University of Nottingham
Department of Mining Engineering

The Automatic Optimisation of Drilling Performance

by

Philip J. Rowsell
B.Eng

Thesis Submitted to the University of Nottingham
for the Degree of Doctor of Philosophy

January 1991

Affirmation

The work submitted in this thesis is my own and has not been previously submitted for any other degree. The following publications have been based on this research:-

P.J.Rowsell and M.D.Waller
'Automatic Optimisation of Rotary Drilling Parameters'
Drillex 90

P.J.Rowsell and M.D.Waller
'An Intelligent Drill'
4th Canadian Symposium of Mining Automation, 16-18th September 90.
Saskatoon,Canada.

P.J.Rowsell and M.D.Waller
'Intelligent Control of Drilling Systems'
SPE/IADC 1991 Drilling Conference,11-13th March. RAI Congrescentrum,
Amsterdam.

Acknowledgements

The author would like to express his sincere thanks to all those people who have been of assistance during the course of this study.

The author would particularly like to thank:-

From the University of Nottingham,

Mr Martin Waller my supervisor, for his consistent guidance, assistance, generation of ideas and financial assistance. In addition for being a good friend, tolerating the continual pestering with which he was subjected to.

Dr Bryan Denby for his help with various computer problems which have confronted the author, as well as other useful advice.

Gratitude is also extended to the staff of the Mining Department Laboratories for their help during the research project.

From Industry,

John Beswick, Kenting Drilling Services Ltd, for his time, help and advice given over the course of this research project.

Stuart Wilson, DeBeers Industrial Diamond Division, Charters, Ascot for his help.

Abstract

The drilling industry, along with many others, is becoming increasingly competitive, demanding greater efforts to improve safety and reduce costs. For this reason, companies are progressively looking towards computerised automation to enhance performance. Unlike most industries however, the drilling industry has been slow to take advantage of the advances in computer and automation technology. Only recently have automatic operations such as tubular handling been placed under computer control. These activities relate to peripheral mechanical handling problems which are relatively easy to solve. The concept of an automatic intelligent drill, capable of making its own or assisted decisions about drilling parameters such as weight on bit or rotational speed, may seem remote and far into the future.

Research in drilling automation, at the University of Nottingham, has the ultimate objective of achieving computerized drill control through the the application of an intelligent knowledge induction system. At the University, a laboratory rig has been developed with such a system installed. Decisions for optimal performance are based on either maximum penetration or minimum cost drilling. The system has a self-learning capability, allowing a progressive improvement in performance. The prototype system is currently undergoing trials, using real data collected while the laboratory rig is drilling and artificial data. The results are very encouraging and demonstrate the feasibility and advantages of optimised drill performance.

This thesis describes the design and development of this drill optimisation scheme produced by the author. Both the theory behind the optimisation system, and the results of the initial phase of Laboratory testing are included.

Contents

Chapter 1 - Introduction

√Chapter 2 - Modifications to the Laboratory Drill Rig and Wear Measurement Jig

√Chapter 3 - Preliminary Drilling Tests and Developments

Chapter 4 - Optimisation Theory

Chapter 5 - Bit Wear and Wear Prediction

Chapter 6 - The Control Algorithm

Chapter 7 - The Results of the Optimisation System

Chapter 8 - Conclusions

Chapter 9 - Recommendations for Future Work

List of Figures

Figure No.		Page No.

Figure No.		Page

Figure No.		Page

Figure No.		Page

Figure No. **Page**

List of Tables

Table No. | **Page No.**

Thesis Outline

The design and development of the optimisation system described in this thesis is fairly complex and thus difficult to describe in a logical step by step progression. Every effort has been made to do so. However, many concepts are interrelated and as a consequence, they may require detailed explanation, before a real appreciation is gained. Some of these concepts are complicated in their own right and may require detailed explanation before being interrelated. Consequently, this can lead to some concepts being initially difficult to understand or their relevance seen, which later become clear once the whole system has been developed.

Therefore a brief description of the layout of the thesis has been included, highlighting the contents of each chapter, to give the reader a general overview and aid initial understanding.

Chapter 1 provides an introduction to drill optimisation and outlines the proposal of this research project, to develop an 'on-line' drill optimisation system. To be able to develop and test the optimisation system in a real situation, a laboratory drill rig, already in existence was utilized. However, some modifications were required, mainly for computer control and these are covered in Chapter 2. To test these modifications, as well as generate both an understanding of the drill, and initial ideas on the optimisation scheme, a series of tests were performed and are described in Chapter 3. These tests highlighted a number of problems with the control of the drill rig and its inefficiency for initial software testing. This proved invaluable in subsequent work.

The idea's gained from Chapter 3, allowed the initial development of the optimisation scheme could be conducted. In any optimisation system, decisions have to be made on what is the aim of the optimisation scheme, and by what method / parameters this may be achieved. This is covered in Chapter 4, and describes several methods which were investigated, the optimisation scheme finally being based on minimum cost per metre drilling.

The problems of attaining 'on-line' measurements for the parameters required for the optimisation scheme was covered in Chapter 5. A prediction method was developed, (mainly for wear rate prediction), which would enhance the known data to aid prediction of unknown points giving the system some self-learning capability.

In Chapter 6, the developments of Chapter's 4 and 5, were utilized to generate methods for a minimum cost optimisation scheme. Several methods were investigated, with a continuous computer search method being selected. The compete layout and operation of this optimisation system is described, along with the problems of multi strata operations.

Chapter 7 describes the results of the testing programme to validate the optimisation system, with conclusions and recommendations for further work being covered in Chapters 8 and 9 respectively.

Chapter 1 - Introduction

1.1 Drill Optimisation

Holes are drilled in geological strata for a wide range of applications. For example, exploration of an ore body or oil reserve, for extraction purposes, blast hole generation, de-watering, and for many other reasons. Virtually every mineral extraction project will require some form of drilling. As a consequence, drilling expertise is very important for successful operations. Drilling knowledge has progressed through time from a fairly simple operation to a highly complex one, involving a variety of different drilling techniques and methods, each for a particular purposes or situation. This development of technology is aptly summarised by J.L. Lummus *(40)* which shows the progression of rotary drilling - see Table 1.1.

With increasing knowledge and more advance technology, current drilling limits are being pushed further each year *(65)*, with deeper wells in more adverse geology. Combined with increased competition and the harsh economic climate, the demand for more sophisticated equipment and computerization is growing. This is not only to improve performance, but also to reduce cost.

The increase in computer technology, has allowed great advances in the monitoring and control of the drill rigs and drill parameters. This has resulted in more data being available to the drilling engineer for use in performance prediction and optimisation. However, the data is only worthwhile if it truly represents what is actually happening down hole.

In the mining industry, where the majority of holes are shallow and of small diameter, it is believed that monitored data does represent down hole conditions. This is reflected by the degree of monitoring / control equipment on the latest types of drill rig. This not only benefits the drilling engineer, but is useful for many other processes such as reserve calculation and blast design *(32,33,39,46,66)*.

In the oil industry, the picture is slightly different as the complexities of monitoring in deep holes are much greater. Some experts dispute the levels of accuracy of measurements attained and do not believe that the monitored data represents down hole conditions. However with progressive research and the increase in the use of measurement while drilling (MWD) tools *(13,24)*, it is hoped that this discrepancy will be soon eliminated.

Rotary Drilling Development	
Conception Period 1900-1920	**Development Period** 1920-1948
Rotary Drilling Principle *1900 (Spindle Top)* Rotary Bits *1908 (Hughes)* Casing and Cementing *1904-1910 (Halliburton)* Drilling Mud *1914-1916 (National Lead Company)*	More Powerful Rigs Better Bits Specialized Muds Improved Cementing
Scientific Period 1948-1968	**Automation Period** 1968-
Expanded Drilling Research Better understanding of Hydraulic principles Significant Bit Improvements Optimised drilling; Improved Mud Technology	Full Automation of Rig and Mud Handling "Closed-loop" Computer Operation of Rig Control of Drilling Variables Complete planning of Well Drilling from Spud to Production

Table 1.1 Development of Rotary Drilling (After Lummus)

In any optimisation process, a decision has to be made on what parameter is to be optimised. In an operation such as drilling, there are a multitude of parameters which, if optimised could help improve the overall efficiency of the operation, e.g. the percentage core recovery, penetration rate, cost, time to completion, mud circuits, etc. The choice of the parameter comes down to what the hole is actually required for. For exploration holes, in certain sections, the most critical constraint may be the percentage core recovery. In many cases, the desired optimums will conflict with each other e.g. percentage core recovery and maximum penetration rate. However for the majority, or the major part of most holes, the predominant criteria will be to produce the hole as quickly and as cheaply as possible.

In choosing the optimisation parameter, precaution should be exercised as there are many parameters or factors which hinder the drilling operation. Some of these based on a table by McDanial and Lummus *(44)*, are shown in Table 1.2.

If an optimisation system is employed, it can be seen from Table 1.2 that a number of the parameters are unalterable and restrict the optimisation scheme. Others (also unalterable) are unpredictable and interfere with and reduce the efficiency of the optimisation scheme *(1,19,20,39,40,42,49,69)*. Only a small number are under the direct control of the drilling engineer. The extent to which an optimisation scheme can be applied is therefore limited by the unalterable variables. The system also requires a degree of flexibility to cope with the unpredictable ones.

How then can drill optimisation be performed? Many of the currently employed systems in the drilling industry use off-line techniques, where historical data from previous wells are correlated with others, in an attempt to predict the nature of a similar hole to be drilled in the same area. These vary from optimum casing design, methods of evaluating rig performance, to the use of drilling simulators. Many publications and methods, featuring both manual and latterly computerized methods, have been developed throughout drilling history which try to improve the performance of the drilling operation. Each has had varying degrees of success *(4,8,22,36,41,42, 48,55,59,63,66,67)*.

Other methods rely on drill off tests to predict the likely response of the drilling operation in certain rock strata *(5,15,26,27,61)*. The results are fed back through various equations, to determine optimum operating conditions. The most famous is "How to achieve minimum cost drilling?" by Galle and Woods *(26,27)*, which

Variables which restrict the optimisation scheme		Variables which Compromise Implementation	
General	Rig	General	Rig
Program	Pump power	Location	Deviation
Total depth	Rotary power	Logistics	Lost circulation
Geological predictions	Pump pressure	Weather	Abnormal pressures
Hole sizes	Pump liners	Planning	Sloughing shale
Evaluation	Flexibility	Supervision	Hole trouble
Casing program	Pit system		Mud solids
Directional	Drill string		Crew efficiency
	Tripping time		Geological correlation

Table 1.2 Parameters which Hinder and Effect Drilling Optimisation

estimates the correct bit weight and rotary speed to attain minimum cost drilling, taking into account parameters such as bit wear.

With the advances in computer technology, the potential of on-line optimisation techniques has increased dramatically. To the authors knowledge, the first paper published on such a system was in 1968 *(74)*, and to date remains the only known one to be published. The paper describes the attempts by the Humble Oil and Refining company, to develop an on-line drilling optimisation system using a full scale drill rig. The system was developed around a Honeywell DPP 116 digital computer that logged all the main drilling parameters and controlled weight on bit and rotational speed. The system optimised through a cost equation, similar to the one used in this optimisation scheme. Penetration rate characteristics for different combinations of bit and rock types were determined by drill off tests and the wear characteristics of the bit were derived from wear curves form the manufacturer. The trials proved successful, but the current status of this project is unknown to the author.

More recently other "optimisation" systems have been developed *(37,52,64)* particularly by Tamrock, but these do not directly optimise drilling performance. They concentrate on automation of rod handling etc. None however, have been on same the scale of the Humble Oil experiment. Therefore scope exists for the development of such a system and it is understood that within the drilling industry an increasing amount of attention is directed towards optimising drill performance. However much of this research is propriety and currently remains unpublished.

1.2 The Research Project

Drilling research has been conducted at the University of Nottingham for 6 years, predominantly using Diamond Impregnated Core Bits, but latterly with Poly-crystalline Diamond Compact Bits. For the context of this project, the Diamond core drill rig would be used, being more accessible and with more information available.

Initial research on diamond impregnated bits was conducted by Ambrose *(2)*, who analysed bit performance. In this research a number of different rock samples were drilled with a variety of different bits and the results monitored. Amongst the results produced were graphs of penetration rate against bit wear rate. A typical plot produced is shown in Figure 1.1. From this graph it can be seen that there is a trade off between penetration rates and bit wear rates. However how do we decide where the optimum

Graph of Penetration Rate and Wear Rate against Weight on Bit

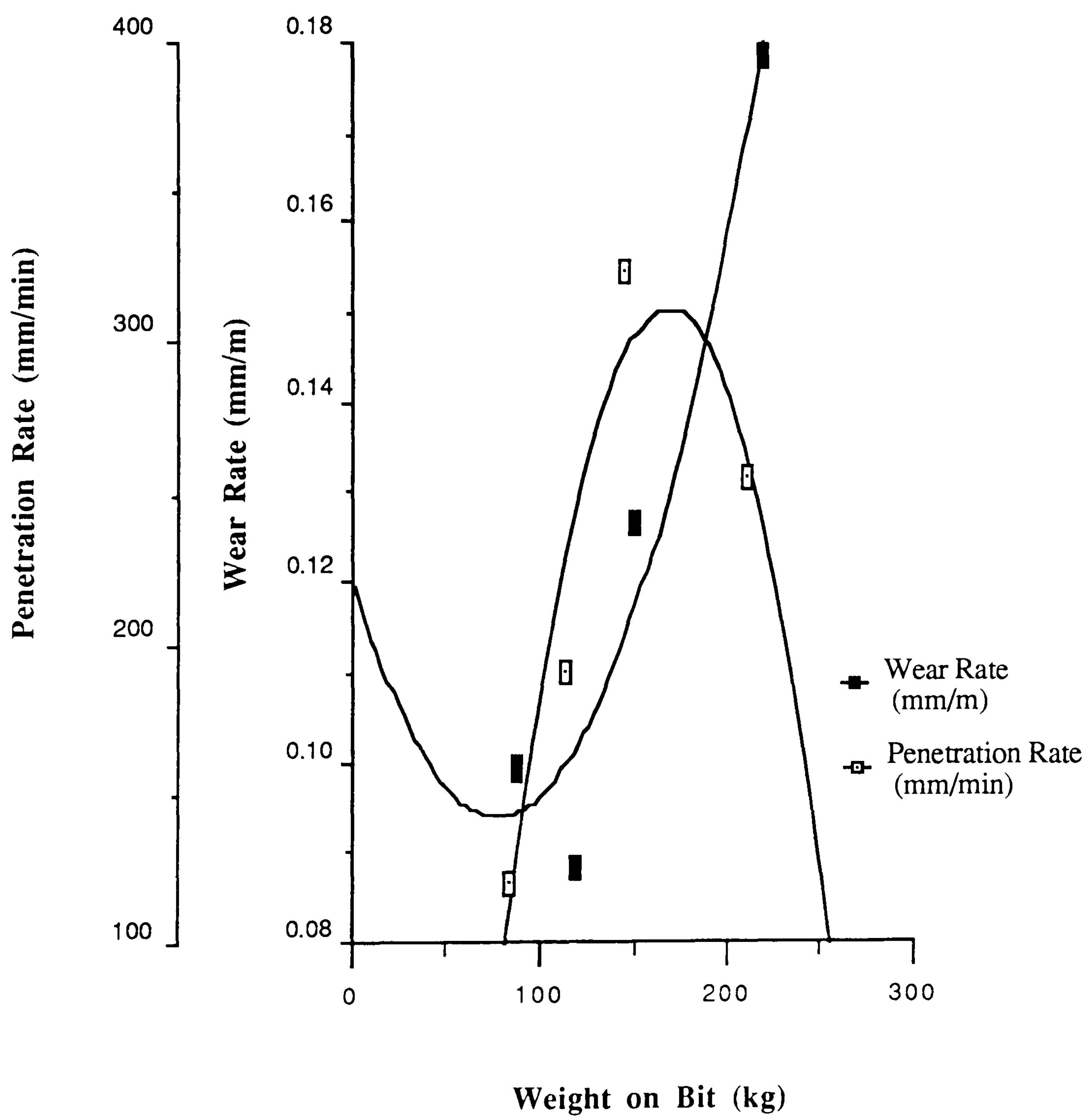


Figure 1.1 A graph showing the trade off between Penetration Rates and Wear Rates

operation point is? What factors effect this operating point, and is it actually achievable?

This was the basic rationale for this research project, i.e. to develop a system to locate and operate a drilling system at the optimum performance point. The idea of such an optimisation system is shown by Figure 1.2. Parameters from the drilling operation are fed to a central location known as an Intelligent Knowledge Induction System. This has the power to process these results and decide which parameters to alter to bring about an improvement in performance. In this hypothetical case, rotational speed and weight on bit (thrust) are indicated. This process would continue until no change of the parameters was seen, hence at this stage the drilling operation would be operating at its optimum performance point.

The project was split into two distinct parts :-

i) To establish feedback control loops on the existing radial arm core drill, and to use them to aid the development of a system to maximise penetration rates.

ii) Find and develop a method to operate the drill at its optimum performance point.

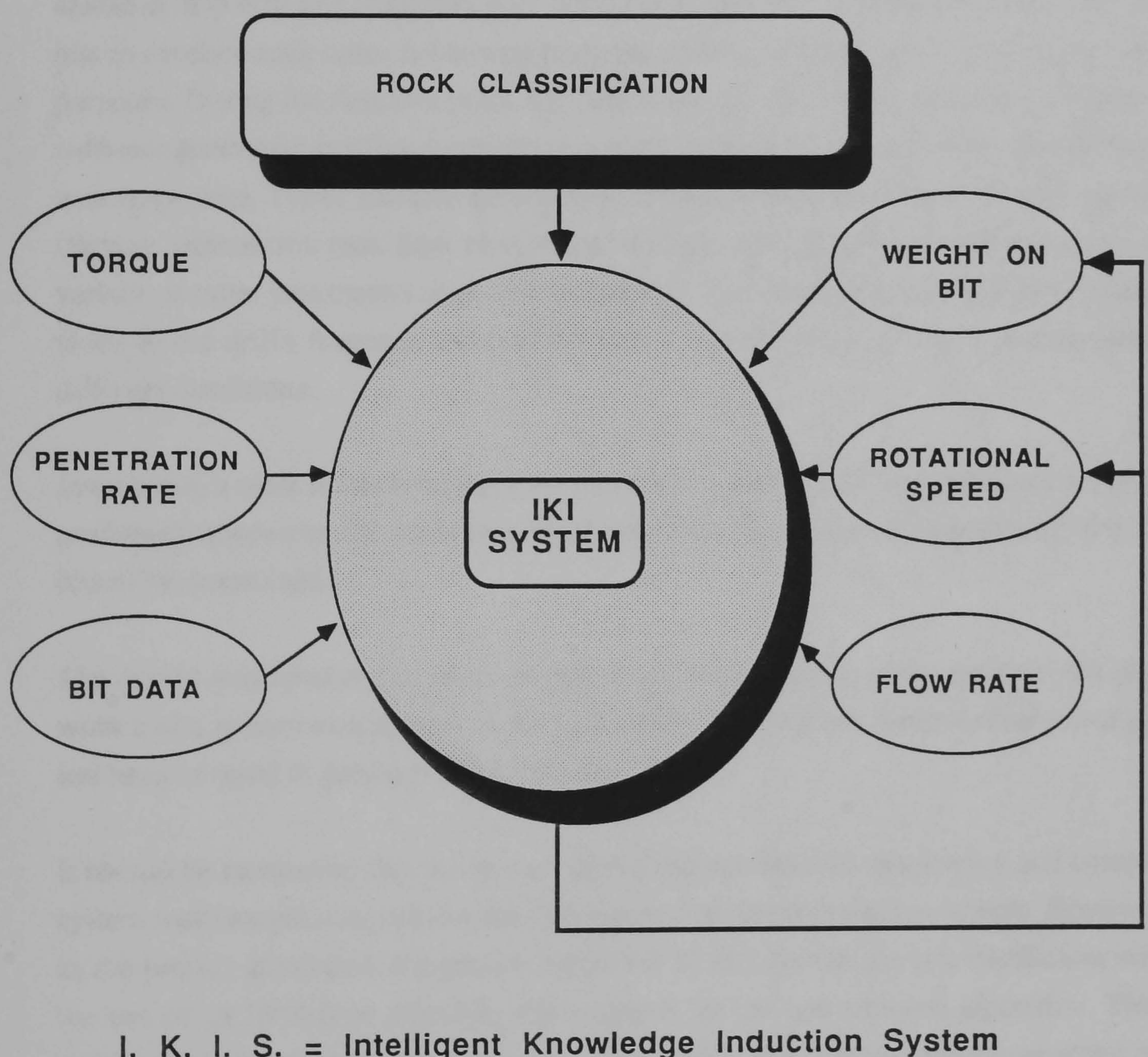


Figure 1.2 A General Scheme for a Drill Optimisation System

Chapter 2 - Modifications to the Laboratory Drill Rig and Wear Measurement Jig

2.1 Introduction

Drilling research at the University started with the conversion of an old radial arm machine shop drill to a laboratory rock coring drill. The drill used diamond impregnated bits to produce rock cores for testing purposes as well as being used for drill research purposes. During the first two years, the laboratory rig was instrumented and computer software generated to allow a variety of measurements to be taken, while the machine was operating. These include parameters such as rotational speed, weight on bit (thrust), penetration rate, flow rate, motor voltage and motor current. From these, a variety of other parameters may also be derived. Consequently, this has allowed the study of the drill's response and performance while drilling a variety of rocks under different conditions.

