sequence of identical input elements. For example, if the Block was presented with A A A A B B B B C C C C, it would only record the changes, and the sequence would be reproduced as A B C.

The experiments have shown that in all but the simplest examples the Block organisation is insufficient to reproduce sequences which contain repetitive elements. The learning process is able to record the changes in the elements of the sequence, and the more often that a change occurs, the more strongly it is recorded (ie the larger the value of W which represents that change). However, the actual reproduction is largely under the control of the relative tiring values of the ten columns, and in the vast majority of examples this has been found to be inadequate for the reproduction of sequences with repetitive elements.

6.4 Simultaneous Retention of Sequence Information.

All of the work described in chapter 6 has involved the range of sequences which can be reproduced by the Block. Consequently, each experiment began by resetting all the Block variables so that the sequence was presented to an"uneducated" Block. This section describes the experiments which involved the simulataneous retention of sequence information in the W matrix. Thus after the first sequence had been trained and tested, the second was presented to the Block without resetting the variables.

6.4.1 Non-overlapping Sequences.

Consider the following two sequences:

Sequence A :	1	Sequence B :	0000001	
	01		00000001	Fig 68.
	001		000000001	

Sequence A was trained and on testing, it was found to be easily reproducible by the Block. Sequence B was then presented several times and subsequent testing showed that it too could be reproduced. Sequence A was then re-tested and reproduced. Sequence B was re-tested and again it was reproduced.

As sequence A involves the first three input channels , all relevant W updating occurs in the top left hand corner of the W matrix. Similarly, the W updating relating to sequence B occurs in the bottom right corner of the W matrix. As neither the input elements nor the 'synapses' which link these elements co-incide, it is not suprising that the two sequences may be learnt, remembered and reproduced without interference.

Further experiments have confirmed that the Block can reproduce more than one sequence, as long as there is no overlap in the elements of these sequences.

6.4.2 Overlapping Sequences.

Consider the following sequences:

Sequence A :	1	Sequence B :	001	
	01		0001	Fig 69.
	001		00001	

Sequence A was presented several times, and on testing was reproduced by the Block. Sequence B was then presented several times; the resulting W matrix looked as follows:

20	15	1	1	1	1	1	1	1	1
1	20	10	2	1	1	1	1	1	1
9	1	20	6	1	1	1	1	1	1
1	1	1	20	8	1	1	1	1	1
1	1	6	2	20	1	1	1	1	1
1	1	1	1	1	20	1	1	1	1
1	1	1	1	1	1	20	1	1	1
1	1	1	1	1	1	1	20	1	1
1	1	1	1	1	1	1	1	20	1
1	1	1	1	1	1	1	1	1	20

Fig 70.

The test on sequence B began with an input of 00001. This gave an output from column 5 which continued until habituation caused the activity to shift to column 3. When column 3 tired, the activity moved to column 1 , and thereafter continued to reproduce sequence A. Examination of the W matrix shows that sequence A had been presented more often than sequence B and that when column 3 (which is common to both sequences) habituates there is a stronger influence due to sequence A than there is due to sequence B. Consequently, sequence B cannot be reproduced at this time.

Further training with sequence B followed. After seven extra presentations the Block was again tested and this time sequence B was reproduced correctly. However, the Block was unable to reproduce sequence A, since the directional association from column 3 to column 4 was stronger than that from column 3 to column 1.

It may be concluded that the Block is able to reproduce either sequence A or sequence B, but that at any one time one of them has to be dominant and, therefore, prevents the reproduction of the other.

6.5 Discussion.

6.5.1 Range of Sequences.

The experiments described in this chapter have demonstrated that the Block is able to reproduce a huge range of simple sequences, but that it is inherently unsuitable for the reproduction of sequences composed from input elements with a high degree of overlap. Two points arise from this:

1) The Block is a small experimental system. Its limited size means that overlap problems emerge quickly. Had the Block been composed of, say, a 100 by 100 matrix, there would have been a considerable range of input elements which could have been used in sequences before the overlap problem emerged.

2) For a sequence to be reproduced, it must be assumed that there is feedback from the output of each column back to those inputs which constitute the element of the sequence which activates that column. Thus, if an input of 111111 is used to fire column 6, then it must be assumed that there is feedback from the output of column 6 back to the first six input channels of the Block. Sequences with a high degree of overlap and complex spatial input elements would, therefore, require a very specific and complex feedback network in order to be reproduced by the Block.

6.5.2 Maximum Length of Sequence.

In section 6.2.1 it was explained how the learning theorem, which depends on a co-incidence of an output signal with a recently activated input (defined by an STW of 6) restricts the length of reproducible sequences to eight elements. From this it follows that if the critical value of STW is lowered, then longer sequences can be remembered. However, this kind of change in basic parameters has other effects on the performance of the Block.

Consider, for example, lowering this critical value of STW from 6 to 4. This would enable longer sequences to have an effect on the W matrix, and consequently to be reproduced, but it would also lead to other irrelevant changes in the W matrix. For example, consider the sequence described in Fig 48. The third input (0010) causes column 3 to fire, and at this instant the value of STW on the first input line is 4.116. Thus the first 'synapse' on column 3 will be updated, and this will result in a connection being made between column 1 and column 3 which is obviously undesirable.

It would appear that this situation involves a "trade-off" : for the Block to maintain a degree of selectivity in its learning behaviour, it must accept some limit in the length of sequence that it can reproduce.

6.5.3 Introduction of Long Term Forgetting.

In section 6.4.2., the data from the experiments involving the simultaneous retention of two sequences composed from overlapping elements was presented. The performance of the Block was found to be unsatisfactory as one sequence has to be dominant, and this can prevent the reproduction of sequences which are presented to the Block at a later date. In order to improve this situation, the program was modified to introduce "long term forgetting" : all W values were lowered by 10% once every twenty iterations. The maximum and minimum values of 20 and 1 respectively were maintained. This produced a significant improvement.

It was found that during the presentation of sequence B, the strength of sequence A (which had already been presented several times) decayed so that the training period needed to establish sequence B was significantly shorter. The long term forgetting ensured that all sequences decayed with time, so that the presentation of new data did not have to"fight" for dominance with older sequences.

From these initial experiments it is likely that a learning system which is to reproduce many sequences must function in the following manner:

a) The initial training period must produce large changes in the relevant W values quickly. These high W values enable the sequence to be reproduced, and are maintained by the reproduction of the sequence until either the columns tire, or new information is presented.

b) During the times that the sequence is not active in the system, the high W values decay to a base level which is significantly higher than the original, uneducated value of W, but well below the high W values which are needed to reproduce the sequence.

c) Restimulation of a sequence which has decayed to the base level restores the W values to the operational level with a much shorter training period than that initially needed in the primary training period.

Thus, once a sequence has been presented regularly enough (primary training) the W values which maintain it will remain at the base level so that the sequence is potentially reproducable with only a very brief re-training.

6.6 Conclusion.

The experimental work described in this chapter has demonstrated that the Block is able to reproduce a large range of sequences provided that the elements of the sequence do not overlap, and that each element is used only one in a single iteration.

Severe problems have been encountered in the reproduction of sequences which involve complex spatial input elements with a high degree of overlap. The Block needs extremely complex feed-back systems to enable the reproduction to take place, and even if all this feed-back is provided only a tiny proportion of the possible permutations can be reproduced accurately.

The Block has also proved to be inadequate in the reproduction of sequences with repetitive elements.

C H A P T E R 7

CONCLUSIONS

CONCLUSIONS

7.1 Introduction.

The objective of this research program is to use models based on the organisation of the C.N.S. in order to synthesise cybernetic systems, and thus to understand the mechanisms which underly the behaviour of these systems especially those concerned with self-organisation. The work has therefore involved simulations of neurons and synapses, and the use of systems of these simulations in a variety of interconnection patterns. Each system is defined by a number of properties, and the experimental work has demonstrated the behaviour which resulted from a particular set of properties.

In this final chapter, the conclusions from the various experiments are gathered together to give a more rounded picture of the way in which a system organises its own behaviour. The chapter begins with a brief summary of the various models which were constructed, and goes on to examine the properties of the 'neurons' and 'synapses' in the light of the behaviour of the experimental systems. The various interconnection patterns are then considered, and the chapter ends by discussing the merits of the two modelling environments used in the research.

7.2 Summary of Systems Described in the Thesis.

SYSTEM	PROPERTIES OF ELEMENTS	LEARNING THEOREM	INTERCONNECTION PATTERN
Single hardware 'neuron' with plastic 'synapses'.	Excitatory inputs Temporal summation Number threshold	W increased if input to and output from 'N-S' coincide.	
Hardware system of plastic 'N-S' models.	Excitatory inputs Temporal summation Number threshold	As above.	Ordered.
Homeostatic network of hardware plastic 'N-S' models.	Excitatory inputs Inhibitory inputs Temporal summation Number threshold.	As above.	Random.
Software homeostatic system of columns of plastic 'N-S' models.	Excitatory inputs Inhibitory inputs Temporal summation Spatial summation Number threshold Tiring.	W increased if column fires and input has been <u>recently</u> activated.	Ordered. (Matrix configuration)

The table illustrated above summarises the various systems which have been described in this thesis. As can be seen, the properties of the elements became more complex, the learning theorem became more powerful, and the interconnection pattern progressed from a simple structured system to a more complex random system, and finally to a matrix configuration.

7.3 Properties of the Elements.

The models described in this thesis have been composed of elemental units based on the properties of neurons and their synaptic interconnections. This section is concerned with the properties of these elemental units and the effect they have had on the behaviour of the resulting systems.

7.3.1 Input Stimulation and Threshold.

The properties of every system described in this thesis are the direct result of the way in which information is processed in the elemental units which compose the various systems. Basically this involves the production of an output signal if the sum of the input stimulation exceeds the threshold of the 'neuron'. This is the basic property on which all else depends.

Throughout the experimental work this has been found both flexible and powerful. As information can only flow once the threshold of an element has been exceeded, the threshold values of the various elements within a system determine the way in which information flows in the system as a whole. Ultimately, all the properties of the overall system must depend on either the threshold of the elements (and in some cases this may change, for example due to tiring) or the effect of input stimulation (which is summated both temporally and spatially in some cases, and is dependent on the 'synaptic' weighting values).

7.3.2 Input Summation Processes.

a) Spatial Summation.

Several inputs to a 'neuron' are more effective in overcoming the threshold and producing an output signal than a single input. This has been used throughout the experimental work, with the following results:

1) The simple structure-dominant models described in section 3.5.3., used a form of spatial summation. For example in Fig 14, the 'neurons' will not fire unless three inputs are presented co-incidentally. This resulted in the output signal responding to one specific pattern of input stimulation.

2) In the random network described in chapter 4, it was found that to introduce stability the excitatory influences had to be balanced by inhibitory influences. Thus the models had to be redesigned so that these two influences could summate spatially, and consequently stabilise the network. In this model spatial summation was found to be essential for stable operation.

3) Although simple forms of spatial summation existed in the hardware models, as described above, complete spatial summation can only be found in the Block, where the signals form all ten inputs are summated. As in the random network, the number of active 'neurons' at any one time is limited to ensure stability (in the case of the Block to one active column) and this pre-supposes a lateral inhibitory structure, and spatial summation in order to balance the excitatory and inhibitory influences.

4) In the Block,spatial summation is essential for the system to exhibit "majority logic" : the various inputs are summated and only the column which is most strongly activated produces an output signal.

5) The generalisation experiments described in section 5.13 are also dependant on spatial summation, for the Block gives an output on the basis of the most stimulated column.

b) Temporal Summation.

In all the models, regular inputs accumulate and eventually cause the 'neuron' to fire. In the hardware models, this was a result of the use of a counter in order to implement the required number threshold for the 'N-S' system. The resulting properties are as follows:

1) In the hardware models temporal summation is the major factor which spreads excitation throughout the systems.

2) In the Block, temporal summation is achieved by the use of STW (short term weighting) : every input leaves its corresponding 'synapse' in an excited state for a short time, thereby enabling several high-frequency inputs to have a greater effect on the 'neuron' , due to the accumulation of these levels of excitation. The STW factor thus helps to increase the level of excitation within the Block.

3) The STW value is of importance as it is used by the learning theorem to tell when an input has been recently activated. Thus the mechanism which produces temporal summation is essential in the learning behaviour of the Block, and consequently in the reproduction of sequences.

7.3.3 Tiring.

Tiring was introduced into the Block by raising the threshold of any column which fired more than five consecutive times. Tiring was found to be essential in the Block, for it ensured that activity was unable to recirculate in closed feedback loops indefinitely. The tiring of the columns is essential for the reproduction of sequences.

7.3.4 Learning Processes.

In the models which have been described, the behaviour of the elemental units has been changed when certain conditions between the input to and the output from these units has been fulfilled. In every case, the change in behaviour resulted from an increase in the 'synaptic' weight of the elemental units. This means that the 'N-S' is more sensitive to information presented to a 'synapse' with an increased weighting value.

The location of the changes due to learning at the 'synapse' has proved to be satisfactory, because a 'synapse' is a one input / one output device and thus any changes in its properties only effect one specific pathway. Had the learning changes been located in the 'neuron' (a many input / one output device) then any change in its properties would have had widespread effects on the system.

a) Hardware Learning.

The hardware models described in chapters 3 and 4 increased their 'synaptic' weighting values whenever there was an exact co-incidence between an input to the 'synapse' and an output from the ' neuron'. This learning theorem produced the following results:

1) A single input to the 'N-S' resulted in an output pulse after a short delay. Thus there was no co-incidence between input and output and consequently no learning.

2) A slow series of inputs (frequency less than 3.5 Hz) did not result in any co-incidence of input and output, because the output from the 'N-S' produced by the Nth input had ended by the time the N+1th pulse was presented. There was, consequently, no learning.

3) A fast series of inputs (frequency greater than 3.5 Hz) resulted in a co-incidence of input and output, because the output from the 'N-S' due to the Nth input was still active at the time that the N+1th input pulse was presented. Thus, only fast input pulses are able to

have a learning effect on the 'N-S'. Throughout the work with hardware models, this was found to be satisfactory for it enabled the systems to be <u>selective</u> in the kind of input information which caused permanent changes in the properties of the 'synapse'. This kind of selection is thought to be of crucial importance in digital systems where all information is retained permanently in the counters.

4) Co-incidental presentation of more than one input facilitates the learning process. This has been explained in section 3.5.2 and may be looked upon as "association". The learning theorem used in the hardware models ensures that every input to a 'N-S' mutually aids all individual learning at every other input. In other words, it ensures that every input can associate with every other input.

5) In the random network described in chapter 4, the learning process enabled the model to set up stable systems of interacting 'neurons', due to high W values in the loops interconnecting the 'neurons'. Once established, these stable systems of 'neurons' enabled the model to exhibit generalisation, selection and elaboration. Thus, it has been demonstrated that the learning process is capable of performing the self-organisation necessary to enable a randomly interconnected system to exhibit relatively complex properties.

b) <u>Learning in the Block</u>.

The Block used a learning theorem which increased the 'synaptic' weightings if a column was active <u>and</u> an input had been recently activated. Thus the Block learns in the same manner as the hardware models but also in the case of a recently activated input co-inciding with the firing of a column. This extension of the hardware learning theorem is the basis of the Block's ability to reproduce sequences: a 'synapse' is updated if an input has been activated by the Nth element of a sequence <u>and</u> a column is fired by the (N+1)th element. This enables the Block to make the connections between the elements of the sequence and subsequently to reproduce the sequence.

c) Learning and Memory.

In all the models which have been simulated, the learning theorem causes specific 'synapses' to be strengthened, thus making particular regions of the models more sensitive. In all cases this means that the 'neurons' that have been stimulated regularly are more likely to fire again. In the random network especially it was seen that once a stable pattern of four 'neurons' had been formed by the learning process, then this stable pattern was likely to be reactivated by subsequent input stimulation. In this case, and more generally in the other models, it may be concluded that the learning process creates regions of highly sensitive 'synapses' due to high W values, and that these regions constitute the "memory traces" of the models.

7.4 Properties of the Overall System.

This section is concerned with the properties of the systems which resulted from interconnecting the individual elements. Thus it is concerned with "global" rather than "local" properties.

7.4.1 Homeostasis

The work with richly interconnected systems of 'neurons' demonstrated that a network with only excitatory influences is bound to tend towards instability. In order to ensure that the network was stable at all times a " homeostatic principle" was introduced which ensured that at any one time no more than a fixed number of 'neurons' could be active. This principle was used in the Block program and has been found of great importance throughout the experimental work.

a) In the random network, the homeostasis permitted activation to spread throughout the system until it reached the predetermined limit. Input stimuli are, therefore, represented on the network as patterns of active 'neurons' of a fixed size, and the learning properties of the system cause the pattern corresponding to a regularly presented input stimulus to become consolidated.

b) As the random network represented its input stimuli as patterns of active 'neurons' of a fixed size, a large input stimulus (which tended to activate more 'neurons' than the permitted maximum) was subjected to "selection", whereas a small input stimulus (which activated less 'neurons' than the permitted maximum) was subjected to "elaboration". Further, an input stimulus which activated a pattern of 'neurons' similar to a well established pattern was "generalised". These properties are a direct result of the homeostatic principle.

c) Homeostasis enables the Block to exhibit "majority logic" : only one column may be active at one time, and the actual column to fire is that column which received the greatest amount of input stimulation.

d) In the Block, learning can only occur when a column is active. Thus homeostasis (which limits the activation to one active column at any one time) limits the learning process to one column at any one time. This means that learning occurs in specific regions, and it is this type of highly specific location of updated 'synapses' which enables the Block to perform its more interesting properties such as the reproduction of sequences.

In summary, the experimental work has shown that homeostasis, which was originally introduced to obviate saturation and instability, plays an important role in the information processing properties of both the random hardware network and the Block simulation program.

7.4.2 Interconnection Pattern.

From the summary given in section 7.2., it can be seen that the initial models were highly structured, that the net was a randomly interconnected system, and that the Block involved an organised matrix structure. Thus the interconnection patterns used in the course of the research have progressed from ordered to random and back to ordered. The conclusions which may be drawn from this progression are as follows:
a) The work described in section 3.5 demonstrated that small structured systems can be easily constructed to perform specific functions. The drawbacks to this type of system arise when attempts are made to design larger systems with more general capabilities. It was found that every extra function which was required necessitated the addition of extra citcuitry, and this rapidly became extremely complex. The inadequacies of these structure dominant systems have been discussed in section 3.5.5.
b) The randomly interconnected network described in chapter 4 resulted from the conclusion that structure dominant systems are an unsatisfactory method of modelling cybernetic systems. As the structure of the network is random, the learning behaviour had to perform the self-organisation

needed to enable the network to exhibit interesting properties. The interconnection pattern acted as a <u>foundation</u> on which the learning properties of the system could build. The experiments showed that as long as the structure permitted stable circuits of 'neurons' to become established, then the network was able to function in the manner described. The actual location of the 'neurons' in these stable circuits, the number of 'neurons' involved, and the nature of the feedback loops are all of secondary importance: these factors effect the stability of the stable circuits, but would not prevent the system from functioning in the manner described. Thus, the network demonstrated that a random system could be self-organised by its learning properties. However, it was found that a degree of organisation would help the performance of the network: it would ensure that input stimuli effect a large number of 'N-S' elements, and would enable information to flow freely throughout the system.

c) The conclusions from the work on random networks together with a study of the structures that are found in the cerebrum and the cerebellum resulted in the organisation of the Block. The structure is not dominant (as in the systems described in chapter 3) but provides the foundation for the self-organisation carried out by the learning processes. The Block uses a matrix structure which performs the following functions: it ensures that every input has an effect on every column, and it defines one non-plastic reflex input for each column. For the Block to function in the manner described in chapter 5, two further structured systems have to be assumed: firstly a system of lateral inhibition to ensure than only one column can fire at any one time, and secondly a feedback system to enable the outputs from the columns to reactivate the corresponding inputs.

7.5 The Modelling Environment.

The work described in this thesis has involved both hardware and software models, and the conclusions are as follows:

a) The use of hardware in the initial stages has validated the factors discussed in chapter 2: in the development of small systems of 'neurons' and 'synapses', hardware simulation provides a flexible system which enables the experimenter to patch up various inter-connection patterns, and to alter them as the situation demands. The hardware environment has helped to stimulate ideas and has proved an invaluable aid to the understanding of 'neural' systems.

b) The drawback to hardware modelling arises when the experimenter wishes to change the properties of the 'neuron' models themselves. The transition from PM4 to PM5 (described in section 4.6) required several weeks work. PM5 had to be designed, patched up, tested and de-bugged. The design was then simplified and topologically transformed to minimise the amount of soldering needed. It was then used in the construction of a prototype PM5 which could be used with a Checkerboard patch board, and finally twelve of these prototypes were constructed. Had the system involved hundreds of elements, this process would have been extremely arduous and expensive.

c) Software modelling does not suffer from this drawback. In the Block simulation program it was found to be a simple task to alter the relative values of threshold, fatigue, and the effect of the learning processes. Had the Block been modelled in hardware, each of these changes would have required extensive reconstruction of the model. Further, the simulation of the Block proved to be a relatively simple task, since its structure is essentially regular.

7.6 Summary of Conclusions.

The aforegoing considerations have shown that simple models of neurons and synapses are capable of exhibiting cybernetic properties. It has been demonstrated that any plastic system (which changes its properties when certain conditions between input and output information are fulfilled) is capable of learning, memory and , consequently, of self organisation. The various models composed of these plastic elements have exhibited several self-organising phenomena, and the models provide an explanation of how the changes in the elements of a system can result in properties such as the ability to learn, remember and reproduce a range of sequences.