In addition, a wear measurement jig was also built, enabling the measurement of wear profiles developed on the diamond impregnated bits. This allows a wear history of drill bits to be determined.

The author was involved in much of this work, mostly on the software side, but this work and a greater explanation of the Laboratory drill rig and wear measurement jig has been covered in previous publications *(2,14,56)*.

It should be mentioned that at the start of this project the drill monitoring and control system was thought adequate for the development of the optimisation system. However as the project developed, the processing power of this system proved insufficient and the use of an IBM type machine was required for the optimisation algorithm. This posed a number of problems which were surmounted, but complicated the structure of the optimisation scheme.

With the benefit of hindsight, and the technological advances in electronics and computer systems that have occurred during this project, a different monitoring system would have been initially developed, based solely upon a IBM type machine. However despite this, a working drill optimisation system was developed, indicating the feasibility and potential for such a system It is expected that for full scale test trials an upgrade to a Micro Vax or Sun Work Station will be required.

2.2 The Laboratory Drill Rig

2.2.1 Hardware Modifications

From the onset of this research project, it was apparent that the laboratory drill rig would need some major modifications to achieve the ultimate aim of optimising drill performance. Documentation on the drill monitoring electronics already in existence was sparse. In addition, there had been no provision made for future expansion, which would be required for the inclusion of feedback loops to several of the drills parameters. Therefore it was decided to rebuild the electronics, salvaging what was necessary.

The drill electronics were based around a BBC Micro Computer. The BBC was an ideal computer with which to develop a low cost monitoring system, having many additional features compared with other computers. The Basic language was enhanced from those normally available, allowing a degree of structured programming. It was also readily suitable to electronic interfacing, having ports readily available to do so i.e. the User Port and the 1 MHz Bus. These and many other features make the BBC an extremely versatile machine readily suitable to interfacing projects.

Figure 2.1, shows the electrical system in its entirety and serves to give the non-electrical reader an idea of how the complete system works. From Figure 2.1, it can be seen that the main communication line between the computer and the external drill electronics is the 1 Megahertz bus. The 1MHz Bus is extremely useful for interfacing as it has up to 502 memory addresses specially allocated to it in the BBC. Consequently it is possible to service a large number of peripheral devices, and hence its use as the back bone of drill electronics system. To allow for ready expansion of the drill electronics, a common pin configuration was linked across the entire back plane of the electronics rack, Figure 2.2. This configuration consisted of the 1 MHz Bus lines and the common voltages used on the boards. In so doing each board could have direct access to the 1 MHz bus if required. Those not, such as the signal conditioning board could be located next to their controlling boards for easy direct linkage.

With the addition of hardware to 1 Mhz Bus, address decoding is essential to ensure that only the required chip / peripheral device is accessed by a pre-set range of address values. A typical circuit is shown in Figure 2.3.

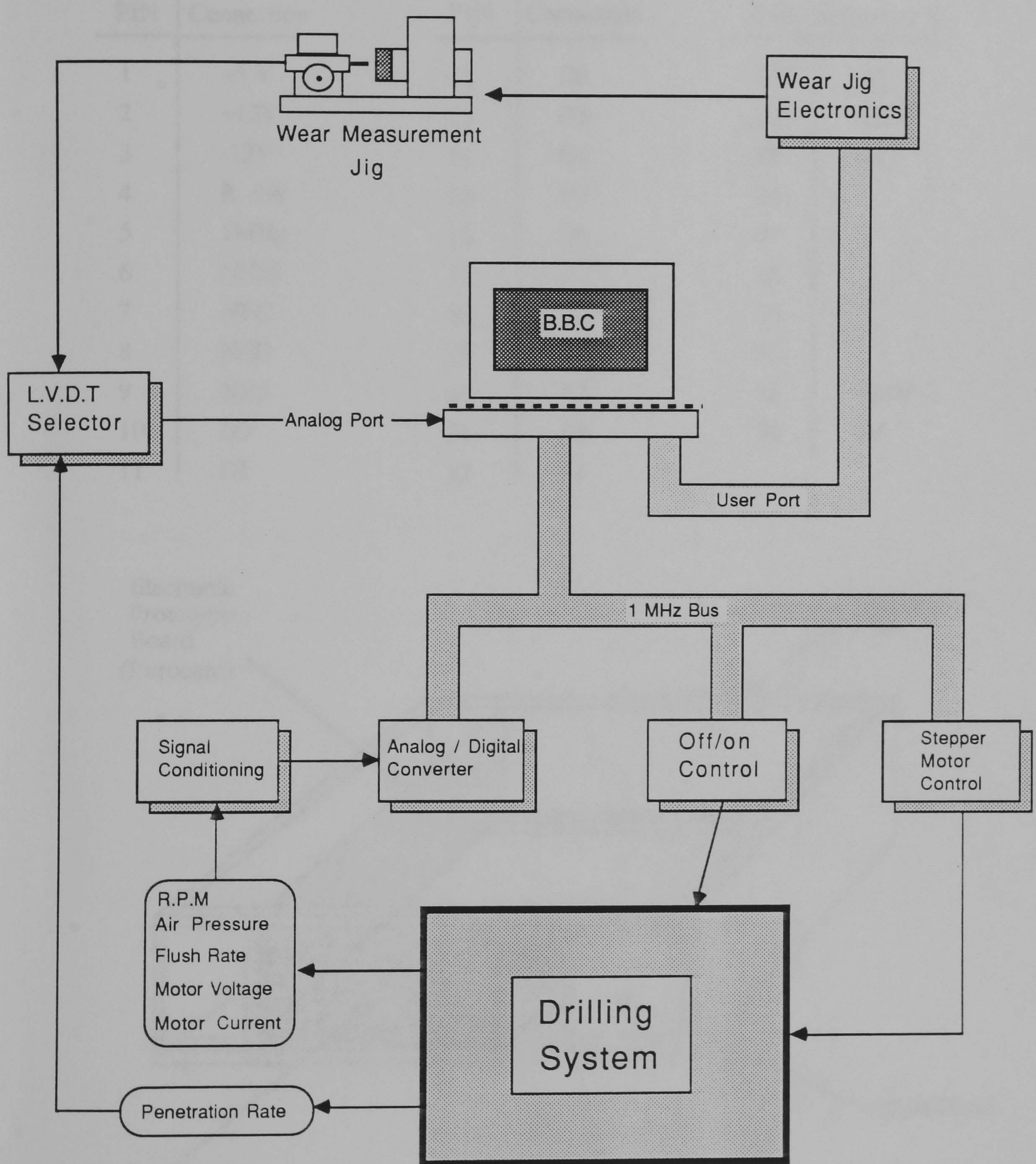


Figure 2.1 General View of the Drill Electronics System

Eurocard Back Plane Rail Etiquette

PIN	Connection	PIN	Connection	PIN	Connection
1	+5 V	12	D2	23	A5
2	+12V	13	D3	24	A6
3	-12V	14	D4	25	A7
4	R / W	15	D5	26	
5	1MHz	16	D6	27	
6	NIQR	17	D7	28	
7	NFC	18	A0	29	
8	NFD	19	A1	30	
9	NRS	20	A2	31	+24V
10	D0	21	A3	32	0V
11	D1	22	A4		

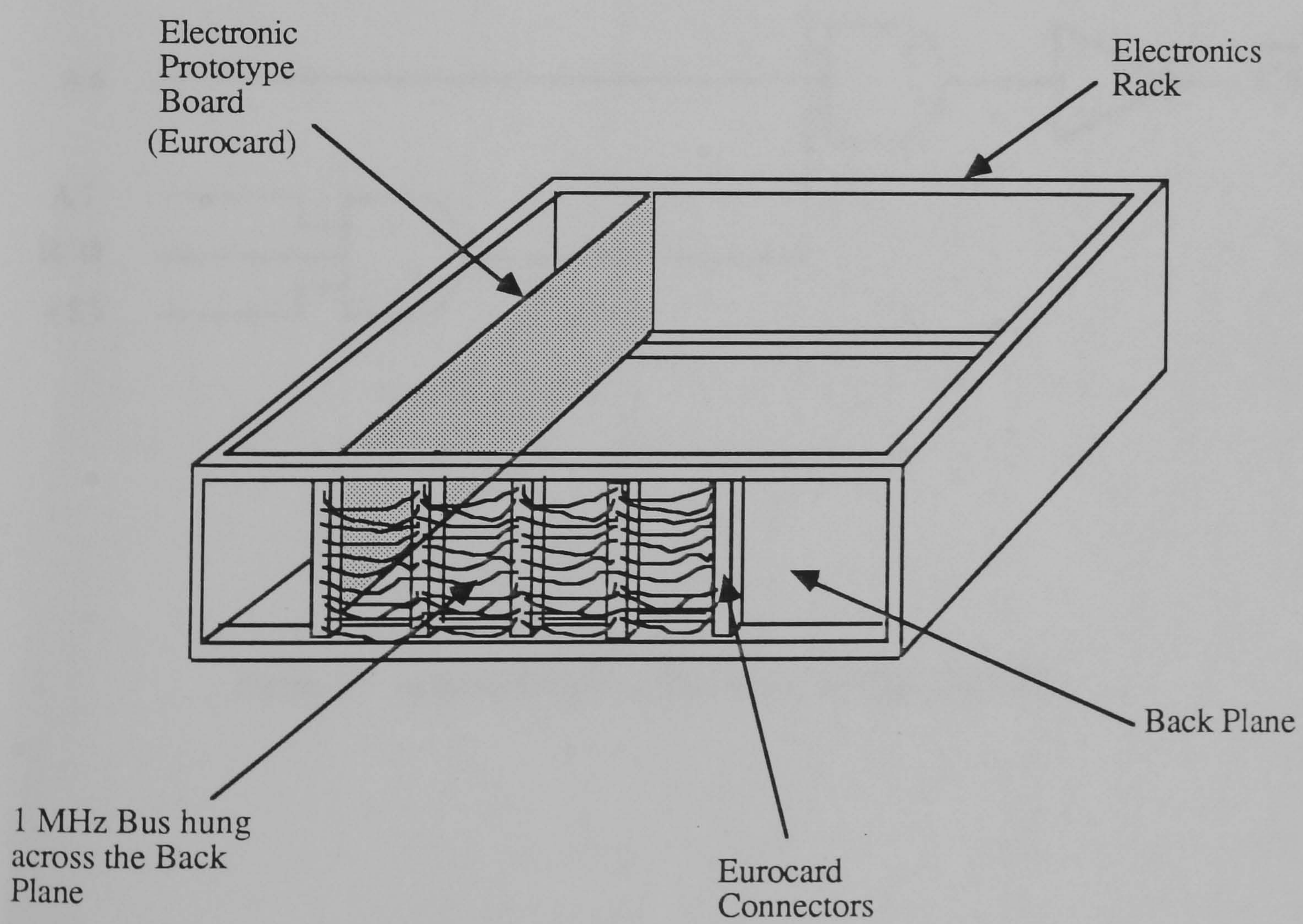


Figure 2.2 :- The 1 MHz Bus pin connections and the electronics rack.

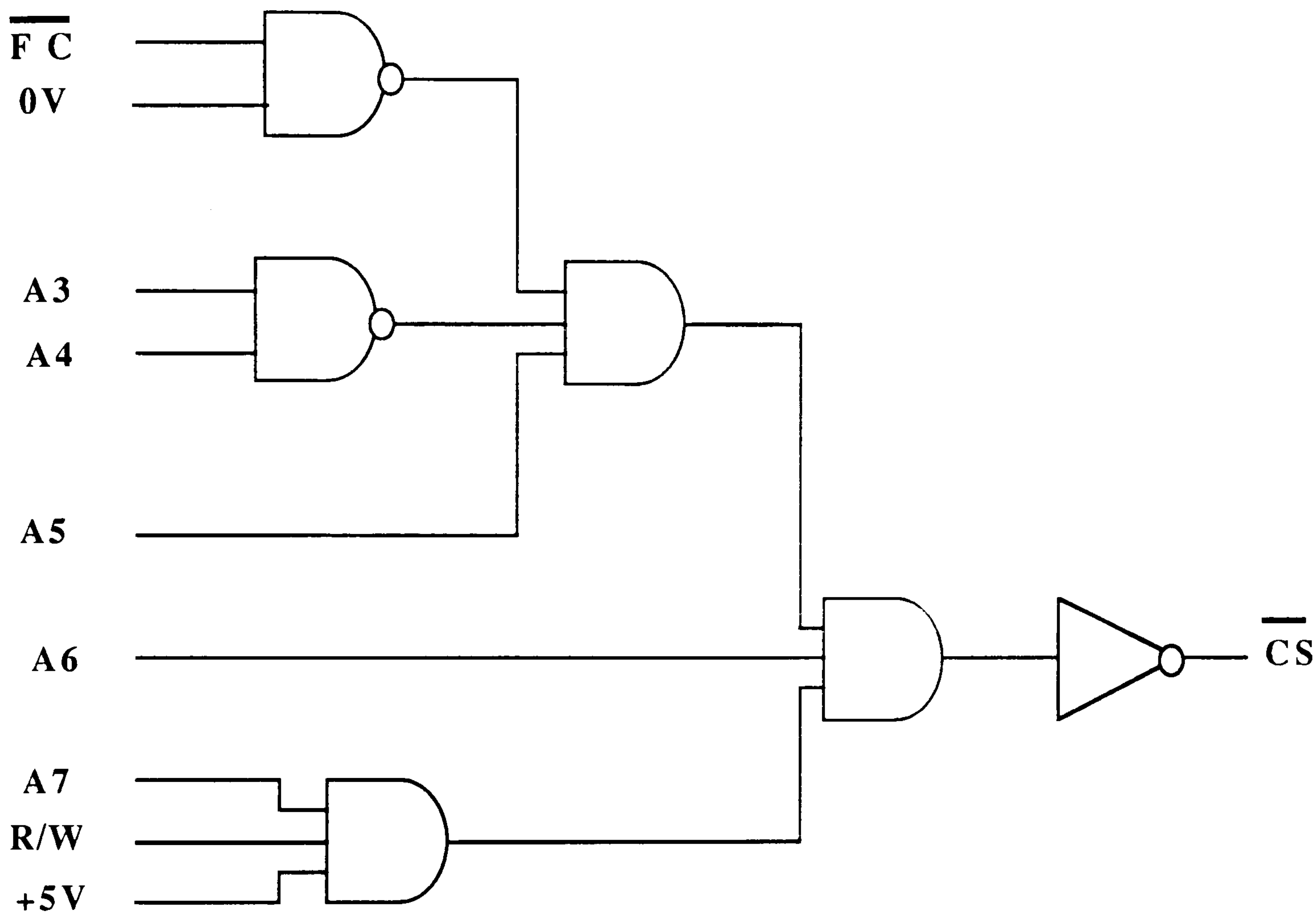


Figure 2.3 Address Decoding Circuit for &FCE0 - &FCE8

2.2.1.1 Monitoring Hardware

The majority of the various transducer signals were fed to a central electronics board which conditioned and converted the signals to a range of 0 - 10 Volts required by the Analog to Digital (A/D) convertor. As no changes were made to the monitoring transducers, the original signal conditioning board was directly incorporated into the new system. The conditioned signals were passed to a 8 bit 8 channel A/D converter located on a separate adjacent board, directly accessing the 1 MHz Bus.

Penetration Rate is measured using a Linear Variable Differential Transformer Transducer (L.V.D.T.). L.V.D.T.'s utilise the coupling generated by a soft iron plunger in a series of coils to relate the position of the plunger. A similar device was also used for the wear measurement jig. As both L.V.D.T.'s were never used at the same time, it was decided to bring them under a common circuit. A four pole relay was used to select the appropriate L.V.D.T. output, and this was fed to an Oscillator Demodulator, which translates the L.V.D.T.'s signals to a linear response ranging from -1 to +1 volt. The internal 12 bit A/D of the BBC was used for converting this signal, but as this required a 0 - 2 volt input, the Oscillator Demodulator output was passed through a voltage shifting circuit shown in Figure 2.4.

The measurement of flow rate, had previously been based on an orifice plate and a differential pressure transducer. This had resulted in a multitude of problems, generally due to large pressure transients and the transducers incompatibility with water. This caused the failure of a number of such transducers. A new method has been developed (on the PDC rig) using a low cost water turbine, which while installed on the radial arm drill rig, the electronics have not yet been commissioned.

2.2.1.2 Control Hardware

The control of external electronics from computers, generally has to be made through interface adapters either Versatile Interface Adaptors (VIA) or Peripheral Interface Adapters (PIA). Both are very similar, the VIA containing such features as internal clocks, useful for more complex interfacing. These devices allow both the reading and writing of data to a series of data lines (collectively known as a port) which can either be used for monitoring or control purposes. The BBC has an internal VIA for use by the programmer, accessing both the printer and the User port. The User port in this case however, has been dedicated to the wear jig and therefore and additional VIA or PIA was necessary. As no external timing was required in the control circuits, a PIA,

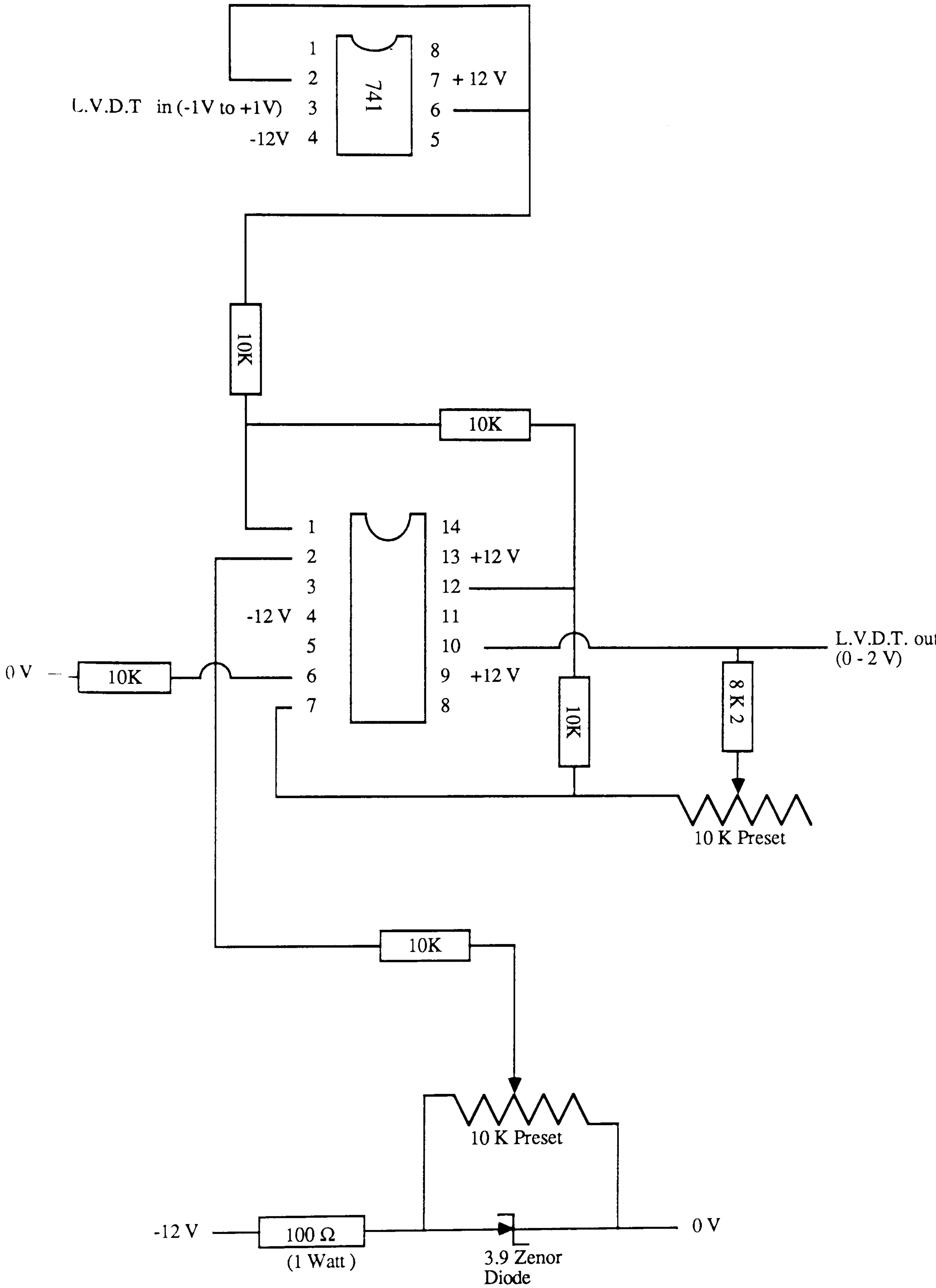


Figure 2.4 Voltage Shifting Circuit From (-1V to +1V) to (0V to +2V)

was selected and hung on the 1 MHz bus. This gave access to an additional 16 data lines for use in control or monitoring purposes.

2.2.1.2.1 Stop / Start Control

To enable a fair degree of automation, drill stop / start control from the micro processor was incorporated. This also added a safety feature as the machine could be instructed to switch off if torque levels were too high or if the drill had reached the bottom of the hole.

Figure 2.5 shows a circuit diagram for the drill stop / start circuit. By pressing the start button, the resulting brief contact closure energises the primary coil, closing the drill contacts and the primary contacts and hence primary circuit. The primary and machine contacts remain closed until such time as the stop button is pressed, breaking the circuit, de-energising the coil and allowing the contacts to open.

By adding two relays as shown in Figure 2.5, direct control from the computer can be established, utilising two data lines from the PIA chip, one for start control the other for stop control. As the PIA lines are only at TTL logic levels (i.e. 0-5 volts) and of limited current capacity, they are incapable of directly driving a relay. Figure 2.6 shows the driving circuit for the two relays triggered by positive logic levels on the control lines. This is known as a Darlington pair.

2.2.1.2.2 Feedback Loops

From previous drilling tests it was known that both rotational speed and weight on bit had a major influence on drill performance, and thus both these parameters were to be placed under micro processor control. It was also known that flow rate also had an effect, although not significant on this laboratory rig. However due to the difficulties experienced in monitoring the flow rate, and its negligible influence, it was decided not to control flow rate at this stage. However, the systems electronics were designed to allow easy inclusion at later date.

Manual speed control utilised a potentiometer, to vary the demand signal to the motor speed control electronics. As a low budget solution was necessary, it was decided to motorize this unit, such that when the motor was energised the computer could control the rotation of the potentiometer, and when de-energised manual control would remain.

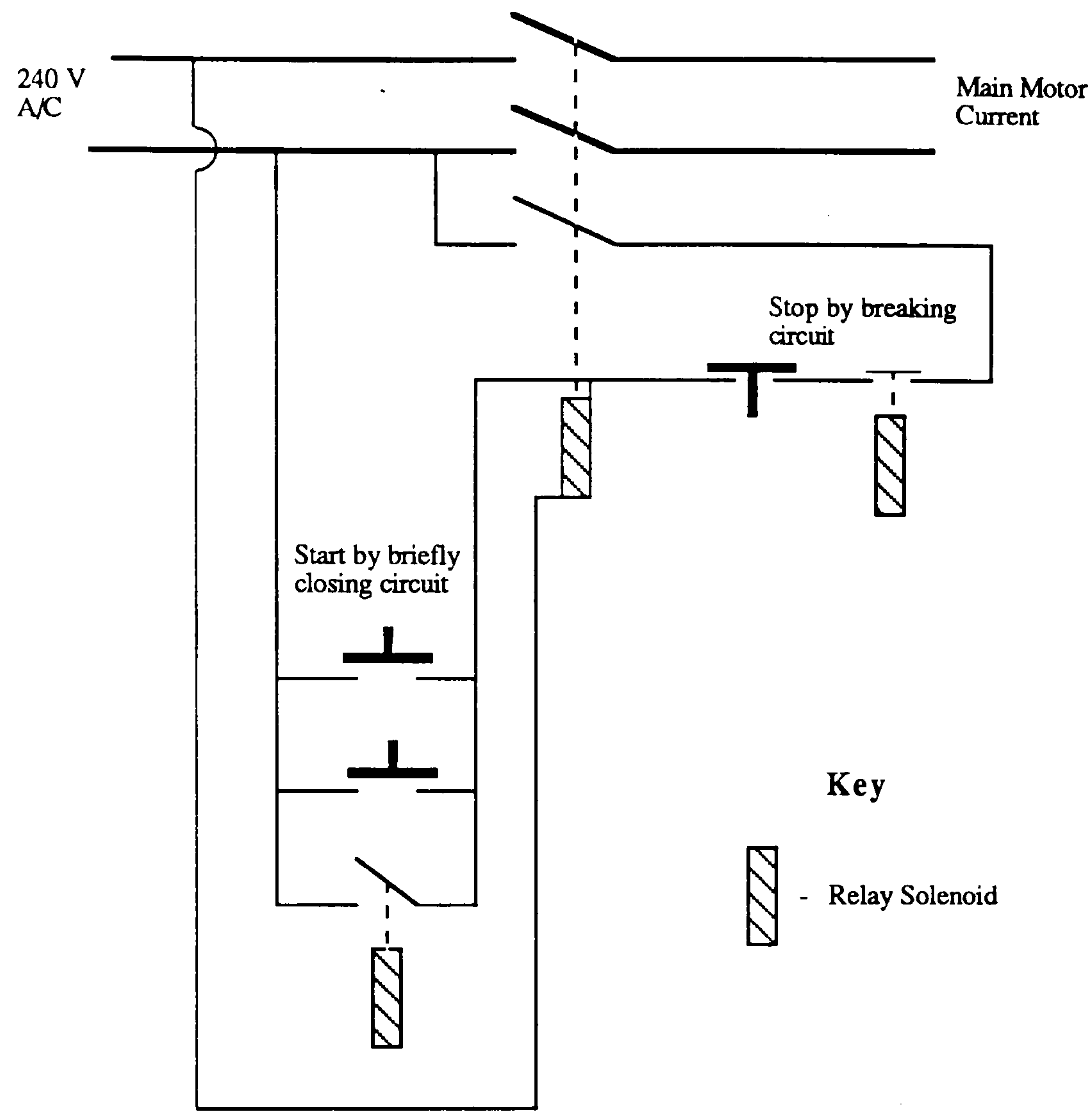


Figure 2.5 The Drill Stop / Start Circuit Diagram

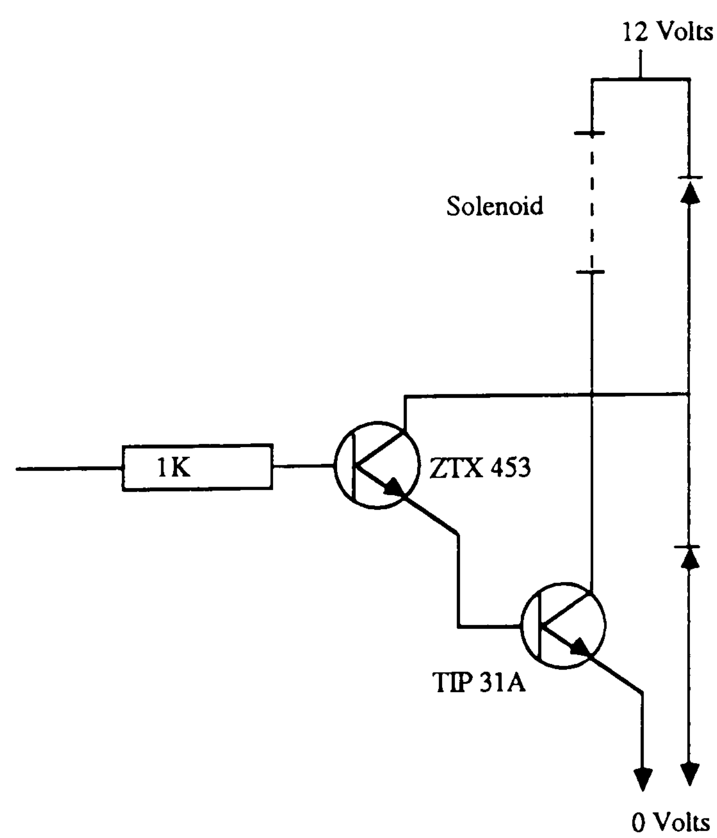


Figure 2.6 A Darlington Pair Used to Drive the Stop / Start Solenoids

To control the rotation of the potentiometer with any accuracy would require stepper motor control. These motors turn a specific angle of rotation for each pulse sent to their control circuit. The motor used in this case was an old three phase stepper motor which had been salvaged from another piece of equipment. However, most modern stepper motors are now four phase, and thus no off the shelf control circuit chips could be found. A circuit designed by M.D.Waller for a the conversion of a three phase to six phase, was examined and simplified, and proved satisfactory - Figure 2.7. An on / off control for the motor was also added to reduce the time for which the motor was energised, and thus minimise power supply drain.

A prototype system for the motorised potentiometer was built out of Metal Mechano to prove the principle, using several gear ratio's to attain the desired resolution. This system was so successful, it was used for the actual drill speed controller.

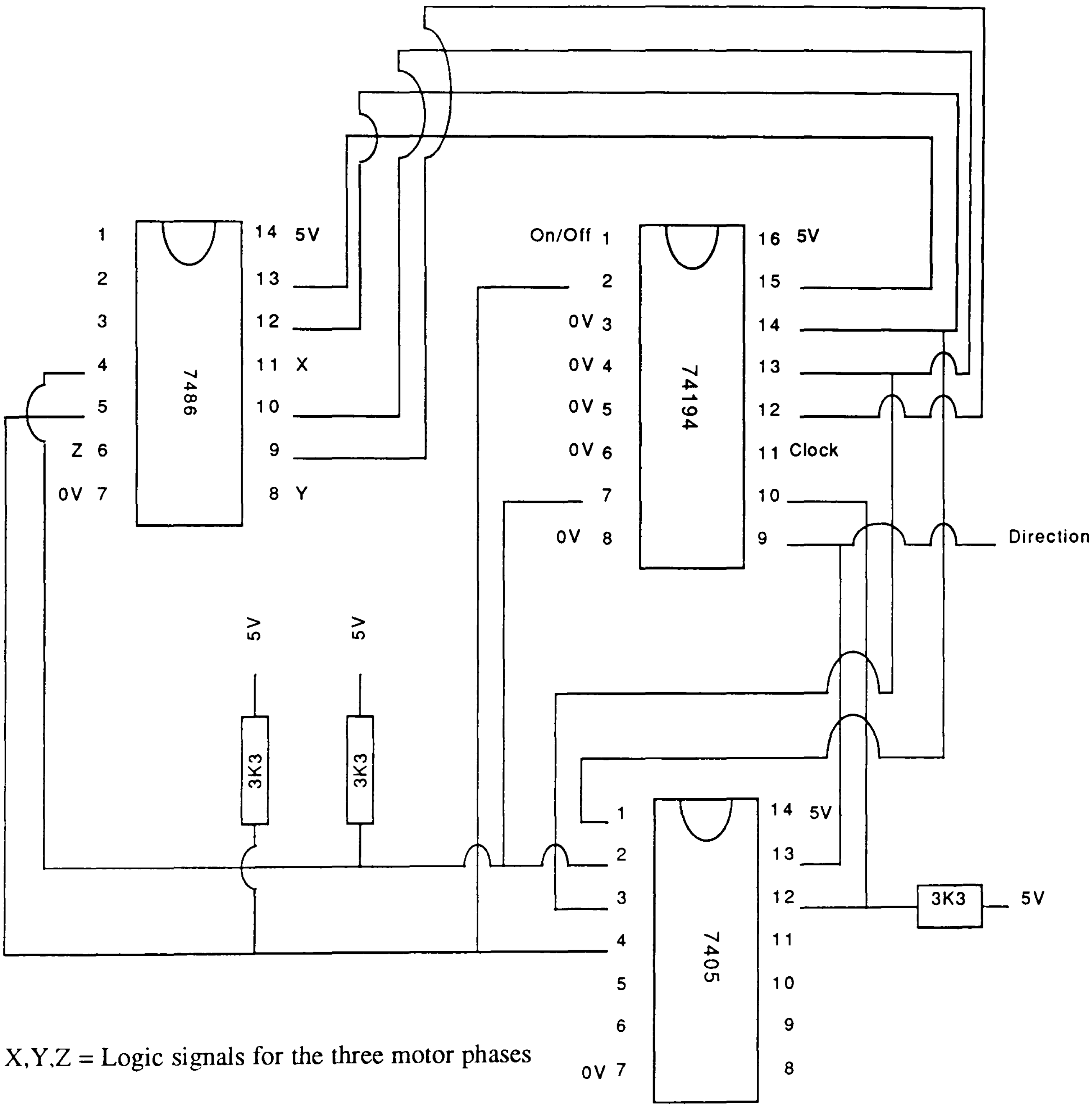
With the success of the speed controller, a similar approach was sought to control the weight on bit. Weight on bit was provided by a piston in which air pressure was varied to give differing loads. Unfortunately the existing pressure regulator was old and too complex to motorize in the same way. However an additional regulator was found, which could easily be adapted. This was placed in series with the other. By opening the original pressure regulator fully, pressure regulation could be passed to the motorised regulator and hence under computer control.

2.2.2 Software Modifications

The drill rig software had previously been developed to a fairly high degree *(56)*. Consequently only several modifications were made.

Throughout the history of the rig, the accuracy of penetration rate measurements have caused problems due to the electrical noise associated with the internal A/D converter on the BBC. Many attempts to smooth the resulting fluctuations had improved the reading. However, as these were written in Basic, it was thought that an interrupt routine (through assembler) could be used to improve the current system.

Interrupts take priority over the general running of the computer e.g. the execution of a programme, and thus give a means of attaining a higher priority over the programme. Many devices work using interrupts e.g. disc system, keyboards etc, and all have designated priorities. Care therefore must be taken at which level the interrupt is set at as the results can otherwise be disastrous.



X,Y,Z = Logic signals for the three motor phases

Figure 2.7 A Driving Circuit for a Three Phase Stepper Motor

For this application, the lowest priority is used, as only priority over programme execution is required, in BBC terms, this is the IRQ2V vector. The interrupt routine written utilises the internal VIA timer, which causes an interrupt after a certain time has passed. In this case the time set was a twentieth of a second. On each interrupt, the timer would be reset and the analog port (penetration measurement) would be read and stored accumulatively. On every twentieth reading i.e one second intervals, the analog port values would be averaged and stored to disc along with the other drill parameters.

Previous problems had also occurred with the spin up time of the disc system causing the programme to hang, while the disc attained the correct speed and the disc buffer emptied. This was also catered for in the interrupt routine by flushing the disc buffer each time data was written to the disc, i.e. every second. Consequently, the disc was constantly spinning and immediately accessed.
The interrupt routine proved highly successful and smoothed the penetration rate measurements to an acceptable level. However, the only real way to improve the system would be to build an external 12 bit A/d convertor. For the marginal benefits gained, it was not thought worthwhile at this stage.

As the project developed, the optimisation routine ran on a P.C for reasons discussed later. In so doing, the storage of drilling data on the BBC was abandoned. The data was transferred directly to the P.C for storage on a hard disc. Consequently the disc system access parts were removed from the BBC monitoring programme.

For general drilling and specific energy research, data is still stored on the BBC disc, and these programmes i.e. Monitoring , Plotting routines etc, have been brought to a menu driven option for ease of operation.

2.3 Wear Measurement Jig

A prototype wear jig had been already built, with the software being written by the author. The current wear jig electronics were housed in a number of boxes making transportation difficult. With the re-building of the drill electronics, it was thought worthwhile combining the wear jig electronics into a single board and adding it to the drill electrical rack.

This modification was conducted at the same time as an additional wear jig was being manufactured for DeBeers Industrial Diamond Division. Consequently, because of the commercial nature of this project, two printed circuit boards (one for the University and the other for DeBeers) were produced, rather than using prototype boards. While the DeBeers project proved highly successful, later modifications to the University board through progressive developments, resulted in the PCB becoming untidy. In hindsight would have been better to produce the University board on eurocard allowing greater flexibility.

2.3.1 Improvements to the Wear Jig

With regular use, it was found that the L.V.D.T. pointers tended to flatten with use, the flattening being most pronounced when the pointers were new. This was mainly due to the pointers being made of mild steel with no heat treatment being applied. In addition to this, the shape of the pointers had an adverse effect on the measured profile. The difficulty of machining such small items, resulted in the pointers tending towards a conical shape. This had the effect of exaggerating the rounding at the crown extremities as shown in Figure 2.8.