The properties of the 'neurons' and 'synapses' have been examined individually and in some cases it may be seen how a specific property causes a specific behaviour to result (for example how 'synaptic' facilitation causes a 'neuron' to become more sensitive to input stimulation). However in the case of more complex behaviour, the system may only be understood in terms of an interaction of all the properties of the 'neuron' and 'synapse' together with the influences of the interconnection pattern, and the homeostasis of the overall system.

In summary, the work has shown how internally-controlled plastic change can lead to learning, memory and self organisation at the elemental level, and how this in conjunction with a homeostatic system of 'neurons' and 'synapses' enables such properties as association, generalisation and sequence reproduction to be learnt by the overall system.

P O S T S C R I P T

A SPECULATIVE MANY-BLOCK SYSTEM.

A SPECULATIVE MANY-BLOCK SYSTEM

P.1 Introduction.

The work involved in the Ph.D. program described in the previous pages culminated with the Block simulation program and an investigation of its propeties. During the period involved in writing up this work, several new ideas emerged concerned with a system consisting of several Blocks working together in parallel. As there was no remaining time to build models of these ideas they remain highly speculative, and consequently do not merit inclusion in the main body of the research.

However the many-Block system is a direct result of the work described in the thesis, and is discussed in this chapter for two reasons: firstly the Block has been described as a "building brick" for a large cybernetic system, and it is in the context of this albeit theoretical system that the Block organisation may be better understood, and secondly, the theoretical implications of a many Block system suggest an explanation of the mechanics of a distributed memory trace, and outlines the organisation and expected behaviour of a large cybernetic system.

These speculative ideas were felt to be sufficiently interesting to merit their inclusion as a postscript to the experimental work.

P.2 Proposed Structure of Four-Block System.

Consider the four-Block system illustrated in Fig 71. The outputs of Block 1 (abbreviated to B1) connect with the inputs of B2 only, the outputs of B2 connect with the inputs of B3 only, the outputs of B3 connect with the inputs of B4 only, and the outputs of B4 connect with the inputs of B1 only. In all cases output 1 connects with input 1, output 2 with input 2 and so on, until output 10 connects with input 10. This is the simplest level of interconnection to be considered: it consists of a loop from B1 to B2 to B3 to B4 and back to B1.

P.2.1 Response of Four-Block System to Input Stimulation.

Consider an input (whose source is external to the four-Block system) to the sixth input channel in B4. Column 6 in B4 (abbreviated to C6(B4)) will be activated and output 6 in B4 will give an output signal. This output signal connects with input 6 in B1, which activates C6(B1). This in turn activates C6(B2) and C6(B3). The loop is then completed as the output from C6(B3) activates input 6 in B4.

Thus, the activity circulates in a loop from B4 to B1 to B2 to B3 and back to B4. The pattern of activity consists of C6(B1), C6(B2), C6(B3) and C6(B4). It is likely that this pattern of activity will be stable until either the columns habituate or further inputs are presented.

Consider now an input consisting of a signal to input 4 in B1 and simultaneously input 8 in B3. Initially C4(B1) and C8(B3) will be activated. The former leads to the activation of C4(B2), the latter to the activation of C8(B4).

Subsequently both B1 and B3 are excited by two input signals: B1 by input 4 (due to the input stimulus) and by input 8 (due to the output from C8(B4)) and B3 by input 8 (due to the input stimulus)

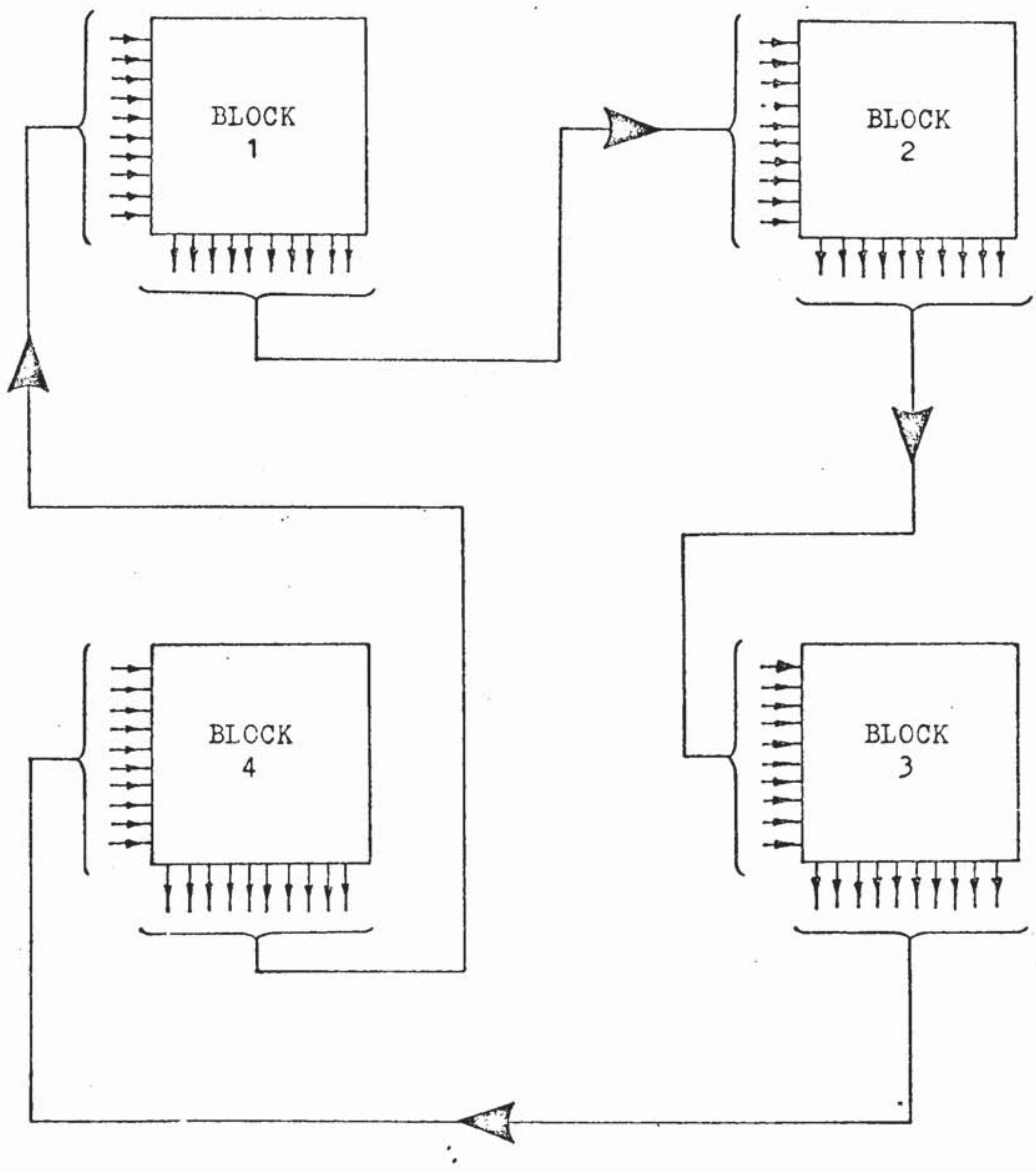
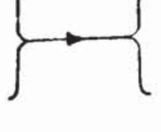


Fig 71: Proposed Four-Block system.



: Output 1 connects with input 1,
output 2 connects with input 2, etc.,
output 10 connects with input 10.

and by input 4 (due to the output from C4(B2)).

It is proposed that the effect of the external stimulation is stronger than the internal feedback, and that therefore the stimulus in the present example maintains the activity of C4(B1) and C8(B3). This means that in B1, column 4 is active at the same time as input 8, and that consequently the eighth 'synapse' on column 4 in Block 1 (abbreviated to W8,C4(B1)) will update due to the learning theorem. Similarly W4,C8(B3) will update since in B3 column 8 is active at the same time as input 4.

As this process continues a stable pattern of activation will be produced consisting of C4(B1), C4(B2), C8(B3) and C8(B4). The connection between B4 and B1 is maintained by the updated'synapse' W8,C4(B1) : the connection between B2 and B3 by the updated 'synapse' W4,C8(B3). Again, the recirculating activity will maintain this pattern until either the columns habituate or further inputs are presented. The pattern of activity, the relevant interconnections, and the facilitated 'synapses' are illustrated below in Fig 72.

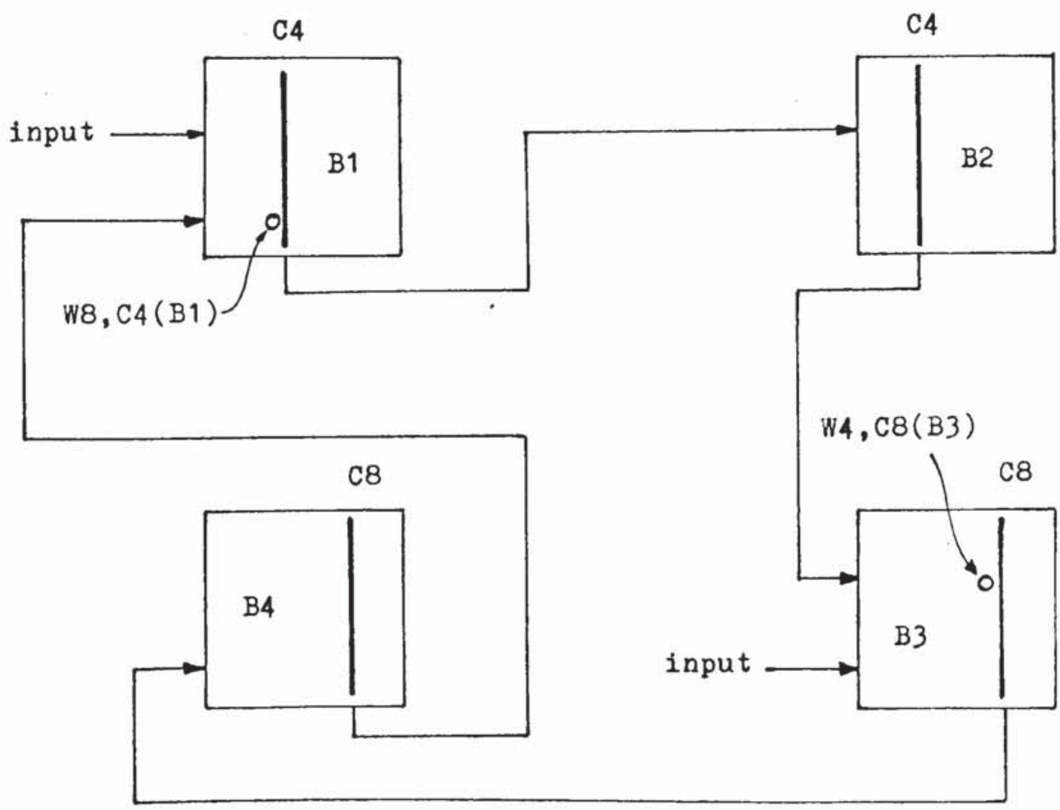


Fig 72.