Therefore, a solution to eliminate both problems was necessary, i.e. a pointer needle like in shape, good wear/ impact resistance and readily available. The solution was found in household picture nails. These were readily available in any hardware shop, made of hardened steel and needle like in shape. A suitable holder for these nails was made to allow for regular replacement. The improvement on the measured profiles is shown in Figure 2.9.

With the development of the volume loss calculator described later, it was found that the method of locating the drill bit in the jig was too inaccurate. Originally the drill bit was butted up to a boss which was set at the beginning of an experiment. If the drill bit was too small, a blank would be screwed into the bit, effectively elongating it - Figure 2.10. An additional drawback, was that once the apparatus had been set up for one bit type, other bits could not be measured without moving the position of the boss, which would invalidate any further measurements of the initial bit.

A new system (Figure 2.11) was designed in which the location method was directly onto the core bit. A small counter sunk hole was drilled into the shank of the drill, care being taken not to drill right through. The hole was used to locate a pin which ran through the mounting "V" block. This method also insured that the same portion of the segment was measured each time. Subsequent testingby the re-measuring of the same

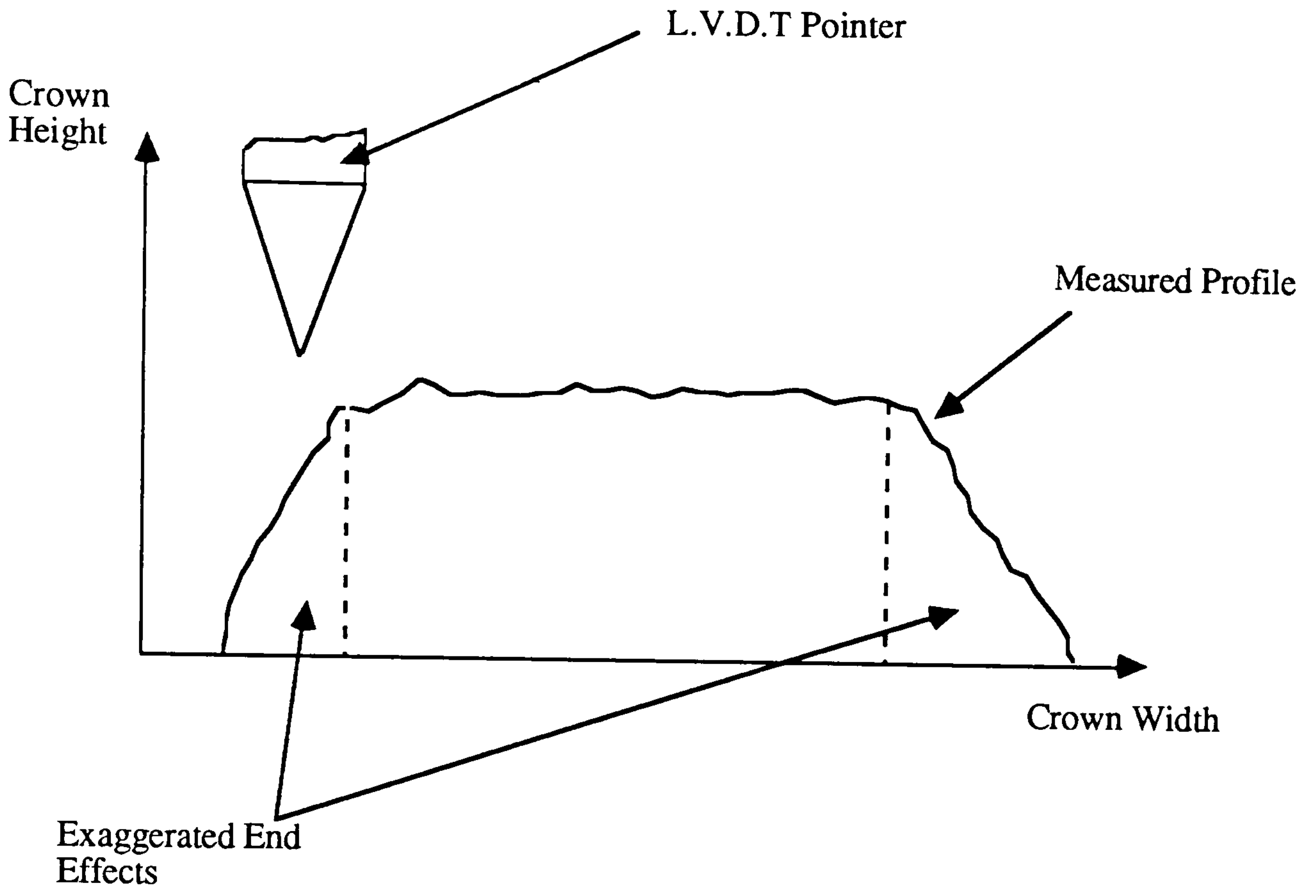


Figure 2.8 End Effects Caused by the Old Type of L.V.D.T. Pointer

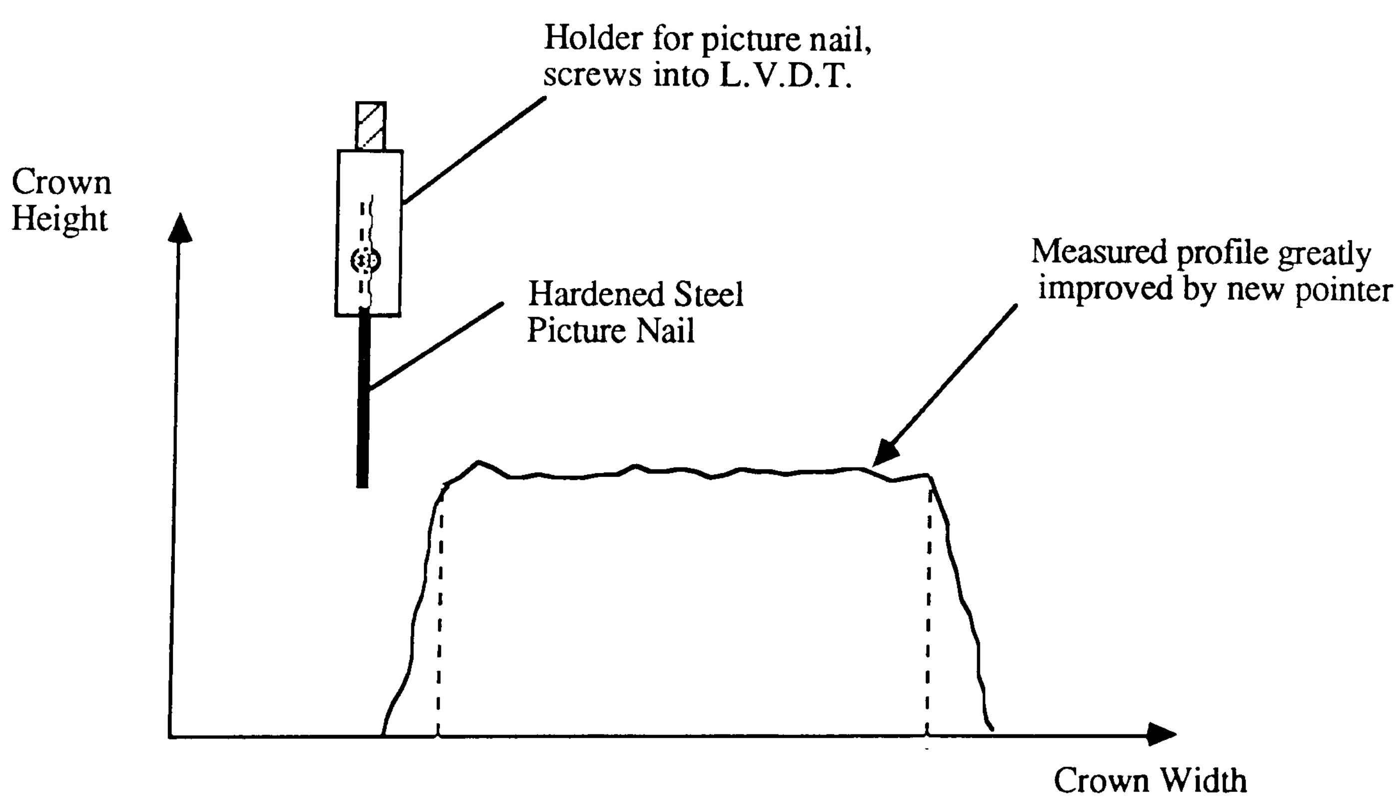


Figure 2.9 Improvements to the Measured Profile by the New L.V.D.T. Pointer System

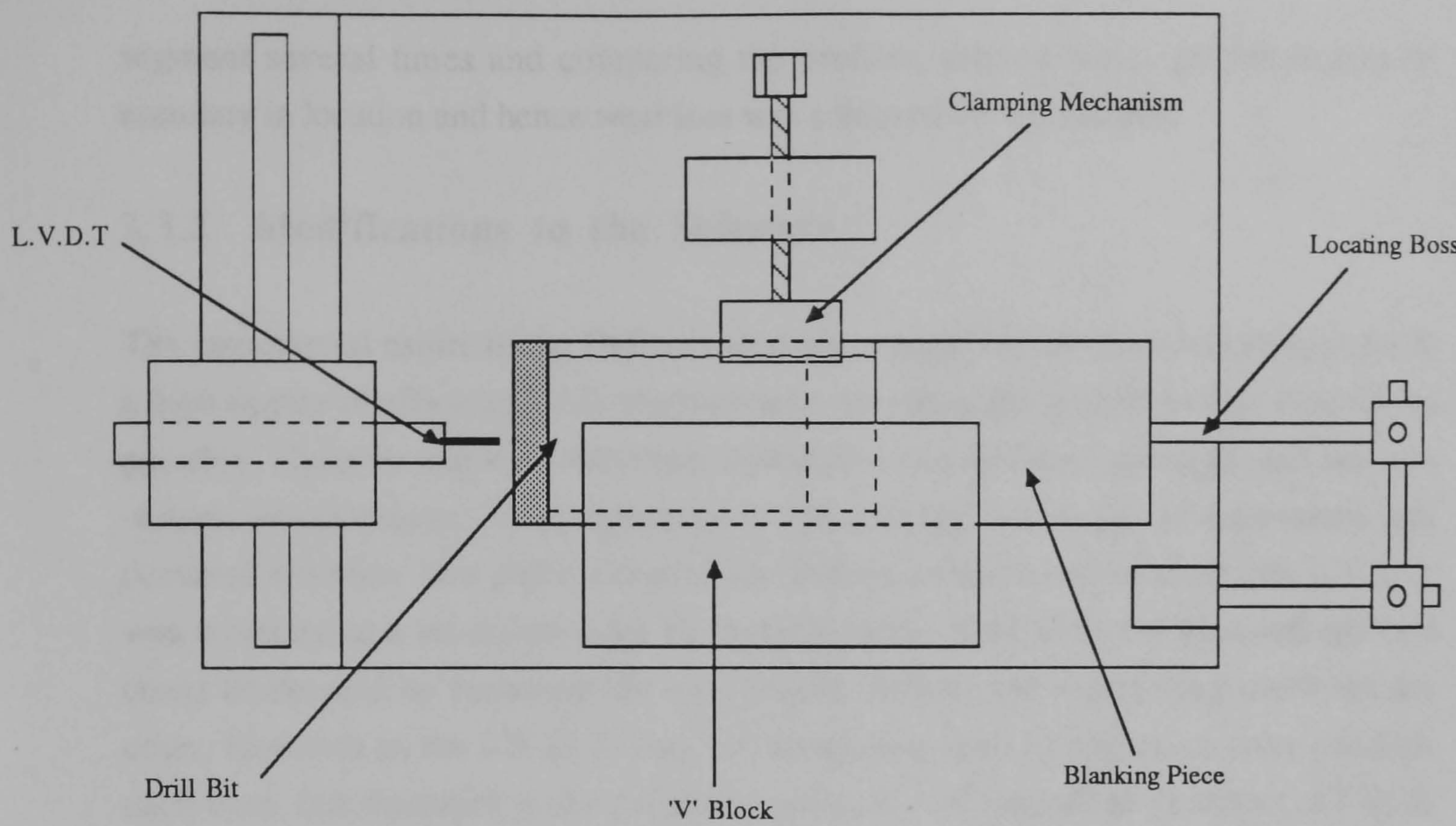


Figure 2.10 The Old Method of Locating the Drill Bit in the Wear Measurement Jig

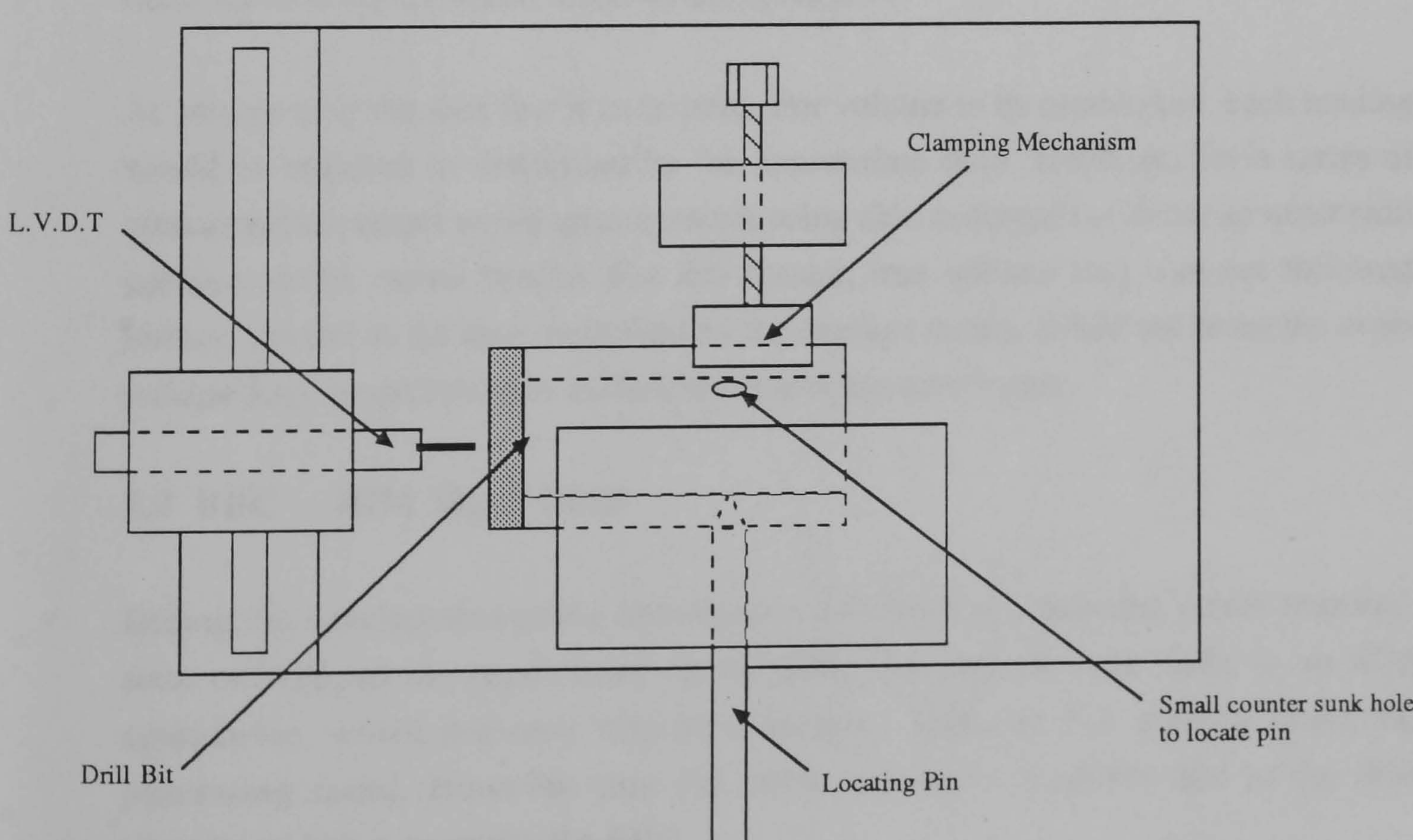


Figure 2.11 The New Method of Locating the Drill Bit in the Wear Measurement Jig

segment several times and comparing the profiles, proved that a greater degree of accuracy in location and hence wear loss was achieved by this method.

2.3.2 Modifications to the Software

The commercial nature of the DeBeers wear jig ensured the software was developed to a high degree of efficiency. All programmes were menu driven and as user-friendly as possible. The only major development undertaken during this research project was the volume loss calculator. This programme would calculate the amount of wear which had occurred between two particular profiles. During profile measurement, the L.V.D.T was traversed at a set distance for all measurements. Therefore, the total volume lost could be derived by summing the total profile heights, and subtracting one from the other. However as the L.V.D.T. may not necessarily start in the exact same position each time, discrepancies in the calculated volumes were observed as shown in Figure 2.12.

To compensate for this, a routine was written in which the two profiles could be superimposed on each other until the best fit was observed - Figure 2.13 . To remove end effects and rogue values, inner and outer boundaries could be positioned, and only the centre portion sumated. The profile with the new boundaries was re-drawn after calculation. A typical result is shown in Figure 2.14.

At present only the area lost is calculated. For volume to be established, each reading would be required to multiplied by the appropriate radii. However, for a series of measurements, errors would arise from not being able to accurately locate an exact radii position to the crown profile. For this reason, true volume loss was not followed further, but left as the area multiplied by the average radius. While not being the exact volume lost, it was felt to be sufficient to show the wear trends.

2.4 BBC - IBM Data Link

During the development of the optimisation system, the processing power required, soon outstripped the capabilities of the BBC. An upgrade was made to an IBM compatible, which not only improved memory capacity, but equally important processing speed. However, this did cause one major problem due to the drill electronics being geared to the BBC.

Figure 2.12 Profiles Before Superimposition

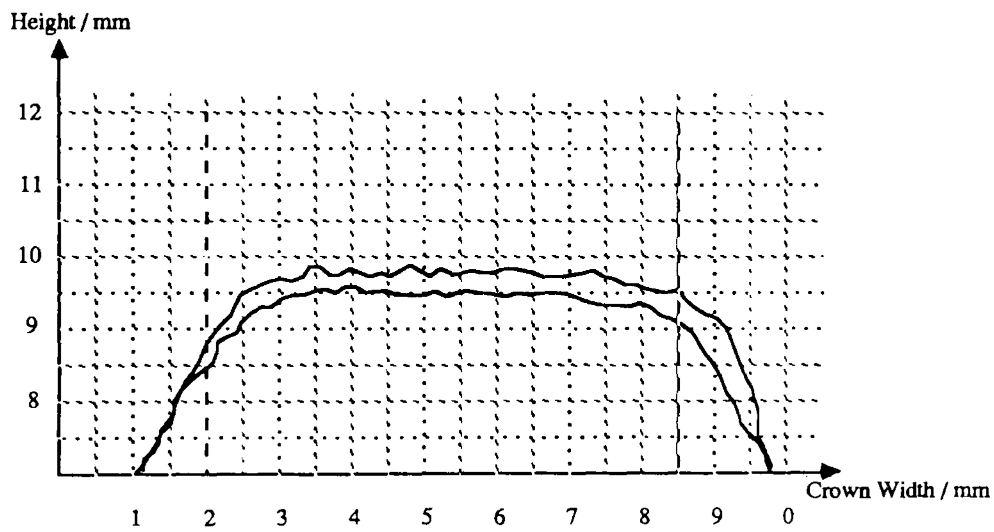
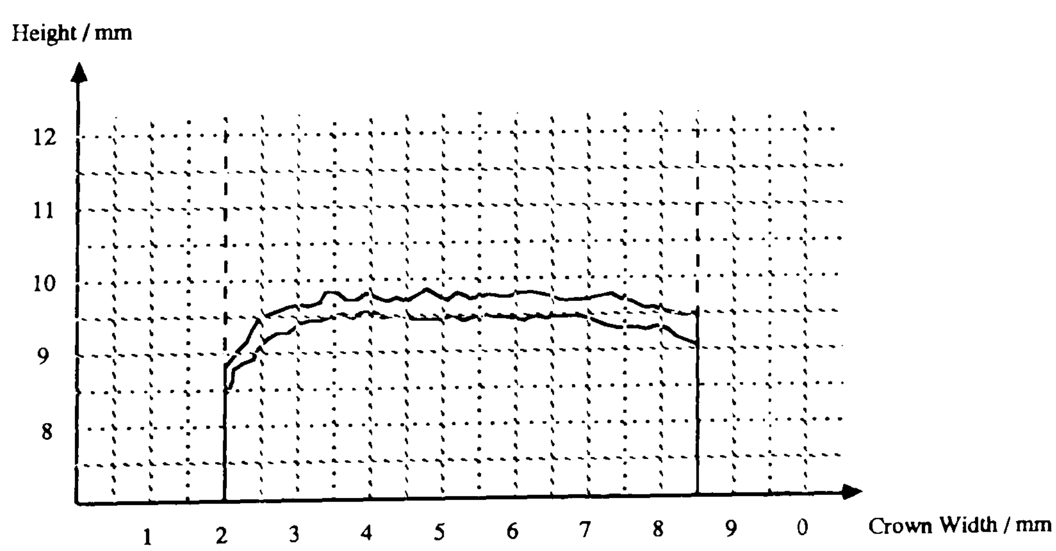


Figure 2.13 The Superimposed Profiles

Volume Loss of Profile 11 - Profile 20



Length of Cut = 28 to 181 = 154 (6.5 mm)

Area loss = 0.963 mm^2

Figure 2.14 A Typical Volume / Area Loss Calculation Result

Interfacing from the IBM is much more complex than from the BBC as it does not have many of the built in features akin to interfacing as seen on the BBC. Consequently, special boards etc have to be brought in. Even with these boards, large scale modifications would be required to adapt the electronics to work from a IBM. The time taken to do this and generate a suite of monitoring programmes similar to those on the BBC, was thought to great to be worthwhile at this demonstration phase of the research project. Therefore a different approach was sought.

The concept of using the BBC as a front end processor was developed. In this, the BBC would be designated solely to data acquisition and control of the drill. The main optimisation system would run on the IBM and send control commands to the BBC, to access data, or to instruct a parameter change. The two machines would communicate through the RS232 interface common to both machines.

The establishment of the RS232 data link was originally thought to be a relatively straight forward and easy task. Unfortunately, it proved to be to the contrary. The control of the RS232 from the BBC was relatively easy and well documented. The IBM on the other hand was the complete opposite, with information on the hardware side extremely sparse. With a great deal of experimentation using a breakout box, the correct pin configuration was established.

However the use of an unorthodox solution was necessary. Problems occurred at the IBM end, where data could not be read from the RS232 port. The only solution found to this problem was to short the CTR and RTS lines on each computer, leaving only the two data lines and ground connected between the two computers. Obviously this is not an ideal solution but it proved to be the only solution.

The shorting of the respective lines, removed any handshaking capabilities between the two computers for data transfer control. This made data transfer very complicated as data could be easily lost. This would typically happen if the IBM sent data to the BBC and the BBC was busy. The input buffer on the BBC would progressively fill as the IBM sent more data. If the BBC remained busy and the buffer not accessed, the buffer would eventually fill. As the CTS line had been shorted no instruction could be sent to the IBM to stop it sending data. Consequently any subsequent data sent by the IBM would be lost.

To overcome this problem, some sort of software computer handshaking was required, such that one computer would indicate that it was ready to send data, and would hang until such time the other indicated it was ready to receive the data. This has the immediate disadvantage that the machines have to wait until the other is ready to receive to transmit data, compared to normal transfer where the data is buffered and dealt with when the machine is less busy.

To complicate matters further, it was found also that spurious data appeared on the data lines. Unless excluded, this would be be treated as normal data and thus corrupt values sent subsequently. To solve this problem, the transferred data was marked with a stop and start character to ensure the correct data value was deciphered by the other machine.

It had originally been intended that the IBM would control the BBC by an interrupt routine, such that a character sent by the IBM would cause an interrupt routine to be called on the BBC. Depending on the character set, this routine would either transfer data to the IBM or accept control information. This would allow the BBC to spend most of its time monitoring, and transfer data only when requested. Several assembler programmes were written to do this, but all proved unsuccessful. All the data transfer programmes however worked well in Basic, and therefore the requests from the IBM, had to be serviced by a polling routine on the BBC, which regularly checked the RS232 port to see if a request had been sent.

2.5 Conclusion

In concluding this chapter, the laboratory drill rig and wear measurement jig underwent a series of modifications to allow the development and testing of the optimisation system. Many modifications have also improved the general use of the drill, when utilised for general drilling or coring purposes. An RS232 link to a I.B.M was also established which enables the transferring of data between the two machines. This allowed the BBC to take the role of a front end processor.

Chapter 3 :- Preliminary Drilling Tests and Developments

3.1 Introduction

A series of preliminary drilling tests were conducted with the aim of gaining experience on the drilling apparatus, as well as generating any ideas on optimisation techniques and highlighting any problems that may occur during optimisation tests.

3.2 Drill Response Tests

From Ambrose's work, it was apparent that both rotational speed and weight on bit had an influence on penetration rate. Therefore it was decided to conduct a series of experiments to validate these results and establish general trends. The tests would involve the manipulation of rotational speed and weight on bit to see the response of penetration rate. Flush would also be manipulated. As only general trends were required only one rock type was used. The results of these tests are shown in Figures 3.1-3.3.

From these graphs it can be seen that weight on bit has the greatest influence on penetration rate. Rotational speed has some influence, but not as pronounced. However, from the tests, it was apparent that a certain speed was required for differing weight on bit values to ensure the drill did not stall. From the graph showing flush variation, it can be seen that for the majority of mid range values, its influence (on this machine) is negligible. However at the extremities it does have quite an adverse affect, too little causing a build up of cuttings and too great causing hydraulic lift of the bit, both causing a reduction in cutting efficiency and hence, a reduction in penetration rate. Therefore all subsequent experiments were conducted with the flush rate being maintained in the range of 6-12 litres per minute.

† It should be noted that while in this laboratory system the influence of flush is negligible, in field operations, especially in deep well drilling, the influence of hole hydraulics is critical, not only for hole generation but also well control. Therefore, for any field application, hole hydraulics must be taken into account within the optimisation scheme.

Graph of Penetration Rate Vs Weight On Bit

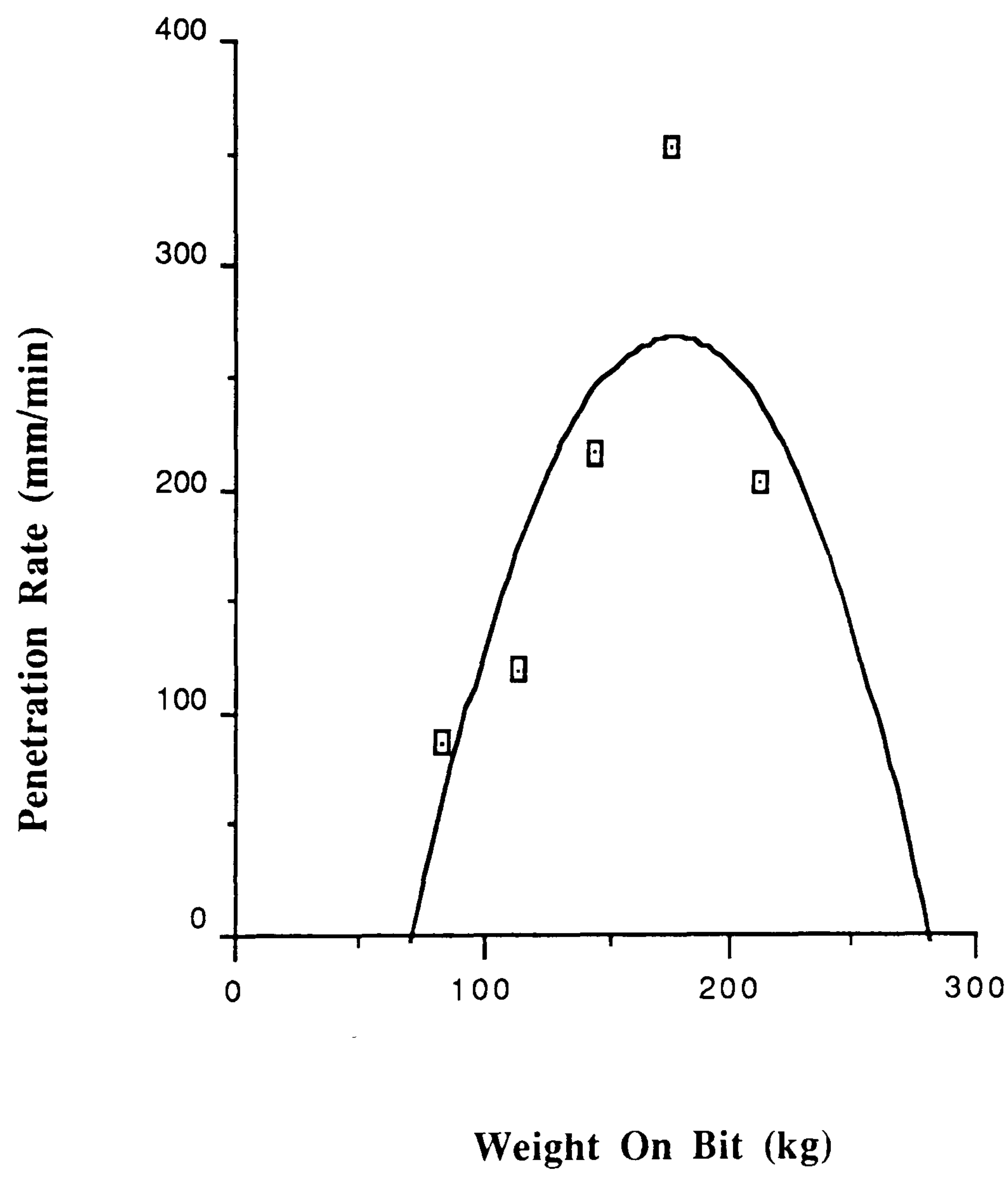


Figure 3.1 A Graph to Show the Influence of Weight On Bit on Penetration Rate

Graph of Penetration Rate Vs Rotational Speed

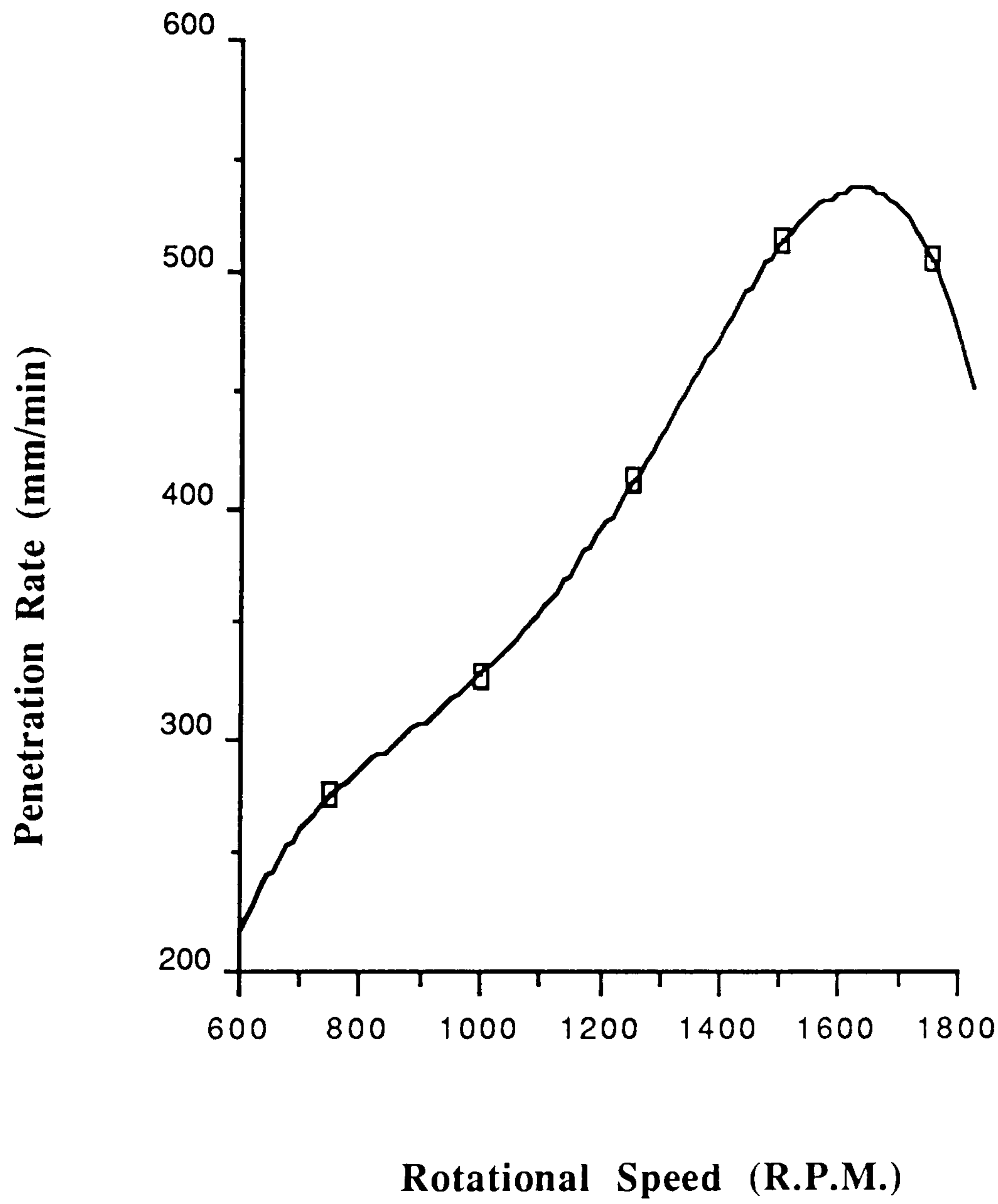


Figure 3.2 A graph Showing the Influence of Rotational Speed on Penetration Rate

Graph of Penetration Rate Vs Flow Rate

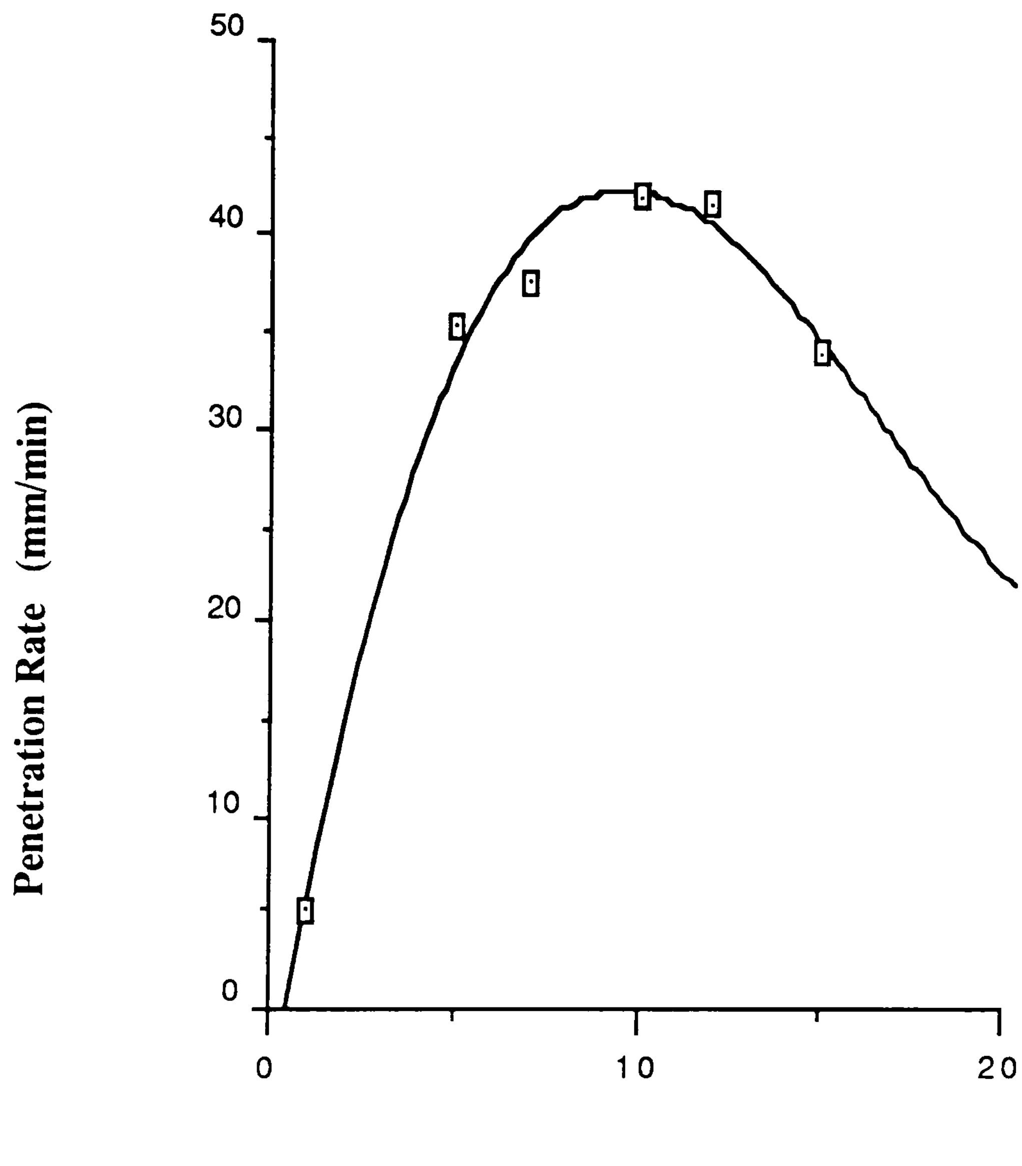


Figure 3.3 A Graph Showing the Influence of Flow Rate on Penetration Rate

3.3 The Development and Testing of a Simple Drill Optimisation Scheme

With the lessons learnt from these initial experiments, a control strategy for optimising penetration rates was designed and is shown in Figure 3.4. For a given starting condition, weight on bit and rotational speed were increased in steps until such time as the speed started to drop and a stall condition was occurring. The weight on bit was then reduced to regain the speed of the drill. A stall marker would be set and the process returned to the initial mode of increasing weight on bit and rotational speed once again. If this was performed correctly the stall marker would be cleared. However, if on the next increase of weight on bit, stalling occurred again, the drill was deemed to be near its optimum point. At this point, the speed was manipulated in either direction to see if any improvements in penetration rate could be attained. Once completed, the optimisation process would repeat itself but with reduced step increments. In this way, the computer would search out the optimum operating point for maximum penetration rate.