Let us now consider an input of four simultaneous signals: input 1 in B1, input 3 in B2, input 5 in B3, and input 7 in B4. From the aforegoing discussion it is likely that four columns will be directly activated (C1(B1), C3(B2), C5(B3) and C7(B4)) and that as this pattern of activation is maintained by the four input signals,four'synapses'will be updated (W7,C1(B1), W1,C3(B2), W3,C5(B3) and W5,C7(B4)).

This pattern of activity will be maintained by the signals circulating in the loop created by the updated 'synapses'.

From these considerations it is proposed that no matter what the input stimulus, the four-Block system will always be able to respond with a pattern of activation consisting of one active column in each of the four Blocks, and that the learning theorem will update the 'synapses' which are needed to maintain that pattern of activity after the input stimulus has been withdrawn.

P.3 Proposed Structure of Nine-Block System.

The four-Block system discussed in the previous section has helped to describe the organisation of a simple many-Block system, but its small size and single feedback loop were felt to be inadequate for a satisfactory discussion. The present section is concerned, therefore, with a nine-Block system in which Block to Block connections are made in a more random manner as illustrated in Fig 73.

The actual interconnection pattern does not seem to be of primary importance but it is essential that information can flow freely throughout the nine-Block system, so that any input stimulus will generate a pattern of activation consisting of one active column in each Block.

It is proposed that the presentation of an input stimulus will result in the generation of a stable pattern of activation, due to the learning process which updates the 'synapses' which are needed to maintain that pattern of activity. It is likely that this process of stabilisation will only result from a persistant presentation of the input stimulus.

The nature of the feedback paths which create the proposed stable pattern of activation depends on the interconnection pattern: in some cases the nine Blocks are linked by a single large loop, but generally feedback is carried in several small, interacting loops. These feedback loops define the information pathways within the model and specify, therefore, the type of feedback which was assumed for the sequential experiments with a single Block.

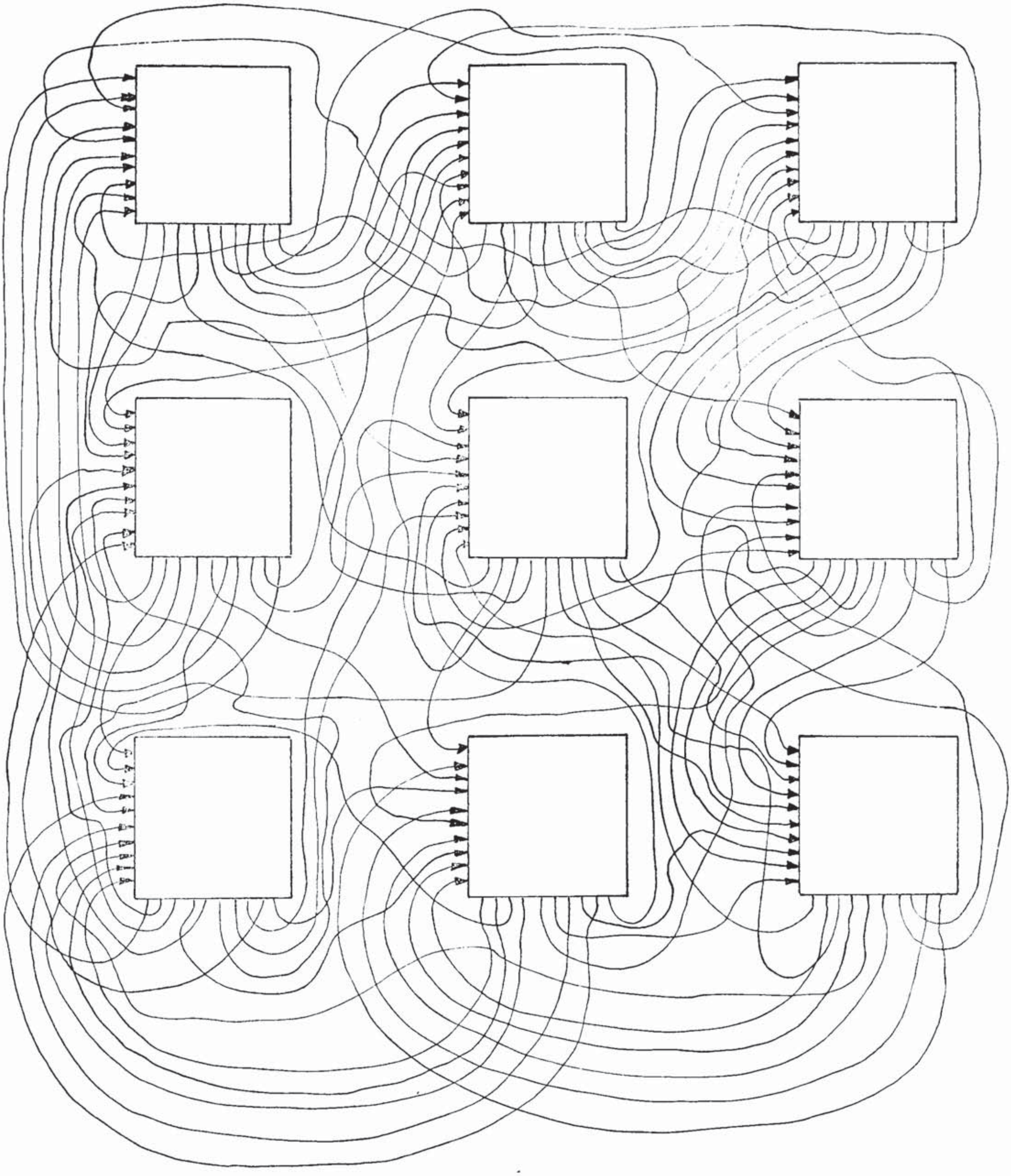


Fig 73: Proposed system consisting of nine interconnected Blocks.

P.4 Nature of the Proposed Pattern of Activation.

It has been proposed that an input to a nine-Block system generates a pattern of activity consisting of one active column in each of the nine Blocks, and that this is stabilised by the feedback paths which interconnect the Blocks.

If this assumption is accurate, then the nine-Block system retains information as distributed patterns of activity. Changes in the input stimulus would, therefore, cause changes in the whole pattern of activity in the nine-Block system. It is interesting to compare this situation with a comment made by Lashley:

"A new stimulus... does not excite an isolated reflex path, but must produce widespread changes in the pattern of excitation throughout a whole system of already interacting neurones" (Ref R.2.9)

For the discussion to proceed, it must also be proposed that the distributed pattern of activity which is generated by an input stimulus is a representation of that input stimulus. Thus, each input stimulus is recorded on the nine-Block system as a stable, distributed pattern of nine active columns.

The mechanics of this process have been described in only the most incomplete fashion, and until experimental verification can be obtained the operation of a nine-Block system must remain a tentative discussion.

P.5 Memory Processes.

a) Short Term Memory: The presentation of an input stimulus causes the proposed nine-Block system to respond with a pattern of nine active columns which are a representation of that stimulus. The pattern of activity is stabilised by the signals that circulate in the feedback loops which interconnect the nine Blocks. This recirculating activity will only be able to maintain the pattern of activity for a short time, as the columns will tire and the activity will then move elsewhere.

The nature of the recirculating activity is to form a short term memory, which allows the system to maintain a stable pattern of activated columns characteristic of a particular input stimulus for a short time after that stimulus has been extinguished.

b) Long Term Memory: The stable patterns of activation which are generated by the persistant presentation of an input stimulus are stabilised by the facilitation of the 'synapses' which interconnect the elements of the patterns. The system is only able to "remember" a characteristic pattern of activity because of the updated 'synapses' which allow information to circulate in the feedback loops which define that pattern of activity.

The changes in the long term weighting values of these 'synapses' constitiute, therefore, the long term memory of the proposed system. As the patterns of activation are distributed, it follows that the long term memory traces will also be distributed throughout the system. Again, Lashley's work is of interest, for his Law of Mass Action (Ref R.2.21) states that the amount of memory loss in the brain is proportional to the amount of brain-matter removed. For the proposed nine-Block system to follow this law, it would have to be assumed that each pattern of activation was composed of a huge number of small, interactive feedback loops. However, the assumed structure with a lesser number of loops is likely to be extremely resistant to damage.

P.6 Behaviour of the Proposed Nine-Block System.

The aforegoing sections have proposed a structure for a nine-Block system, discussed the way in which information would flow through it, and proposed a mechanism whereby an input stimulus would be represented as a distributed pattern of activation and subsequently remembered by the system. The present section is a brief discussion of the expected behaviour of such a system.

a) Generalisation: A regularly presented input stimulus generates a stable pattern of activity which is a representation of that pattern. Consequently, an input pattern which is unfamiliar to the system and which is similar in nature to the well-established input stimulus is likely to trigger the pattern of activity which is representative of the regularly presented input. Thus the system will "see" the second, unfamiliar pattern as the same as the original, familiar pattern. Generalisation has been demonstrated in a single Block, and it seems likely that a many-Block system would exhibit a similar capacity.

b) Association: It has been demonstrated previously that in a single Block, two input stimuli will become associated if they follow each other regularly and persistantly. Thus, within a many-Block system it seems safe to assume that the same mechanism will associate the elements of the representations of two patterns which are presented sequentially on a regular basis, and thus associate the patterns themselves.

This process would probably occur in two stages: firstly the many-Block system would create a representation of each of the input stimuli, and secondly the two representations would be associated due to the mechanics of the individual Blocks.

It is interesting to note that the distributed pattern of activation ensures that every input is represented by one active column in every Block, and that therefore all input stimuli may be associated regardless of their nature. If the system had used localised characteristic patterns of activity, then it would be extremely difficult to explain how all patterns distant from each other could become associated: it would involve astronomical numbers of interconnecting fibres. Thus, the distributed pattern of activation not only makes the system extremely stable and reliable, it also ensures that any two input stimuli may be associated.

c) Sequential Properties: A single Block has been shown to be capable of reproducing a large number of sequences, as long as there is no overlap. Examination of the proposed many-Block system reveals that with the feedback as described in Fig 73, there is no overlap whatsoever and that therefore the individual Blocks are likely to operate in optimum conditions. It follows that, if the individual Blocks are able to reproduce the elements of each input representation of the sequence, then the system as a whole will be able to reproduce the sequence.

The problem of overlapping inputs is obviated as the process occurs in two stages: a) every input stimulus, no matter how complex, is assumed to be represented as a pattern of one active column in each Block, and b) it is then these representations which are combined into a sequence, and with the assumed feedback structure there will be no overlap.