The algorithm was programmed into the BBC computer used for drill monitoring, and a series of test perform in the laboratory to validate the algorithm. A typical plot is shown in Figure 3.5. It can be seen from the plot that the penetration rate has increased to near optimum.

3.3.1 Problems Arising from the Initial Tests

From 3.5, it can also be seen that the computer has recovered from two potential stall conditions. However in so doing, the amount the computer has reduced weight on bit is too great, causing the penetration rates to drop dramatically.

This is obviously not desirable and requires some modification to the control algorithm. The problem arises through the weight on bit actuator. Load on the bit is applied through a compressed air piston controlled by a motorized pressure regulator. The regulator was treated as having a linear response, i.e. a certain number of steps cause a certain increase, and the same number in the opposite, the same pressure decrease. This was clearly not the case.

When a stall condition was encountered, pressure would be reduced as fast as possible. However, large number of motor steps /turns were required before the pressure began to drop, after which small numbers of turns would cause large pressure

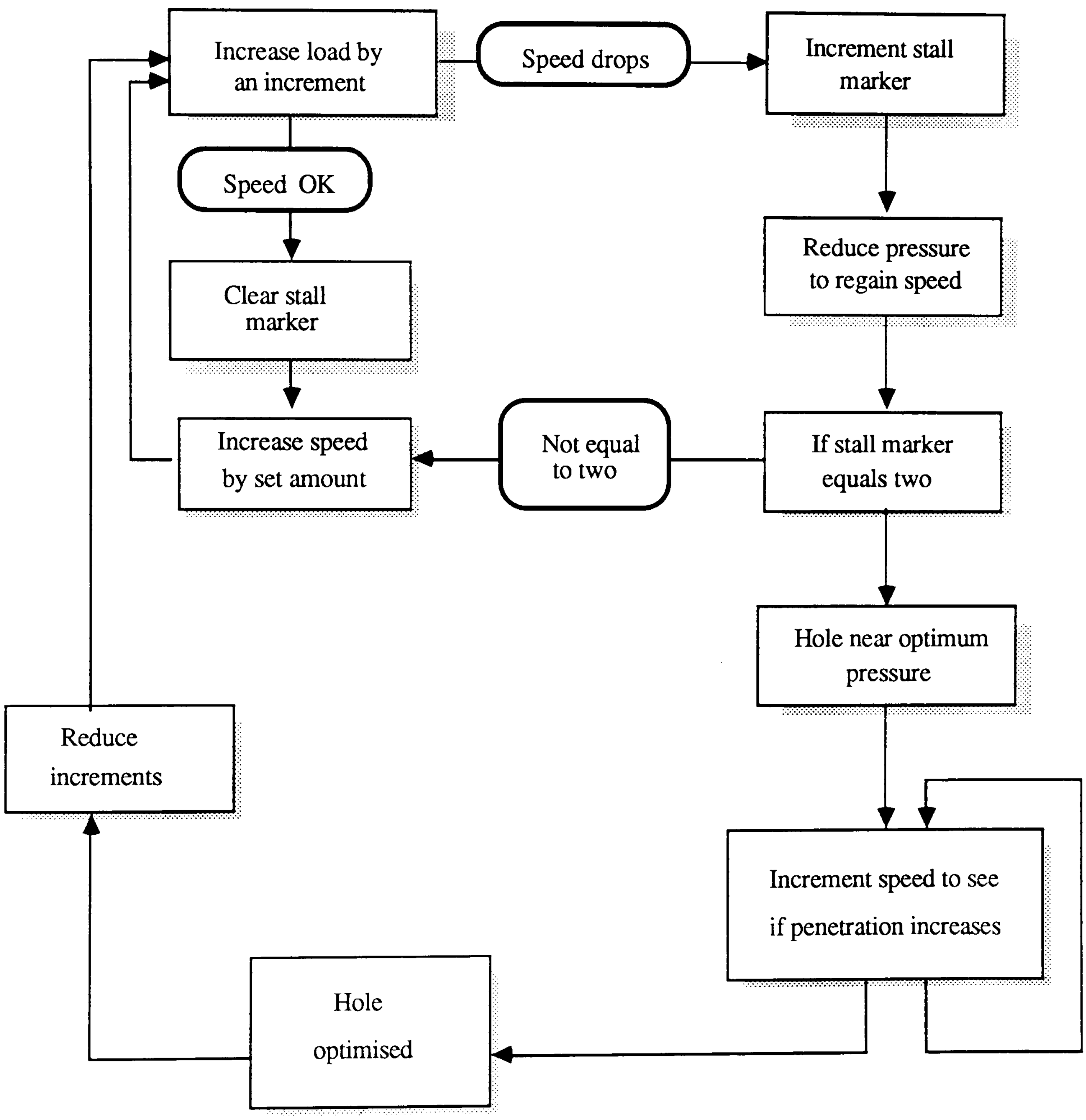


Figure 3.4 A Simple Optimisation Algorithm for Maximising Penetration Rates

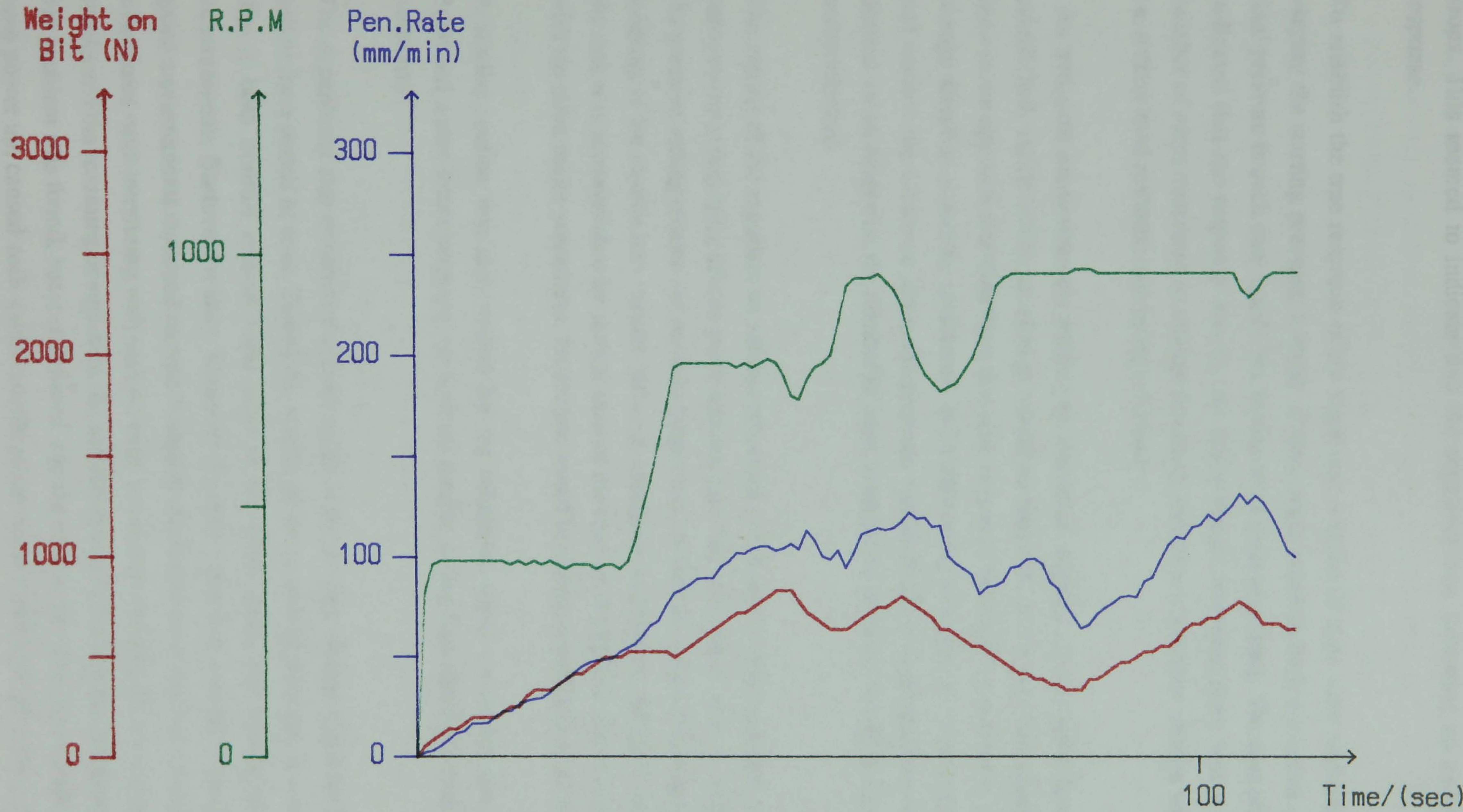


Figure 3.5 A Plot of the Laboratory Drill's Response to the Maxinisation of Penetration Rate Algorithm

drops. This seemed to indicate that the regulator was following an exponential response.

To establish the true response of the regulator, a series of tests were performed. By varying the starting pressure, a range of steps were taken in both directions and the final pressure in each case noted. The results were quite surprising. The data produced indicated that the response was in fact fairly linear! However there was a certain number of steps necessary to change direction, before any pressure change was seen i.e. a dead band response was being exhibited.

As pressure measurements tended to fluctuate slightly, a tolerance band was established, inside which no change would be required. If the previous change had been in the opposite direction from that now required, the required number of steps to change direction would be performed. With the correct direction set, if changes were just outside the tolerance limit, the pressure would be slowly adjusted towards the desired value, otherwise the number of steps to attain the pressure would be calculated and performed.

The setting of the regulator to various pressures could take several seconds and with some routines requiring access every second, care had to be taken that on each pass, the pressure setting routine did not take longer that 30 seconds to run. This required the splitting of the routine into various parts e.g. changing the pressure direction, such that the task was accomplished by several calls of the routine. By polling the routine along with the other major procedures, the routine would be called as regularly as possible.

A similar routine was also written for the rotational speed controller, but as this exhibited a true linear response, no reversal routine to facilitate direction change was necessary.

The experiment also established another quirk of the drilling system which baffled the author for a period of time. During the testing of the control procedures, it was found that if both control motors were used at the same time, the rotational speed measurements fluctuated widely. However if either procedure was run individually, speed measurements remained normal. Naturally the first conclusions were that the two procedures were interfering with each other by a common variable. However extensive checks and the renaming of variables, did not alleviate the problem. No actual reason to this problem was found, but it is believed that the current required when both motors were power up, caused such a drain on the power supply that voltage drops occurred.

This caused other circuits including the rotational speed measurement to malfunction. Therefore, each motor was switched off after use and thus the two were never energised at the same time, preventing the associated voltage drops.

These changes could have been incorporated into the maximisation of penetration rate algorithm previously described and further improvements made. However, as this algorithm was only generated for test purposes, it was not developed further despite being successful. The main reason for this, was that no self-learning process was involved. Consequently, no benefit from the information gained from previous holes could be used to aid the drilling of the next hole. However the optimisation system described in the subsequent chapters has this capability and could readily be applied to the maximisation of penetration rates.

3.4 The Drill Simulator

These tests, also highlighted the difficulty of debugging and developing the software while using the drilling machine. Software errors often required the drilling tests to be re-run, consequently involving drill re-positioning, collaring, etc, which when debugging is very time consuming and frustrating. In addition to this problem, regular access to the drilling machine was needed, the drill often being required for other purposes, such as laboratory coring as well as its use being bounded by University hours.

To alleviate this problem and aid software development, a simulator was developed which would simulate to some degree the action of of the drilling machine. The simulation procedure would be held in the monitoring computer, and allow a realistic representation of the drilling rig. Therefore, development work could be conducted away from the drilling machine in a clean and pleasant atmosphere with increased efficiency, rather than in the laboratory environment.

Furthermore, as mentioned in Chapter 2, the large processing power required by the main optimisation system, had resulted in the programme being developed on an I.B.M. system, with the BBC monitoring computer being solely used as a front end processor. The two computers were linked by an RS232 data link. While this link had already been established, the data transfer concepts had to be combined into the monitoring (BBC) and optimisation (IBM) routines, to allow control to take place. The concept of this data transfer mechanism is similar to that of parallel programming, each computer running a part of its own programme, before requiring data to be transferred.

Consequently, debugging the software is complex as either machine could be the initiator and not necessarily the recorder of an error. The testing of the data transfer software would have been extremely time consuming if not impossible, if a simulator had not been produced.

The design of the simulator was such that different processes i.e. drill responses, could be interchanged. This would allow the optimisation system to be tested under a variety of conditions. To enable a variation in processes, the simulator information was contained in a matrix form, which could be loaded into the computer from a data file. A typical response is shown in Figure 3.6. This represents a hypothetical penetration rate against the variables, rotational speed and weight on bit. Therefore for a certain value of rotational speed and weight on bit, a certain penetration rate would be returned by the simulator. It can be seen from Figure 3.6 that this only describes a two variate process, but it could easily be extended to incorporate other parameters such as flush rate by adding extra dimensions to the matrix. This allows the optimisation algorithm to be developed to a high degree involving many different parameters. However conceptually these become impossible to visualise.

As the processes are generated artificially, complex surfaces may be tested to establish whether the algorithm will cope with a wide range of complex surfaces. This is particularly useful for testing of multi-hump surfaces such as shown in Figure 3.7. Methods for this type of prediction are described in later chapters.

With the simulation data being contained in a matrix form, real or historical data generated either from general core drilling or from optimisation test work could be transferred into a matrix form. This could be used to load the simulator and thus allow the simulator to imitate a real process for the particular rock type being drilled.

This highlighted several other improvements which could be made to the simulator. When using artificial data, the response of the simulator was always exact, i.e. at a certain rotational speed and weight on bit, a certain rate of penetration rate was observed. However, in the real drilling process, the response of the drill is more varied, giving data fluctuations, as shown in Figure 3.8 showing the range of standard deviation measured during an optimisation test.

Therefore to enhance the efficiency of the simulator and aid the development of the optimisation algorithm, a variation in the simulated data was produced. This was left as an optional mode, as with initial development exact known values were beneficial.

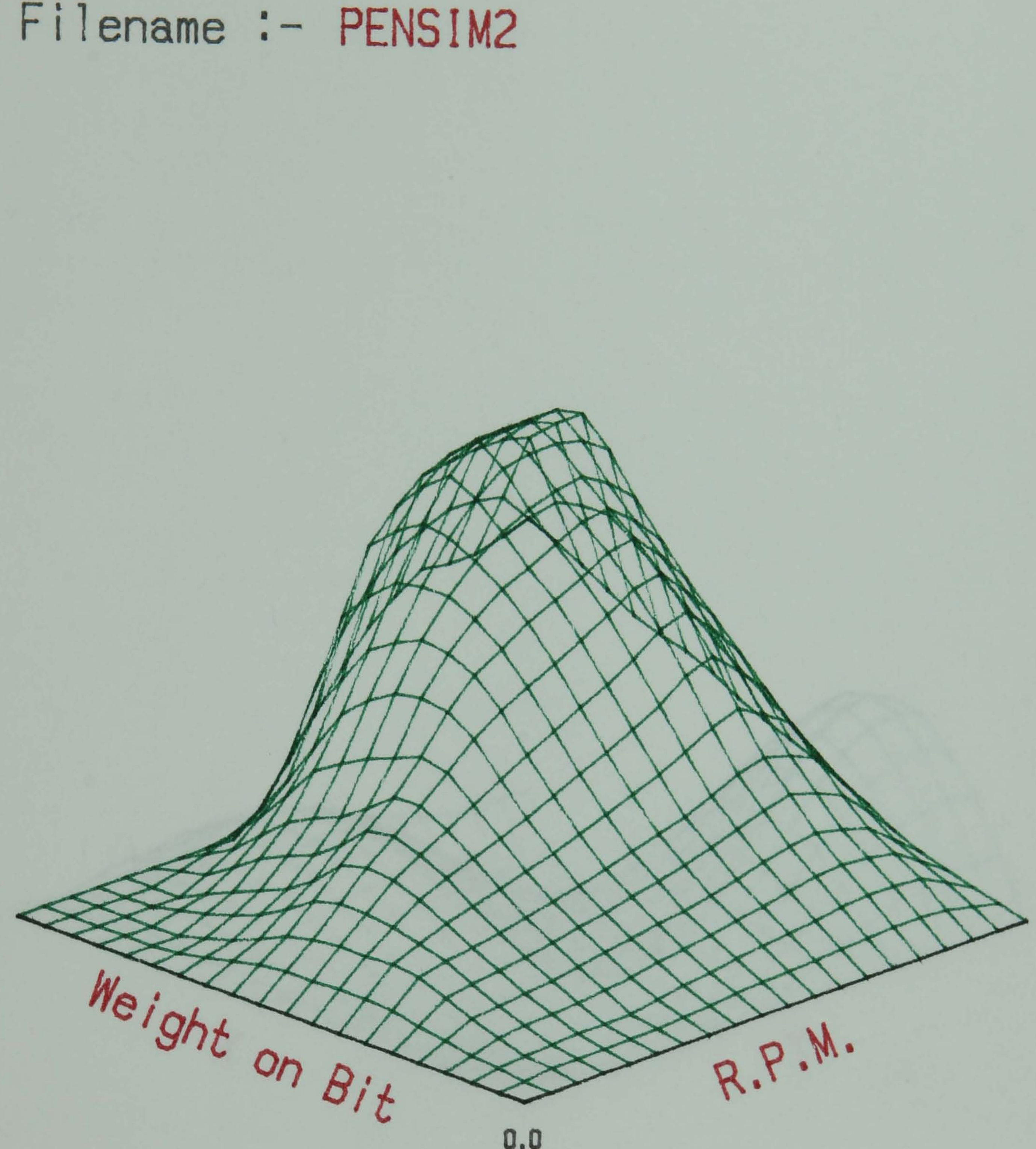


Figure 3.6 A Typical Plot of the Penetration Rate Response Used by the Drill Simulator