The question of the sequential properties of a many-Block system is an extremely complex one, and until experimental verification can be performed these considerations must be regarded as highly speculative.

P.7 The Many-Block System and Cell Assemblies.

The proposed many-Block system has special relevance to the theoretical cell assembly models, since the work of both Hebb and Milner (Refs R.2.1., R.2.2., R.2.16) has played a considerable part in the development of the Block.

In the context of the many-Block system a "cell assembly" consists of the pattern of active columns distributed throughout the system, which is a representation of a particular input stimulus. If the proposed many-Block system organisation can be validated experimentally, it may well help to define the cellular mechanism which underly the formation of cell assemblies.. It is at this level that the work of Hebb and Milner seems to be incompletely specified. Milner extended Hebb's original postulates to cover inhibition and a dominant vertical organisation, but was still forced into theories involving "fringe neurons" which the present author has found of little value in the simulation of a learning system. The proposed many-Block system would explain not only the formation of a "cell assembly" but also the way in which "phase sequences" - the sequential reproduction of associated cell assemblies - are organised.

If the connection can be made between the cell assembly theories of neural organisation and the proposed many-Block system, not only will the mechanistic basis of the cell assembly be clarified, but also the theoretical work will provide a definite direction in which the many-Block research work could proceed.

P.8 The Many Block System, Holograms, and Matrix Learning Systems.

In the last few years, the hologram has attracted a great deal of attention as a model of the brain. Both its method of information storage and its vast capacity have parallels with the brain, and these considerations have led to several papers that suggest that memory is basically a holographic process (Refs. R.1.24. R.1.25., R.2.20).

However in a recent paper Willshaw et al (Ref R.1.26) have demonstrated that a simple associatory net arranged in a matrix configuration can mimick "actually improve on" the performance of hologram as a model of associatory memory. Their conclusion suggests an explanation for the widespread use of associatory matrix learning systems, for example by Young (Ref R.13.17) and Steinbuch (Ref R.13.9) in the simulation of learning behaviour.

Both the model described by Willshaw, and those of Young and Steinbuch use localised memory traces and are, therefore, unable to have any relevance to the distributed storage of information which is found both in the brain and the hologram. The many-Block system may well provide the link between these models: it is basically an associatory network which is similar enough to that described by Willshaw to "mimick and actually improve on" the performance of the hologram, and it retains its information as a distributed memory trace.

P.9 Simulation of the Many-Block System.

The preliminary considerations concerning the simulation of a many-Block system presented something of a dilemma. Two choices were apparent:

1) Hardware simulation: The construction of a single hardware Block was considered in chapter 5, and dismissed as too complex and costly. Further, the changes that were made during the experimental period with a single Block would have involved months of work had the Block been constructed from hardware components. The work described in chapter 4 has shown that hardware systems are extremely difficult to modify, where the properties of the individual elements are concerned.

2) Software simulation: This proved to be an ideal environment in which to model a single Block. However, the digital computer has been shown to be unsuitable for the simulation of the parallel nature of the C.N.S., and the prospect of simulating a many-Block system such as that illustrated in Fig 73 does not appear attractive. It would also be useful to have a flexible interconnection system which would enable the experimenter to patch up different Block to Block interconnection patterns as suggested by the experimental process.

Thus, both hardware and software simulations seemed to be unsuitable for a many-Block simulation. There is, however, one possible solution to this dilemma; it involves the use of several micro-processors in parallel. In essence the idea is very simple: if a single micro-processor with its memory and interface systems can be used to simulate a single Block, then a many-Block system may be implemented by hard-wiring several such micro-processors in parallel. The expected advantages of such a system are as follows:

1) Each Block would be simulated by a programmable computer system. The changes in the relative Block parameters (which are bound to occur during the experimental period) could be easily implemented by modifying the program which simulated the Block.

2) The use of several micro-processors would enable the system to operate in a truly parallel manner, and thus obviate the problems involved with serial simulations.

3) The advantages of hardware models described in chapter 2 would all apply, for the individual micro-processors would each constitute a hardware unit which could be hardwired together at the control of the experimenter. This kind of flexibility has been found to be extremely valuable in hardware simulations, for it enables the system to be quickly modified.

4) The teletype could be used to give a written record of the progress of the various experiments. Thus, at each critical step the values of long term weighting and other critical parameters would be accessible to the experimenter.

In summary, the proposed system would exhibit the most valuable attributes of both hardware and software simulations without any of the drawbacks. It would be flexible both in the simulation of the individual Blocks and in their interconnection into large cybernetic systems. It would also allow a complete study to be made of the effect of the learning process on the 'synaptic' weights of the elements and on the consequent behaviour of the system.

A preliminary investigation of the Intel 8 bit micro-processor that an 8 by 8 Block may be simulated without involving overcomplex memory and interface systems, and that many such micro-processors could be run in parallel by using the same clocking circuitry for each one.

P.10 Summary.

If the assumptions and arguments proposed in this chapter are correct, then a many-Block system would exhibit the following characteristics:

a) It would represent input stimuli as a characteristic pattern of active columns. This pattern would be distributed throughout the system, and would be resistant to local damage since it is composed from many interactive feedback loops.

b) The long term memory trace for each of these characteristic patterns would be distributed throughout the system.

c) The system would be homeostatic: at any one time only 10% of the total number of columns would be active.

d) The system would be able to generalise, associate, and reproduce a large range of sequences.

If the proposed system functions in the manner which has been suggested in this chapter, then it defines a theory which explains how an assembly of neuron like elements can interact so as exhibit association, generalisation, sequence reproduction and a distributed memory trace.

A proposal has been made to simulate the many-Block system using several micro-processors hardwired together in parallel. Preliminary investigations of this scheme suggest that it would enable a large system of 'neurons' and 'synapses' to be constructed by exploiting the most useful aspects of both hardware and software simulation.

It is foreseeable that the outlines which have been presented will prove to be both inaccurate and incomplete, and yet there appears at present to be no reason to prevent the construction of a system which functions in essentially the same manner as the many-Block system hypothesised in this chapter.

A P P E N D I C E S

APPENDIX 1 : THE PLASTIC N-S MODELS.

Appendix 1 contains details of the hardware models that were constructed during the course of the research. The basic system conception is described, and the following six pages are a reproduction of a paper which describes the first three models to be built.

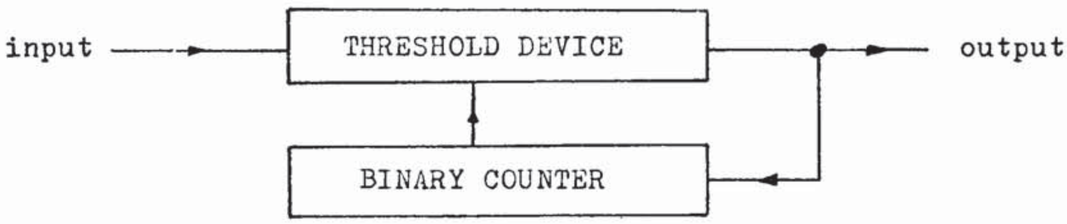
APPENDIX 1 : THE PLASTIC N-S MODELS

Basic System Conception.

Six models are described in Appendix 1, all of which exhibit "plasticity" as defined in section 3.2, and have the same basic system conception.

Basically, there is a threshold device which determines the number of input pulses that are required to produce an output signal. This threshold device is influenced by a binary counter which is incremented whenever certain conditions between input and output pulses are fulfilled.

In the simplest case (illustrated below), the binary counter is incremented whenever the threshold device produces an output.



The contents of the counter affect the threshold device in such a way that the larger the contents of the counter, the lower the number of pulses required to produce an output.

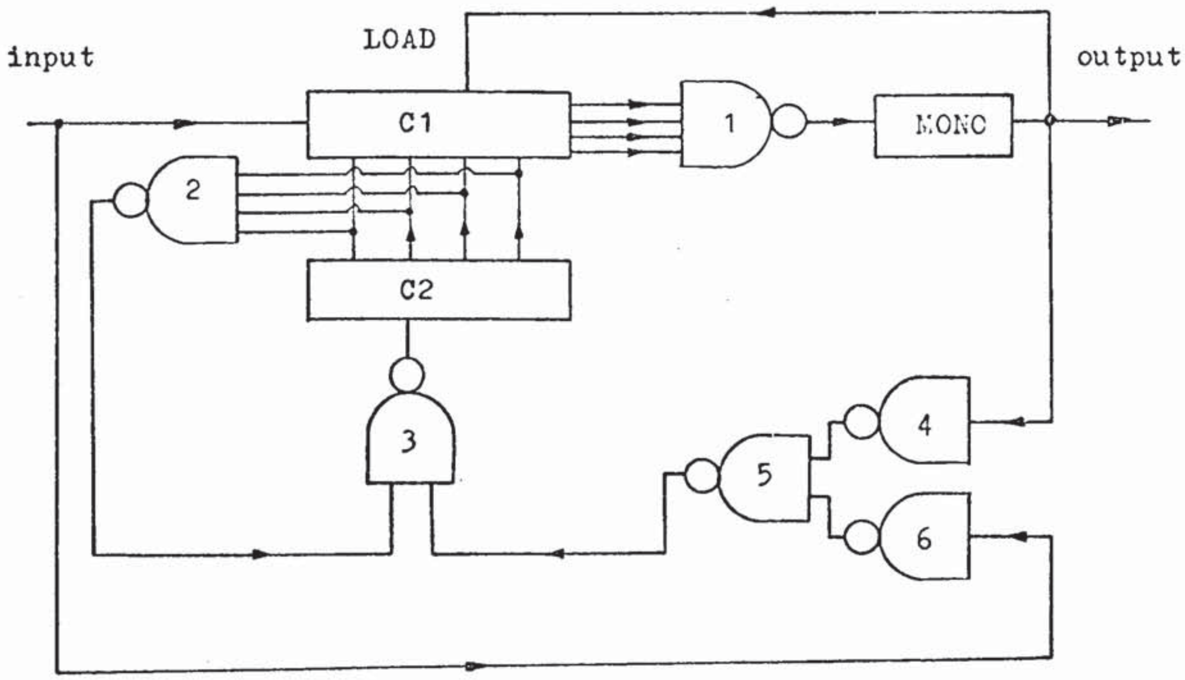
Thus, initially several pulses are needed to produce an output. Every output causes the counter to accumulate one count. Every count accumulated lowers the number of pulses needed to produce an output by one.

In this way the regular use of the device causes the number of input pulses needed to produce an output to fall progressively: its threshold is lowered by use.

The details of the six models, and the reasons for their increasing complexity, are described in the remainder of Appendix 1.

Plastic Model 4.

PM4 is a more advanced version of PNM2. It works in essentially the same way, but involves simpler circuitry due to the use of Texas SN74193 binary counters. It is illustrated below:



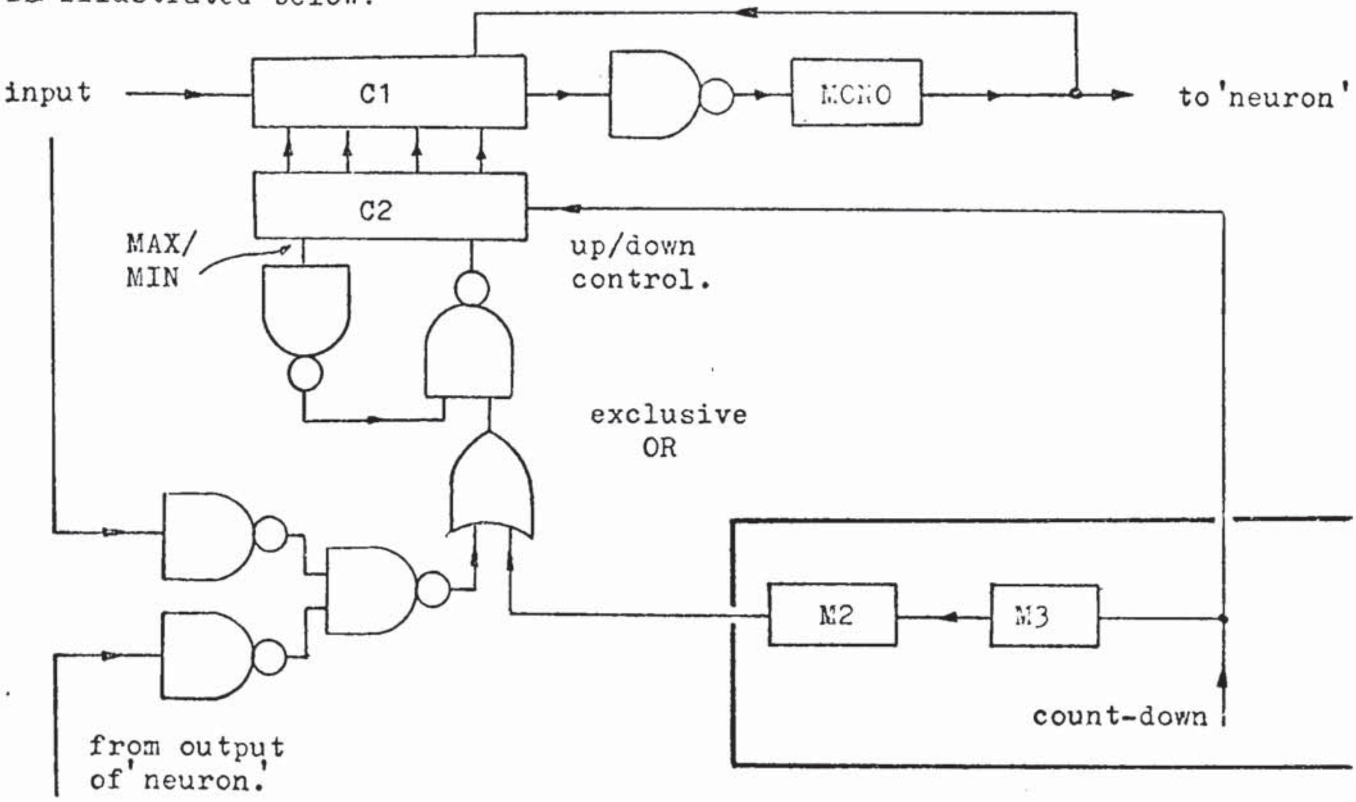
The contents of C2 are fed into C1 when the 'LOAD' input to C1 is set to 0v. This obviates the need for the complex gating between C1 and C2 that was used in PNM2.

As the counters are capable of counting from 0 to 15, the 'synaptic' weighting of the model can vary between 1/16 and 1. This means it is twice as sensitive as PNM2.

Apart from these simplifications, the modelling philosophy is identical to that used in PNM2. The construction of PM4 was essential, as the author intended to synthesise a system consisting of several plastic elements. As PNM2 was rather complicated, it became imperative to build a simpler, engineered version. The result was PM4.

Plastic Model 5

PM5 was built in order to implement the need for a plastic model which is susceptible to both excitatory and inhibitory influences. It is illustrated below:



PM5 uses Texas SN74191 counters, which enable the basic circuitry to be simplified even further: they contain a 'MAX/MIN' output which gives a pulse when the counter holds 15 in the count up mode, and 0 in the count down mode. This obviates the need for the 4-input NAND gates used in PM4. The 'MAX/MIN' output enables the 'synaptic' weighting of the model to vary between 1/16 and 1 without danger of recirculation at either end.

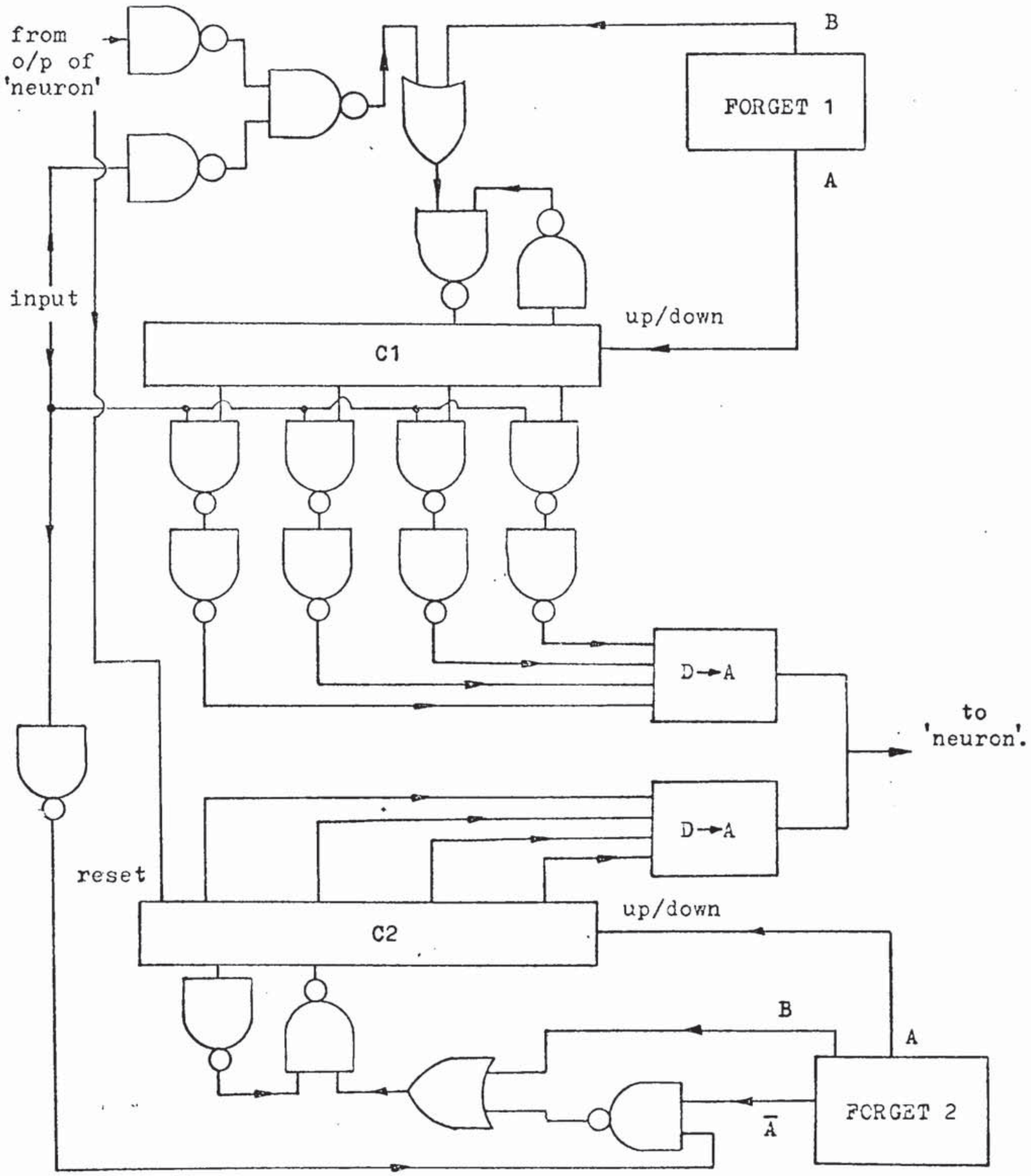
The 'count-down' signal sets the count control on C2 to count-down and sends a delayed pulse (via M2 and M3) which decrements the contents of C2. Thus every PM5 has two inputs from the 'count-down' system.

The exclusive-or gate is needed to stop interference between the count-up pulses that occur during the learning phase, and the count-down pulses that produce the inhibitory influence.

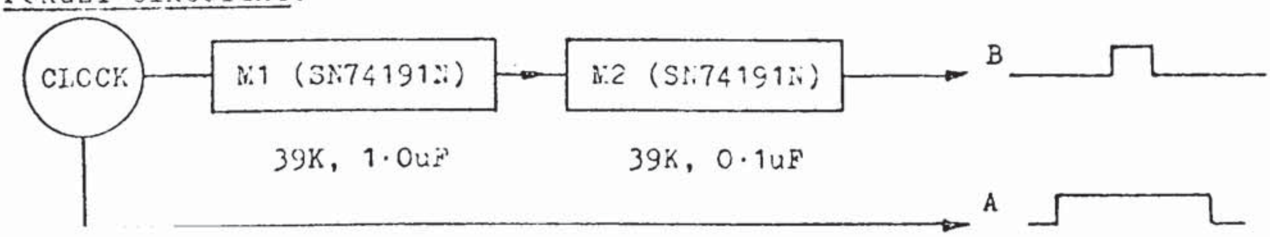
The model learns in exactly the same way as PNM2 and PM4, but the behaviour of the model can be dominated by the external inhibition.

Plastic Model 6.

PM6 was designed and built in order to construct a hardware Block. It is the final plastic model to be constructed during the research, and the most complex.



FORGET CIRCUITRY.



The upper half of the diagram will be recognised as the 'synapse' module in PNM3. C1 therefore contains the 'synaptic' weight of the model which may be raised by a co-incidence between input and output. The FORGET 1 circuitry was added so that the model could forget : it decrements the contents of C1.