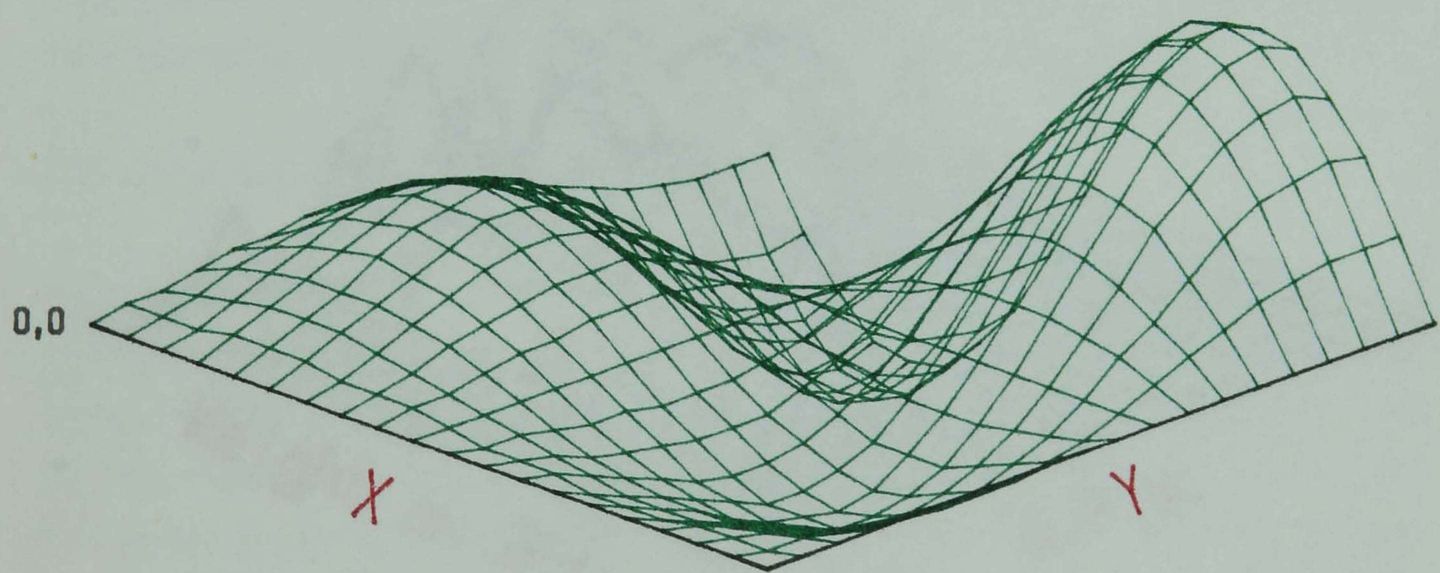


Figure 3.7 A Multi-Hump Surface

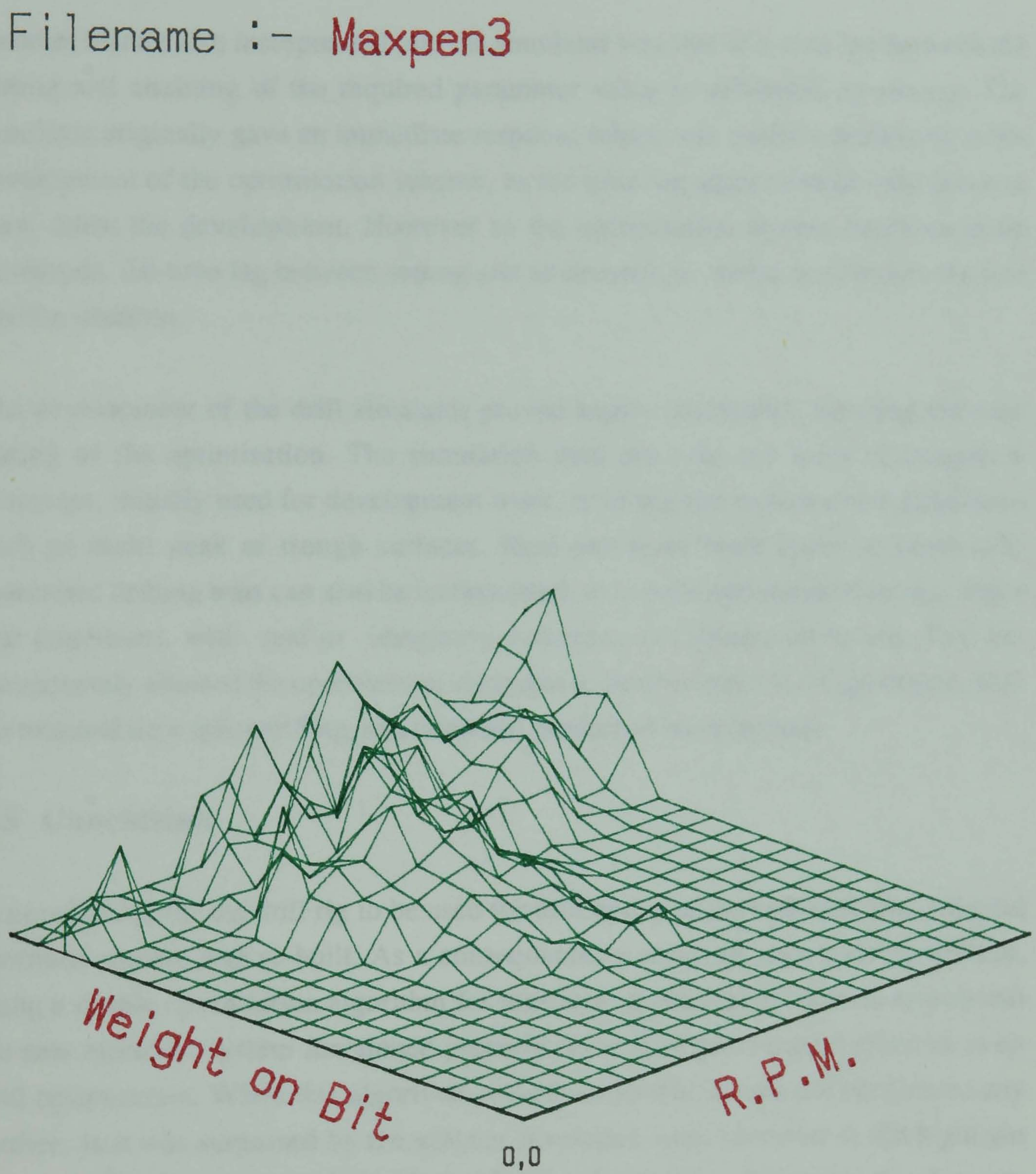


Figure 3.8 The Range of Standard Deviation Values Measured During an Optimisation Test

However as the system becomes more developed, a range of standard deviation values could be incorporated, either imaginary, or real values such as those measured form a particular test. In so doing, this would allow more authentic simulation.

Another feature also incorporated into the simulator was that of a time lag between the setting and attaining of the required parameter value as exhibited by the rig. The simulator originally gave an immediate response which was initially beneficial to the development of the optimisation scheme, as the time lag aspect would only serve to slow down the development. However as the optimisation system becomes more developed, the time lag between setting and attainment, is useful to simulate the real drilling situation.

The development of the drill simulator proved highly successful, allowing the easy testing of the optimisation. The simulation data can take the form of imaginary processes, initially used for development work, or to test the system under conditions such as multi peak or trough surfaces. Real processes from those of previously monitored drilling tests can also be incorporated, to test the optimisation system under real conditions, with real or imaginary variations in standard deviation. This has consequently allowed the optimisation algorithm to be developed to a high degree, with the minimal time spent drilling, in a clean and productive environment.

3.5 Conclusion

In concluding, for the drill rig to be used for drill optimisation research, the complete electrical system was re-built. As a consequence, a series of tests were performed, using a simple optimisation algorithm for maximising penetration rates to ensure that the new electrical system functioned properly, as well as generating further ideas on drill optimisation. While this algorithm proved successful, it was not progressed any further, as it was surpassed by the scheme developed later. However it did highlight several problems both in control and optimisation techniques, which aided development of the main optimisation scheme.

The testing of the maximisation of penetration rate algorithm also highlighted the problem and inefficiency of developing software in connection with a real process i.e. the drilling rig. For this reason, a simulator was established which greatly enhanced the development of the optimisation scheme. The simulator also allowed the optimisation process to be studied under a wide range of complex surfaces which would otherwise be difficult to produce on the drill rig.

Chapter 4 - Optimisation Theory

4.1 Introduction

In Chapter 1, the basic rationale for the optimisation system developed during this research project was introduced. It mentioned that from the work done by Ambrose, an optimum point for a given set of conditions existed between penetration rates and wear rates. This point, in the drilling operation was deemed to be most efficient. To find this optimum point, a parameter and governing relationship must be developed which combines the trade off between penetration rate and the associated wear rate.

This trade off is well known by drillers that at the start of the hole, penetration rates are generally maximised to ensure rapid hole generation. However as the hole becomes progressively deeper, the time taken to pull and change the bit when worn ie the tripping time, increases. In deep holes the tripping time can be considerable and therefore more emphasis is placed on conserving bit life to reduce the time spent tripping.

From this, it can be seen the optimum operating point between penetration rate and wear rates is not constant throughout the length of the hole. The depth affects the position of the optimum operating point. It is also well known that wear and penetration rates are not solely interdependent i.e. penetration rate is not a sole function of wear rate and vice versa, but many other parameters effect one or both. For example, rock type will effect both whereas abrasivity will only directly effect wear. Furthermore, there are other parameters, possibly unknown, who's effects will also be unknown. With the complex interaction of all these possible parameters, a prototype system designed to cope with them would be extremely complex if not impossible to develop.

Therefore, simplifications have to be made to enable a system to be developed. Once this has been proved, other parameters which were otherwise ignored and held constant, can be introduced into the optimisation system. Bearing this in mind, the choice of a governing parameter and its relationship with others, should aim to remove / accommodate as many parameters as possible, without becoming too complex. Those that are excluded from it, but still have influence on the result, must be dealt with separately.

4.2 The Governing Parameter and Its Relationship

As has been mentioned previously, to enable any optimisation system to be developed, the desired aim of the optimisation system must be defined along with its relationship to other parameters involved in the operation. In this case, the optimisation system must seek out and maintain the most efficient operating point for a drilling system. Therefore a parameter must be established to achieve this.

4.2.1 Maximised Penetration Rates

If penetration rate was selected, as described in the previous chapter, the optimisation system could maintain maximum penetration rate throughout the entire length of the hole. However as the hole becomes deeper, the increase in tripping time would eventually become detrimental reducing the overall efficiency of hole generation. The use of such a system to maximise penetration rate may be of great benefit where tripping times remain low i.e. in short holes. These are more common in the Mining Industry for blast hole production.

4.2.2 Time

The time taken to drill the hole was initially investigated as a possible control parameter, as it is every drillers aim to complete the hole as quickly as possible.

4.2.2.1 Minimum Time For Each Bit Run

The time taken for each bit run was initially investigated. This comprises the rotating time of the bit, and the time taken to trip the bit out of the hole at the new depth. This can be written as follows:-

$$T_b = T_r + T_t \quad \text{---} \quad (4.1)$$

where T_b = Total time for each bit run.
T_r = Rotating time.
T_t = Tripping time

The time rotating can be expanded in terms of penetration rate(P) and expected distance.

$$T_r = \frac{\text{Expected Distance}}{\text{Penetration Rate}} \quad \text{---} \ (4.2)$$

The Expected Distance is governed by the wear rate (W), and K the expected bit life, at the declared penetration rate(P), such that,

$$\text{Expected Distance} = \frac{K}{W} \quad \text{---} \ (4.3)$$

Therefore

$$Tr = \frac{\left(\frac{K}{W}\right)}{P} \quad \text{---} \ (4.4)$$

$$Tr = \frac{1}{P} \cdot \frac{K}{W} \quad \text{---} \ (4.5)$$

Similarly, the tripping time may also be expanded in to terms of Present Depth (D) and the expected distance drilled with the bit, and the average round trip time per metre (T_m).

$$T_t = (\text{ Present Depth } + \text{Expected Distance}) \,.\, T_m \quad \text{---} \ (4.6)$$

Thus by substitution,

$$T_t = (D + \frac{K}{W}) \,.T_m \quad \text{---} \ (4.7)$$

Therefore, substituting into equation (4.1), gives

$$T_b = \frac{1}{P} \cdot \frac{K}{W} + (D + \frac{K}{W}) \,.T_m \quad \text{--}(4.8)$$

Multiplying out, gives

$$T_b = \frac{1}{P} \cdot \frac{K}{W} + D \,.\, T_m + \frac{K}{W} \cdot T_m \quad \text{---} \ (4.9)$$

By excluding the Present Depth term from the equation (being a constant for each particular bit run), once an optimum point has been established for the first bit run, then since no other influences will effect the equation, this operating point will remain constant for subsequent bit runs. Therefore the drill parameters will remain constant for the rest of the hole.

Clearly this is not desirable and would not provide a successful optimisation algorithm. The failure of this method is that it does not include the effects of other bit runs. Only by doing this i.e, looking at the hole as in entirety, does a time optimisation system become possible. Therefore time to hole completion was investigated.

4.2.2.2 Total Time to Completion

Equation 1 gives the time taken to complete one bit run. Therefore by sumating all the predicted bit runs, a total time to completion can be estimated. This can be written as

$$\text{Time to Completion } (T_c) = \sum (T_r + T_t) \quad \text{--- (4.10)}$$

Expanding this equation in a similar fashion,

$$T_c = \sum_{1}^{n} \frac{1}{P_n} \cdot \frac{K}{W_n} + \left(D_n + \frac{K}{W_n} \right) . T_m \quad \text{--- (4.11)}$$

But the Present Depth (D_n) is the previous depth, plus the distance drilled by the bit i.e.

$$D_n = D_{(n-1)} + \frac{K}{W_{(n-1)}} \quad \text{--- (4.12)}$$

Therefore we can sumate to the total distance tripped now in terms of the previous bit runs, such that the total depth Dn is given by ;-

$$D_n = \sum_{1}^{p=n} D_p \quad \text{--- (4.13)}$$

$$D_n = \sum_{1}^{n} \left(\frac{K}{W_1} + \frac{K}{W_1} + \frac{K}{W_2} + \frac{K}{W_1} + \frac{K}{W_2} + \frac{K}{W_3} + \frac{K}{W_1} \cdots\cdots + \frac{K}{W_n} \right)$$

--- (4.14)

$$D_n = k \sum_{n=1}^{n=j} (j-n+1) \cdot \frac{1}{w_n} \quad \text{--- (4.15)}$$

Therefore total time spent tripping is

$$T_t = T_m \cdot K \sum_{n=1}^{n=j} (j-n+1) \cdot \frac{1}{W_n} \quad \text{--- (4.16)}$$

and thus the total time to completion is given by,

$$T_c = \sum_{1}^{n} \frac{1}{P_n} \cdot \frac{K}{W_n} + T_m \cdot K \sum_{n=1}^{n=j} (j-n+1) \cdot \frac{1}{W_n} \quad \text{--- (4.17)}$$

This gives us an equation which will allow the sumation of total time to completion, from various predicted penetration rates and wear rates, until hole bottom is reached. However to find an optimum, the best combination of all the bit runs must be ascertained to achieve minimum time to completion. Therefore, every combination may have to be searched. For just a simple example, having only 5 combinations of penetration rates and associated wear rates, it can be seen that there is a tremendous build up in the number of possible combinations.

	Number of Computations
1st Bit Run	5
2nd Bit Run	25
3rd Bit Run	125

Mathematically this can be described by the equation

$$\text{Number of combinations} = \text{Number of associations}^{\text{(Number of bit runs)}}$$

For a real situation, the number of associations would be much higher. It may be possible to eliminate some of the combinations, as the calculation proceeds, but what has to be remembered is that some combinations may require less bit runs to reach the required depth and hence less time is spent tripping. Therefore care has to be exercised in eliminating these, to ensure that the true minimum time is derived.

In addition to this, the system is highly inflexible. Any changes in circumstances resulting in early bit failure and / or not attaining the predicted distance drilled, such as differing geology or hole problems, would disrupt the optimisation system. Consequently it would have to be re-run to calculate the new optimised time to completion. Furthermore in the equation developed for optimising time to completion, an assumption was made that the parameters would not change for the whole of the bit run. This would obviously not be the case unless drilling was occurring in homogeneous rock. To generate a system to cope with changing geology within each bit run, would require an exact knowledge of hole geology and increase the calculation time dramatically.

Clearly the inflexibility of this system and the computer time involved to predict the best parameters to attain minimum time to completion makes this method of optimising drill performance unsatisfactory.

4.3 Cost

Other parameters were looked at but were quickly dismissed apart form some form of cost optimisation. This parameter had the immediate benefit that virtually all other parameters could be related to a cost function. The proposed criteria for the optimisation system of trading off penetration rates and wear rates, can also be easily accommodated. Penetration rates have a direct relationship to rotating and therefore rig running costs. Wear rates not only influence bit consumption but also influence tripping time intervals and hence rig costs. Provided an equation can be established relating these parameters to cost, the criteria for the proposed optimisation scheme could be met.

The other big advantage in using cost is that at the end of the day, profit is one of the most important factors and reducing hole production costs is obviously beneficial. In addition, it may be found that by using an optimisation system, wells originally thought un-economic to drill, may prove to be economic.

However for a drilling operation, there are many cost centres, some of which have a direct relation to the generation of the hole and others that do not. To ascertain those that have some direct influence, a brief cost analysis was performed. Two categories were produce: fixed cost (independent to the drilling operation) and variable costs (those having some influence).

The fixed costs are mainly due to the preparatory work done before drilling can occur, or afterwards when the site etc must be restored. Some of these are shown in Figure 4.1. These costs are mostly independent of the drilling performance and cannot as such be incorporated into a cost optimisation scheme. However these costs could be reduced, e.g by improving the efficiency of site restoration, or rig transportation, but although they do bring benefits to the total cost to completion they do not reduce the drilling cost directly.

The inclusion of the casing programme as a fixed cost is for simplicity, as the effects of running casing in this optimisation scheme have been ignored. Generally the depth at which casing is run is governed by the hole geology. Thus while not effecting the drilling costs directly, an optimisation scheme that incorporates the casing programme into its algorithm would be beneficial. This would allow the optimisation system to ensure that when the required depth for casing was reached, the bit would be ready to be pulled anyway.

The variable costs do directly relate to the cost while drilling and these are shown in Figure 4.2. It can be seen, there are a large variety of cost centres, each having a differing influence on the overall drilling cost. Some are also dependant on external influences e.g. manpower costs vary geographically, fuel cost may vary with economic/ political influences.

It would be desirable to establish a relationship to include all of these variable costs and develop an optimisation system, to minimise total drilling costs. However the lessons learnt from the total time to completion, also apply here in that an inflexible system would be developed, which would not be able to cope with problems and unforeseen influences.

Therefore a simpler optimisation method is necessary. To do this, cost per metre was proposed. This would allow the development of a system which could incorporate all of the variable cost mentioned above, including external influences such as geographic location, but allow the system to be very adaptable, as the criteria was to minimise the cost of each metre drilled. While this may not achieve the minimum cost to completion, it does ensure that drilling cost are minimised for the current situation.

An equation for the cost per metre already existed in most drilling text books, (Drilling Practices Manual by P.L. Moore *(47)*), and it was decided to use this as the basis from which to develop the cost optimisation system.