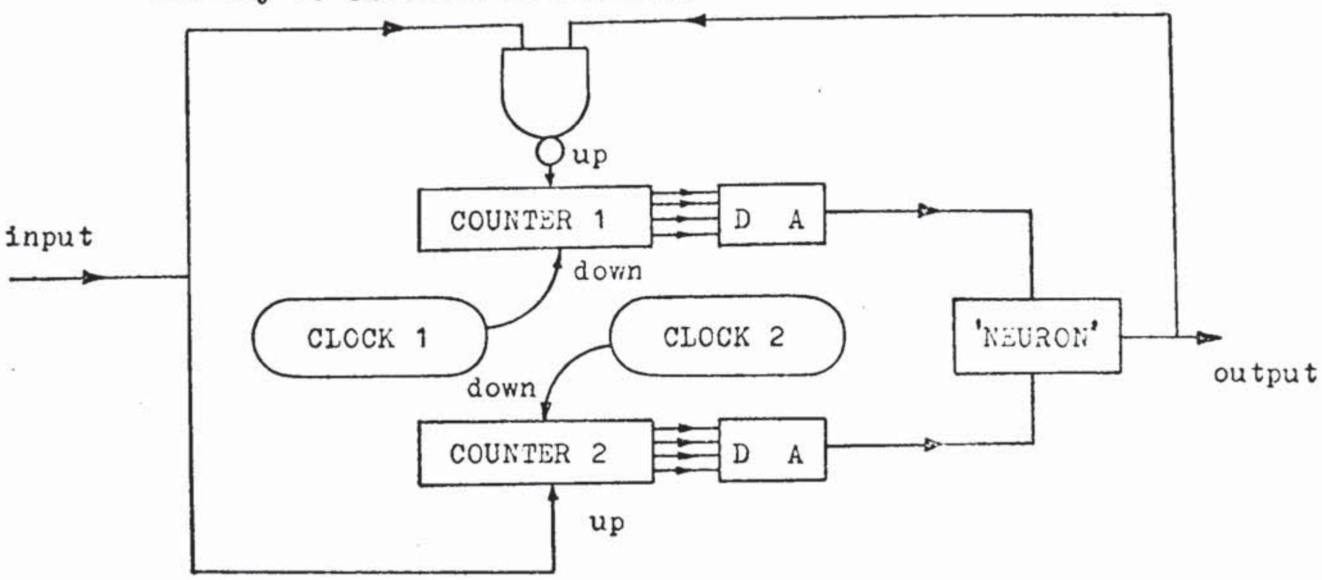
The 'neuron' is modelled by an operational amplifier (spatial summation) and a monostable. Fatigue is implemented by charging a diode pump circuit from the output of the 'neuron' and feeding this charge back into the inverting input of the operational amplifier. Thus the more often the 'neuron' fires, the more difficult it becomes to fire in the future.

The lower part of the diagram illustrates the short term component of the model. Inputs count up C2, assuming that the input pulse frequency is greater than the FORGET 2 frequency (1 Hz). When C2 holds 15, the output from the D → A converter fires the neuron. This output re-sets C2 so that the inputs must re-accumulate in order to re-fire the 'neuron'. This process is the equivalent of the de-polarisation of the biological 'neuron'.

If the N-S model is presented with repeated and persistent input pulses, the content of C1 (the 'synaptic' weight) increases in exactly the same way as in all the other models. This progressive increase continues until C1 contains 15, when C1 is preventing from re-circulating as before. At this point, one input pulse will fire the system.

As the 'neuron' model begins with an operational amplifier, there is ample opportunity to construct an N-S model which has several 'synapses'.

PM6 may be sketched as follows:



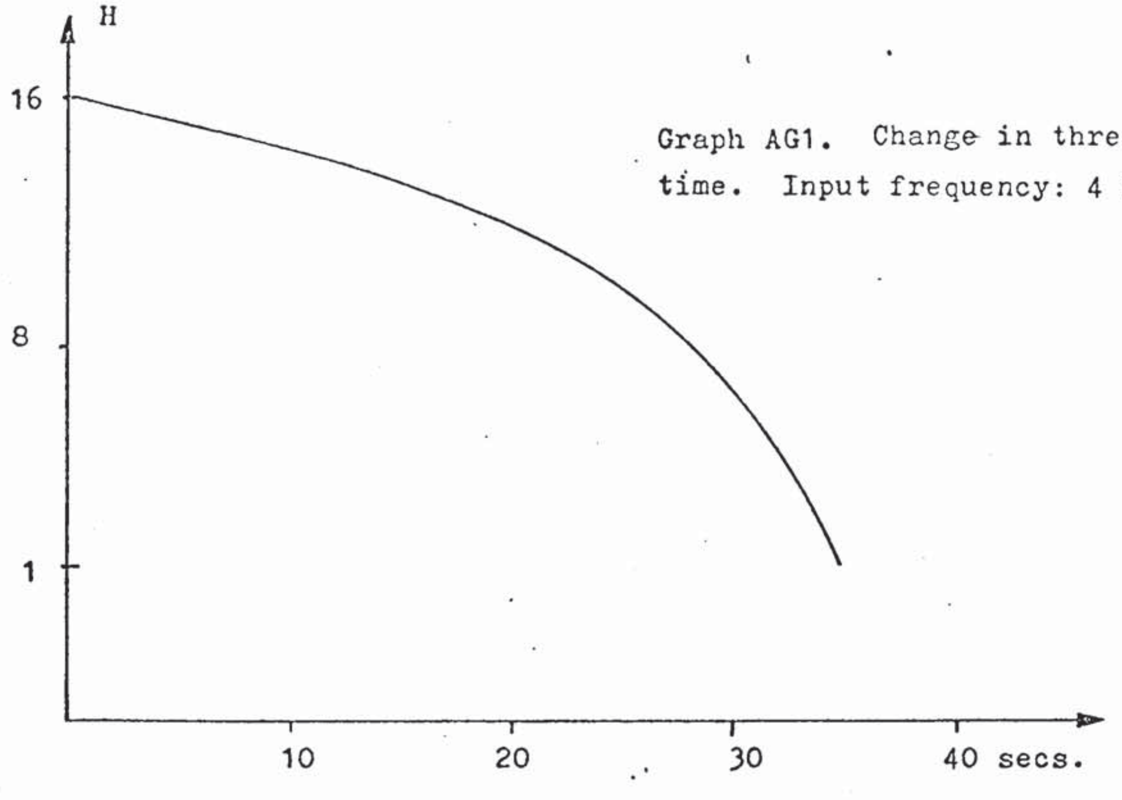
C1 contains the long term memory of the model, and CLOCK 1, therefore, determines the rate of long term forgetting.

C2 contains the short term memory: CLOCK 2 determines its decay.

Thus the behaviour of the model may be described in terms of two parameters, the state of the two counters.

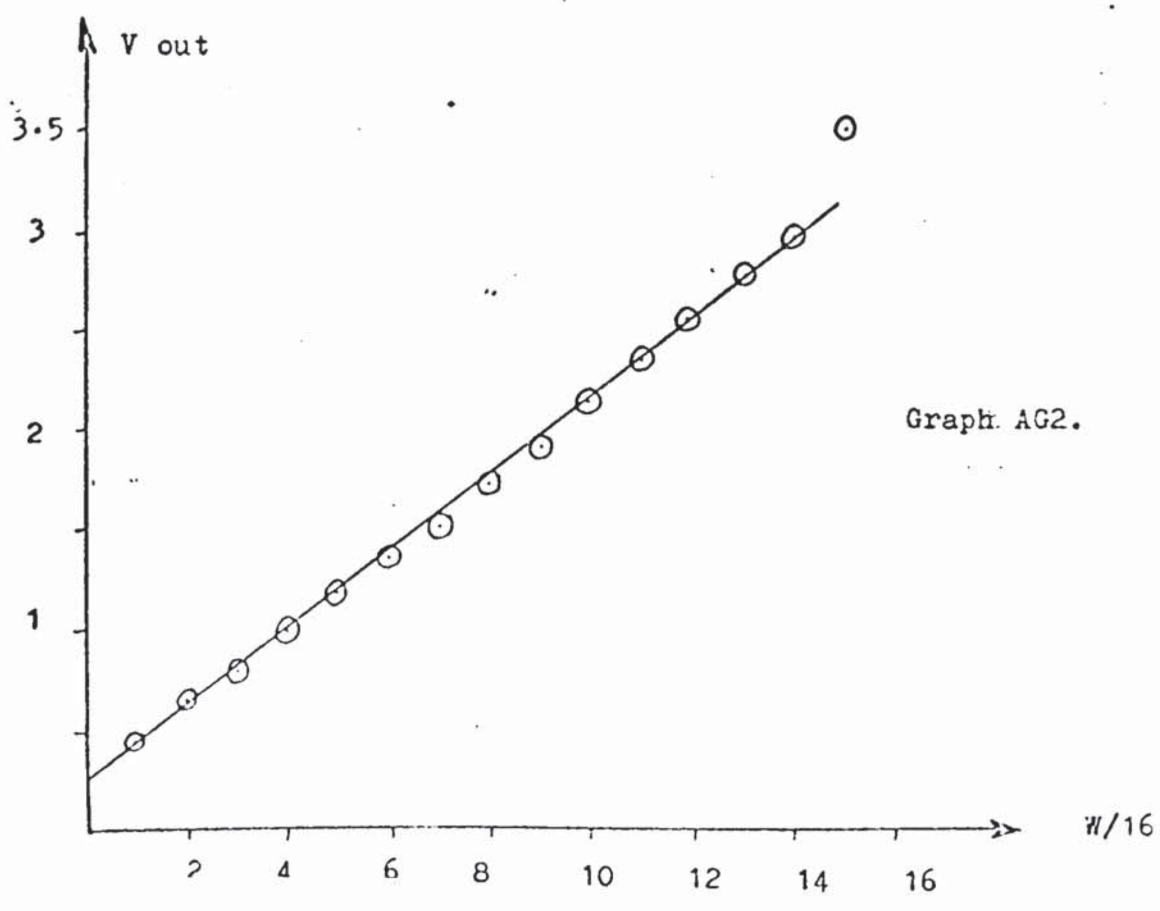
	COUNTER 1 long term effects	COUNTER 2 short term effects
COUNT UP	W facilitation. Depends on co-incidence of input and output. Long term remembering.	Excitation. Every input pulse counts up counter 2. Short term remembering.
COUNT DOWN	Long term forgetting. Slow pulses: 10^{-3} Hz.	Short term forgetting. Faster pulses: 1 Hz.

Graph AG1 illustrates the way in which the learning process happens. It is a plot of the threshold of the N-S' against time, and applies to each of the six plastic models just described.



Graph AG1. Change in threshold with time. Input frequency: 4 Hz.

Graph AG2 illustrates the changes in voltage with 'synaptic' weighting that are produced by the 'synapse' modules in PNM3 and PM6.



Graph AG2.

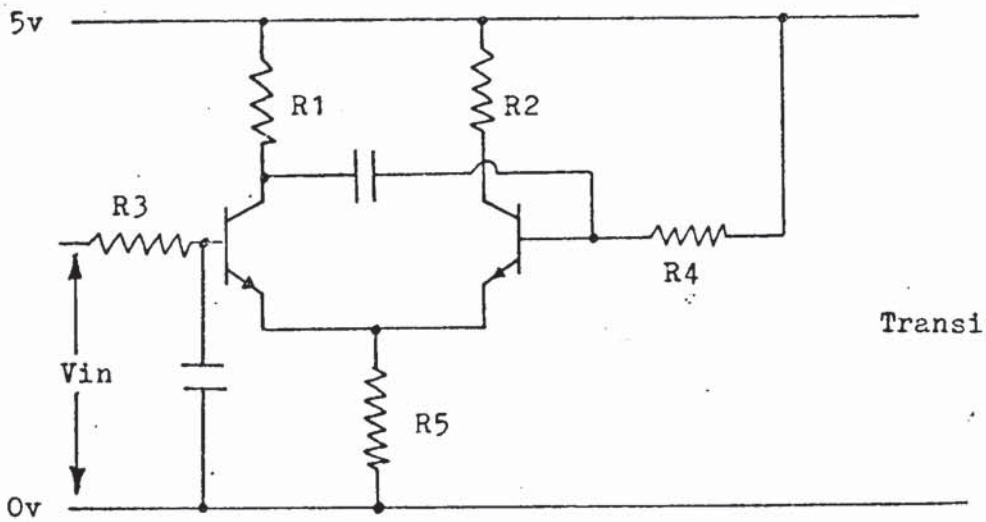
APPENDIX 2 :

CONTROL SYSTEM TO MAINTAIN HOMEOSTASIS.

APPENDIX 2 : CONTROL SYSTEM TO PRODUCE HOMEOSTASIS.

The control system to be described was designed to produce a pulse train when more than a certain number of N-S models were active. This pulse train could then be used to 'inhibit' the models and thus introduce homeostasis.

It was found that the most satisfactory method of achieving this was to monitor the current drawn by the display, as this increased as the activation spread. This current was converted into voltage, and used to feed the following circuit:



R1 : 1·8K
R2 : 1·8K
R3 : 100K
R4 : 100K
R5 : 1·0K

Transistors : BC 107.

As the number of active units increases, Vin increases until it reaches a threshold determined by R_5. The circuit then produces a pulse train which feeds the 'count-down' inputs to the N-S models, and thus decreases the number of active units.

The output frequency is directly proportional to Vin: the amount of inhibition is directly proportional to the degree of activity on the N-S network.

APPENDIX 3:

COMPUTER PROGRAM (FORTRAN) SIMULATING THE BLOCK.

```
C SIMULATION OF BLOCK OF NEURONS
        INTEGER W(10,10),NI(10),NO(10),EMAX,H(10),NUM(10),DIFF(10)
        DIMENSION STW(10,10)
        DO 7 I=1,10
        DO 7 J=1,10
7       W(I,J)=1
        DO 12 N=1,10
12      H(N)=20
5       READ(1,)M
        IF(M.NE.77) GO TO 10
        WRITE(2,120)((W(I1,I2),I2=1,10),I1=1,10)
120     FORMAT(1H ,10I3)
10      READ(1,110)NI
110     FORMAT(10I1)
        EMAX=0
        DO 9 I=1,10
9       W(I,I)=20
        DO 1 N=1,10
        DO 2 I=1,10
        STW(I,N)=STW(I,N)+NI(I)*(0.6*(20-STW(I,N)))
        NO(N)=IFIX( W(I,N)*NI(I)+STW(I,N)+NO(N))
        STW(I,N)=STW(I,N)*0.7
2       CONTINUE
        DIFF(N)=NO(N)-H(N)
        EMAX=MAX0(EMAX,DIFF(N))
        IF(EMAX.EQ.DIFF(N))NMAX=N
1       CONTINUE
        WRITE(2,100)NMAX,EMAX
100     FORMAT(1H ,I3,$,$,I3)
        DO 3 N=1,10
        NUM(N)=NUM(N)-1
        IF(NUM(N).LE.0)NUM(N)=0
3       NO(N)=0
4       DO 6 I=1,10
        IF(STW(I,NMAX).GE.6)W(I,NMAX)=W(I,NMAX)+1
        IF(W(I,NMAX).GE.20)W(I,NMAX)=20
6       CONTINUE
        NUM(NMAX)=NUM(NMAX)+2
        IF(NUM(NMAX).LE.5)GO TO 11
        H(NMAX)=H(NMAX)+6
11      DO 8 N=1,10
        IF(H(N).GT.20)H(N)=H(N)-1
8       CONTINUE
        GO TO 5
        STOP
```

Explanation of Program.

In order to explain the program, it has been divided up into a number of boxes (see over). Each box performs a specific function as described :

Box 1 : this sets up the preliminary W matrix as a 10 by 10 matrix in which all values are 1.

Box 2 : Set up the ten threshold values. Initially they are all 20.

Box 3 : Read in from the teletype. If input is not 77, jump to box 5 which reads in from the teletype. If input is 77, go on to box 4.

Box 4 : Print out the W matrix.

Box 5 : Read in from teletype. This input is taken as the inputs to the Block

Boxes 3, 4 and 5 enable the inputs to the Block to be read into the computer, and give the option of printing out the W matrix.

Box 6 : EMAX set to zero. This is necessary as EMAX is used in the calculations in box 8.

Box 7 : Set up diagonal of W equals 20 within the W matrix. This diagonal is maintained throughout the various experiments, and the simplest way to achieve this was found to be to set it up once every iteration.

Box 8 : Spatial and temporal integration of input information.
If an input line is active, then STW is increased exponentially towards 20. This value is then used to calculate the excitation, for the first input line of the Block. The value is rounded, and accumulates as the program moves down the ten input lines.
STW is then exponentially decayed.
The ten DIFF values are then calculated, and compared in order to find the column with the maximum net excitation.

Box 9 : Print out NMAX (the number of the column with the maximum net excitation) and EMAX (the value of the maximum net excitation)

Division of Program into Boxes to assist Explanation.

```
C SIMULATION OF BLOCK OF NEURONS
      INTEGER W(10,10),NI(10),NO(10),EMAX,H(10),NUM(10),DIFF(10)
      DIMENSION STW(10,10)
      DO 7 I=1,10
      DO 7 J=1,10                                   1
7     W(I,J)=1
      DO 12 N=1,10                                  2
12    H(N)=20
5     READ(1,)M                                     3
      IF(M.NE.77) GO TO 10
      WRITE(2,120)((W(I1,I2),I2=1,10),I1=1,10)      4
120   FORMAT(1H ,10I3)
10    READ(1,110)NI                                 5
110   FORMAT(10I1)
      EMAX=0                                        6
      DO 9 I=1,10                                   7
9     W(I,I)=20
      DO 1 N=1,10
      DO 2 I=1,10
      STW(I,N)=STW(I,N)+NI(I)*(0.6*(20-STW(I,N)))
      NO(N)=IFIX( W(I,N)*NI(I)+STW(I,N)+NO(N))
      STW(I,N)=STW(I,N)*0.7
2     CONTINUE                                      8
      DIFF(N)=NO(N)-H(N)
      EMAX=MAX0(EMAX,DIFF(N))
      IF(EMAX.EQ.DIFF(N))NMAX=N
1     CONTINUE
      WRITE(2,100)NMAX,EMAX                         9
100   FORMAT(1H ,I3,$,$,I3)
      DO 3 N=1,10
      NUM(N)=NUM(N)-1                               10
      IF(NUM(N).LE.0)NUM(N)=0
3     NO(N)=0
4     DO 6 I=1,10
      IF(STW(I,NMAX).GE.6)W(I,NMAX)=W(I,NMAX)+1     11
      IF(W(I,NMAX).GE.20)W(I,NMAX)=20
6     CONTINUE
      NUM(NMAX)=NUM(NMAX)+2
      IF(NUM(NMAX).LE.5)GO TO 11                    12
      H(NMAX)=H(NMAX)+6
11    DO 8 N=1,10
      IF(H(N).GT.20)H(N)=H(N)-1                     13
8     CONTINUE
      GO TO 5
      STOP
```

Box 10 : Decrement all values of NUM, keeping the minimum at 0. Reset NO to zero for all columns. (After a column fires, its level of excitation falls to zero.)

Box 11 : Learning theorem. If a column is active (ie the column specified by NMAX) <u>and</u> an input has been recently activated (specified by STW of 6 or more) then increment the relevant value of W.

Box 12 : Add two to the value of NUM for column NMAX. This - in conjunction with Box 10 - increments NUM for the column that has fired and decrements NUM for the other nine columns. If NUM is more than or equal to 5, the threshold of the column is increased by 6 units.
Thus Box 12 implements the tiring factor by making any column which has fired 5 or more times, more difficult to fire.

If NUM is less than 5, the program jumps the tiring sub-routine and goes to Box 13.

Box 13 : Recovery from habituation. All threshold values greater than 20 are decremented so that all habituated columns gradually return to their original threshold level.

GO TO 5 : return to the start of the iteration.

LIST OF VARIABLES:

NO : Output excitation

NI : Input excitation

H : Threshold.

STW : Short term weighting.

W : Long term weighting.

DIFF : Difference between output excitation and threshold.

EMAX : Maximum value of DIFF.

NMAX : Number of column with maximum value of DIFF.

R E F E R E N C E S

Introduction to References.

The nature of an interdisciplinary study makes it imperative to undertake an immense amount of background reading. In the case of the present research, the author found that apart from previous cybernetic literature, he had to study large areas of physiology, psychology and engineering science, in order to maintain a balanced approach to the synthesis of engineering models of natural systems.

In preparing the thesis it became obvious that the inclusion of the majority of this background material would involve such a large volume of written material that it could well detract from the main argument which has been presented. For this reason the reviews and references included in the text have been kept to a minimum, and only included when strictly relevant.

However, the extensive literature searches that were undertaken in the various disciplines have enabled the author to compile a list of references which have been found to be of assistance in the study of cybernetics, especially with respect to the brain. The main objective in presenting this list is to provide a source of information which is both relevant and accessible. For this reason the references have been categorised into manageable groups, and it is hoped that they will be of assistance to the research worker who is searching for material concerned with the modelling of the brain.

REFERENCE CATEGORIES

R.1 Cybernetics.

R.2 Physiological Psychology.

R.3 Evidence of Plasticity.

R.4 Theories based on the Plasticity Hypothesis.

R.5 Computer Programs that Reproduce Intelligent Behaviour.

R.6 Computer Simulations of Nets of Neurons.

R.7 Neuron Models Based on Binary Logic.

R.8 Electrical Hardware Neuron Models.

R.9 Electro-Magnetic Neuron Models.

R.10 Electro-Chemical Neuron Models.

R.11 Electro-Mechanical Neuron Models.

R.12 Miscellaneous Hardware Neuron Models.

R.13 Large Hardware Cybernetic Systems.

R.14 Mathematical Models of Neurons and Neuron Assemblies.

R.15 Evidence of Columnar Structure in the Brain.

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