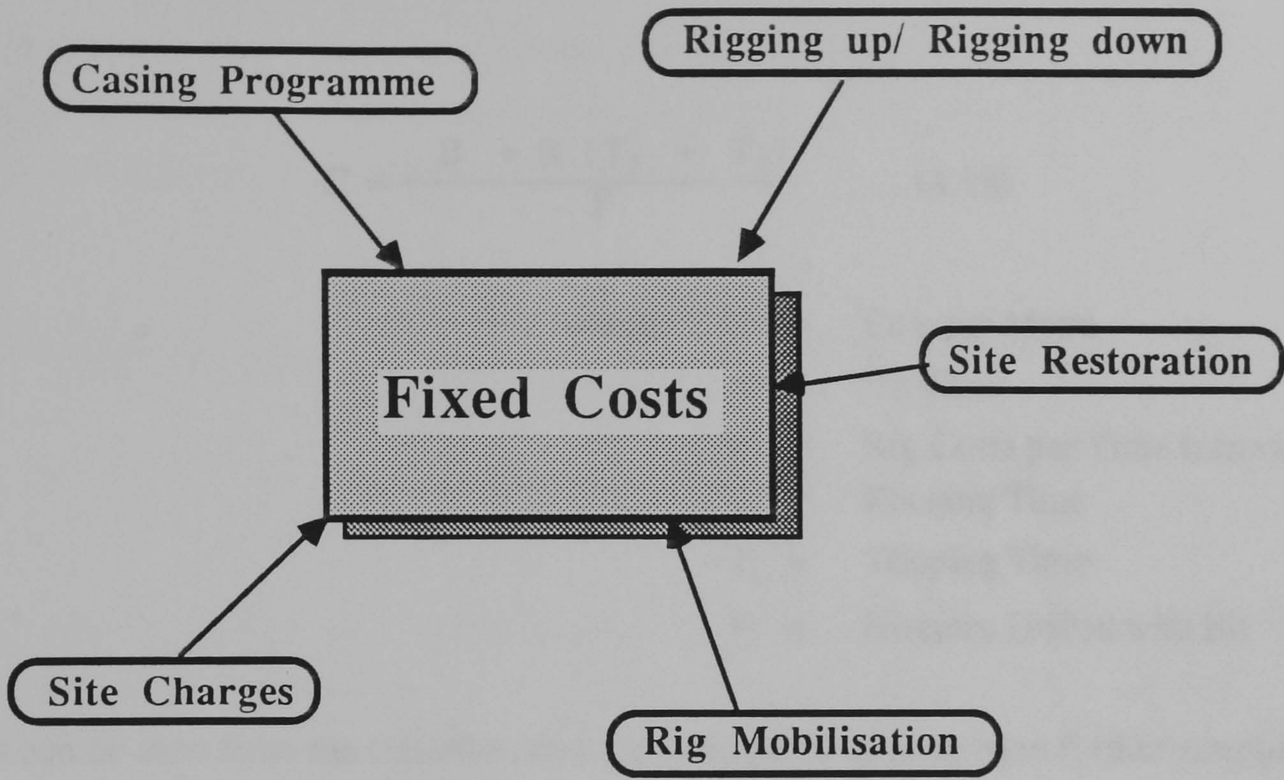


Figure 4.1 Fixed Costs in a Drilling Programme

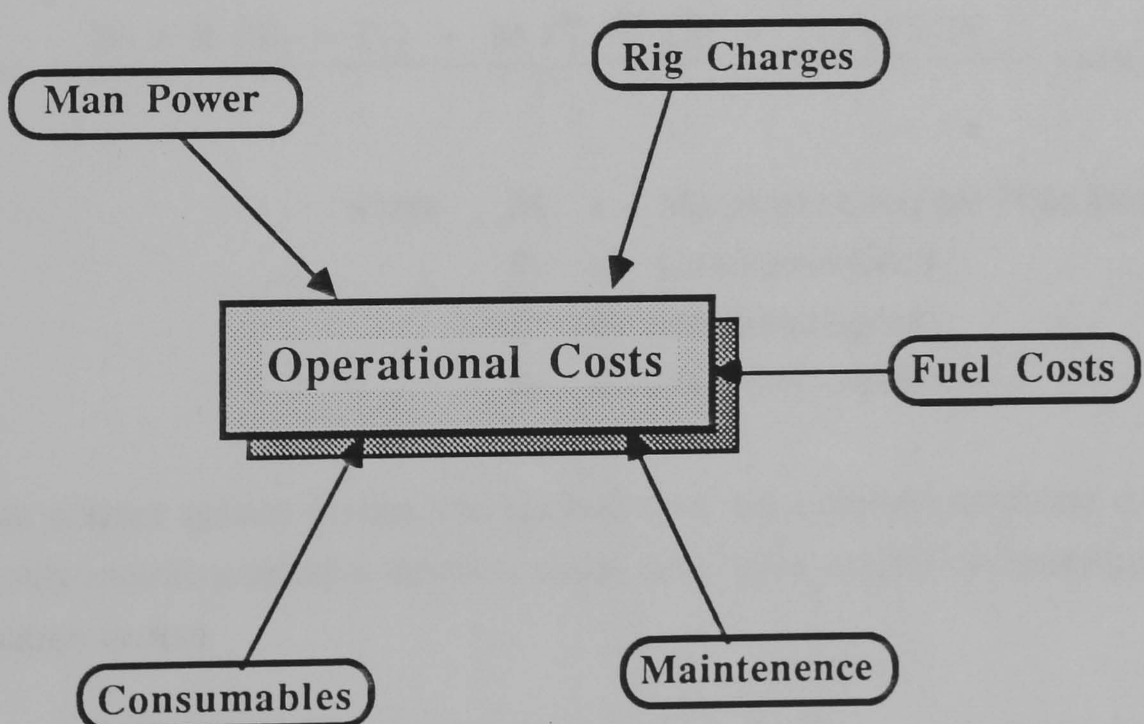


Figure 4.2 Variable Costs in a Drilling Programme

$$C = \frac{B + R\,(T_r + T_t)}{F} \qquad \ldots (4.18)$$

where
C = Cost per Metre
B = Bit Costs
R = Rig Costs per Time Interval
T_r = Rotating Time
T_t = Tripping Time
F = Distance Drilled with Bit

It can be seen from the equation, that the variable costs have been further simplified, and are combined into just two costs, bit and rig costs. While this generalises the variable costs, it does have the great benefit of being a very simple equation to work with, and to develop an optimisation system around. Once the system has been developed, this equation can be expanded to include the other variable costs described previously e.g geographic location may also have an influence on labour costs or a fuel element may be required.

These could be included into the equation and expanded as follows.

$$C = \frac{B + R\,(T_r + T_t) + M\,(T_r + T_t) + P.fn\{S.T_r.\}}{F} \qquad \text{---}(4.19)$$

where
M = Manpower Costs per Time Interval
P = Unit Power Costs
S = Rotational Speed
fn = An Unknown Function

With the correct system design, the upgrade to a more complicated cost equation would only require a straight equation swap, rather than a complete redesign of the optimisation system.

Returning to the original aim of the optimisation system, the basic rational was to locate and maintain the optimum operating performance of a drilling system by using the trade off between penetration rates and wear rates. To do this, cost per metre has been chosen as the optimisation parameter and its relationship given in equation (4.18). However it can be seen that none of these terms directly relate to any of the controllable drill parameters. Therefore some mathematical manipulation of this equation must take place to convert this equation into one which will be suitable for the establishment of an optimisation system.

Multiplying out equation (4.18), gives us :-

$$C = \frac{B.}{F} + \frac{R \cdot T_r}{F} + \frac{R \cdot T_t}{F} \quad \text{--- (4.20)}$$

As with the equations for minimisation of total time to completion, the distance drilled by each bit is determined by the total bit life (K) and its wear rate (W), we have:-

$$\text{Distance Drilled} = \frac{K}{W} \quad \text{--- (4.21)}$$

Also,

$$\text{Penetration Rate (P)} = \frac{\text{Distance Drilled (F)}}{\text{Time Taken } (T_r)} \quad \text{--- (4.22)}$$

Substituting in we have,

$$C = \frac{B}{\left(\frac{K}{W}\right)} + \frac{R}{P} + \frac{R \cdot T_t}{\left(\frac{K}{W}\right)} \quad \text{--- (4.23)}$$

Therefore,

$$C = \frac{B \cdot W}{K} + \frac{R}{P} + \frac{R.T_t \cdot W}{K} \quad \text{--- (4.24)}$$

If the tripping time is expressed on terms of the average time taken for a round trip per meter, using D for depth, we can calculate the tripping time at any depth, thus

$$T_t = D \cdot T_m \quad \text{--- (4.25)}$$

where T_m = Average Round Trip Time per Metre and therefore,

$$C = \frac{B \cdot W}{K} + \frac{R}{P} + \frac{R.T_m . D.W}{K} \quad \text{--- (4.26)}$$

Simplifying gives,

$$C = \frac{(B + R.T_m . D) . W}{K} + \frac{R}{P} \quad \text{--- (4.27)}$$

This equation provides a means of comparing combinations of drilling parameters through minimum cost per metre, with the ultimate intention of finding a minimum. Returning to Figure 1.1, this equation would form the rule base for which decisions would be made to improve the current operating position.

However to do this, both parameters i.e. penetration rates and wear rates must be readily available as the absence of one would totally invalidate the optimisation system. Furthermore, with the data available, how is the equation used to determine the optimum operating point, and is the method used the most efficient? These two issues are covered by the following chapters.

4.4 Cost Equation Sensitivity Analysis

To understand the effects and trends that the various parameters have in the cost equation (4.27), a sensitively analysis was performed. For each test, four different combinations of penetration rate and wear rate were used to cover a broad range of possibilities. They comprised of worst and best scenarios as shown below :-

1) Low Penetration Rate with High Wear Rate.
2) High Penetration Rate with Low Wear Rate
3) Low Penetration Rate With Low Wear Rate
4) High Penetration Rate with High Wear Rate

Although some of these scenarios are unlikely in reality e.g. high penetration rate with low wear rate, they are included to show the boundaries of the system. The values for each of these conditions was based on work by Ambrose. They are shown below and were kept constant for each test.

Low Penetration Rate = 50 mm/min
High Penetration Rate =350 mm/min
Low Wear Rate = 0.05 mm/m
(assuming a 10mm crown Height =200m of drilling)
High Wear Rate = 0.2 mm/m
(assuming a 10mm crown Height =50m of drilling)

Many different graphs were produced relating various parameters to others, but plots of cost against depth illustrate the observations well.

4.4.1 The Effect of Bit and Rig Cost with Respect to Tripping Time

The first series of tests conducted were to establish the effect of Bit and Rig costs, with respect to the Tripping time per Metre. For each test, three tripping times would be used 10,20 and 40 s/m, shown by the three graphs in each of these tests.

The Rig and Bit costs used are shown below:-

1) Bit Costs Greater than Rig Costs (Bit Costs = £1500, Rig Costs = £100)
2) Bit Costs Equal to Rig Costs (Bit Costs = £1000, Rig Costs = £1000)
3) Bit Costs Less than Rig Costs (Bits costs = £1000, Rig Cost = £10000)

4.4.1.1 Bit Costs Greater than Rig costs

From the three graphs shown in Figure 4.3, it can be seen that the tripping time has very little effect at all on the cost per metre increasing the cost only marginally with increasing depth. It can also be distinctly seen the remarkable division of the four penetration and wear rate scenarios into wear rate zones i.e. high and low wear rates. If high wear rates were allowed to occur, then the cost per metre would rise dramatically. Therefore in this situation, low wear rate are the predominant criteria.

4.4.1.2 Bit Cost Equal to Rig Costs

Figure 4.4 shows that with rig and bit costs even, the tripping time is beginning to effect the cost per metre as depth increases. With tripping times slow i.e. 40 s/m, the cost at the greatest depth is nearly double of that when faster tripping times are obtained. The division of wear rates still exists, indicating that wear rates should be

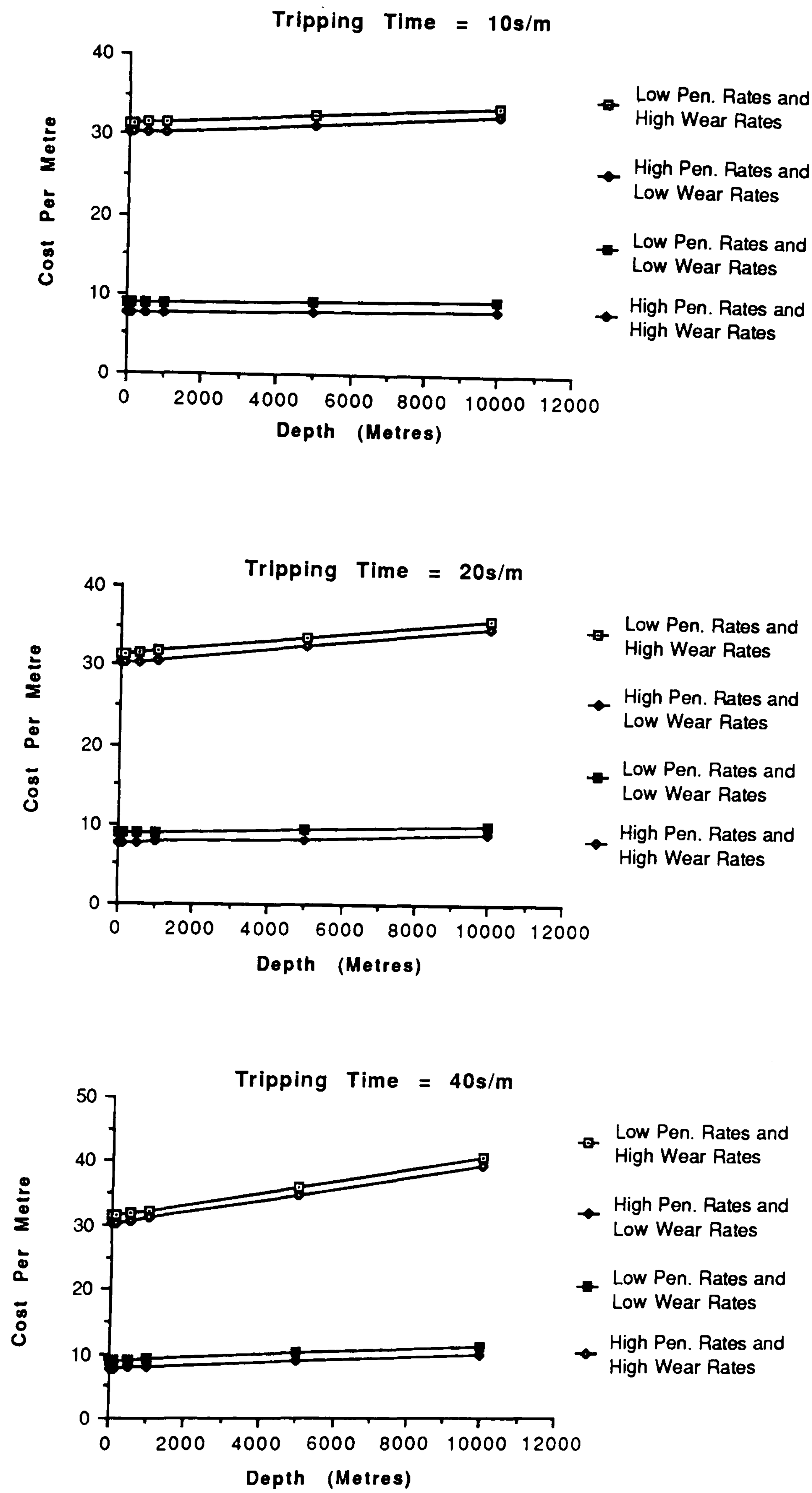


Figure 4.3 The Influence of Tripping Time when Bit Costs (£1500) are Greater than Rig Costs (£100)

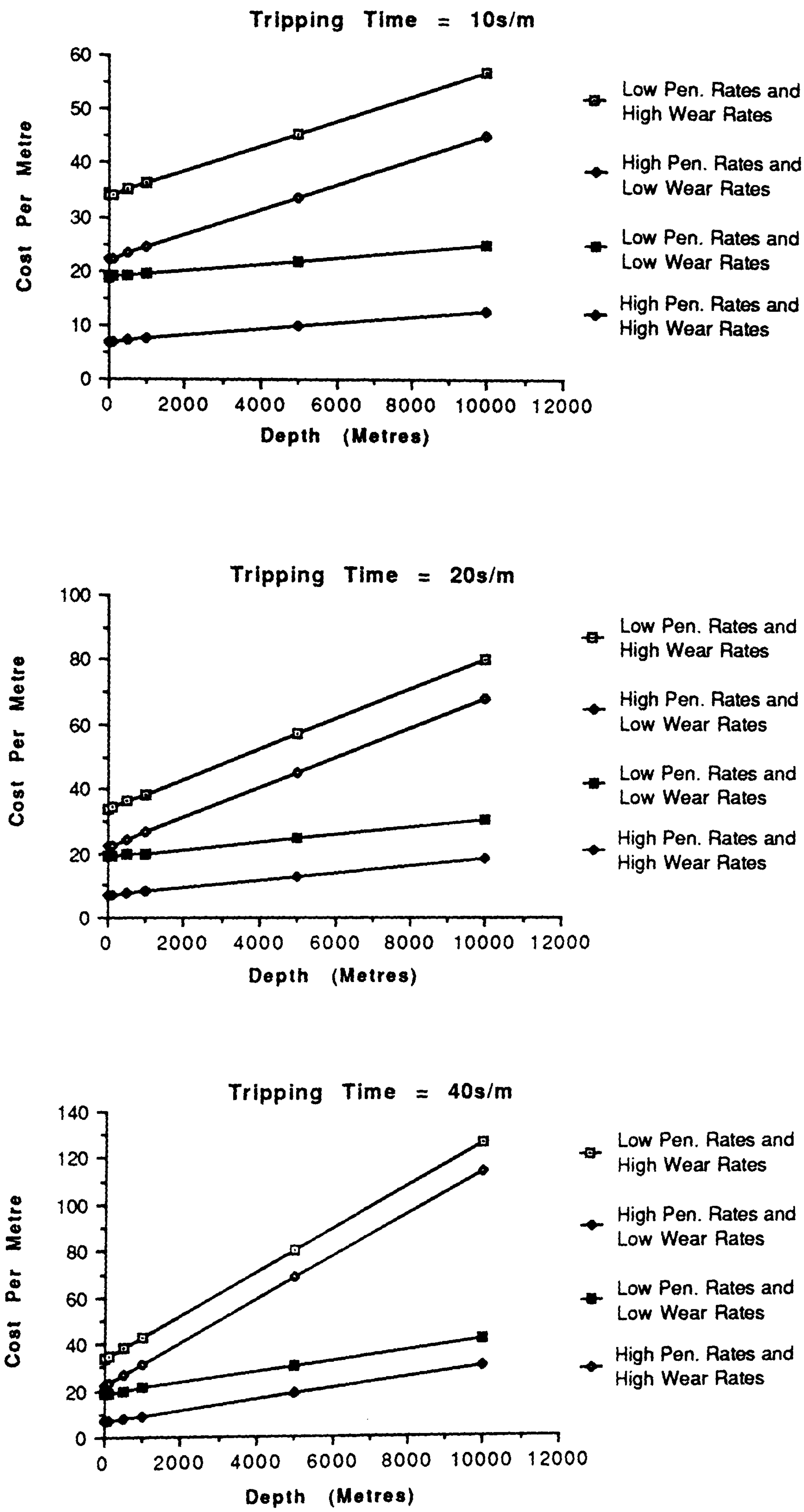


Figure 4.4 The Influence of Tripping Time when Bit Costs (£1000) are Equal to Rig Costs (£1000)

kept as low as possible, but within these divisions, the differing penetration rates is also causing a separation. It can also be seen that at shallower depths, the separation between the two wear rate zones has been reduced substantially.

4.4.1.3 Bit Costs Less than Rig Costs

It can be seen from Figure 4.5 that the continuing separation of the penetration rates and the reduction in separation of the wear rate zones, has occurred to such an extent that two of the lines cross, i.e. Low Penetration Rates and Low Wear Rates, and High Penetration Rate and High Wear Rate. This indicates that at different depths of the bore hole, different criteria are required. The initial part of the hole requires high penetration rates, out weighing the associated high wear rates, and in the latter part, low wear rates become more important.

It can also be seen that increasing tripping time again increase the cost per metre within increasing depth but more importantly, moves the position of the change over point between high penetration rates and low wear rates, thus indicating benefits are realised if tripping rates are kept as high as practicably possible.

4.4.2 The Effect of Bit Costs with Constant Rig Costs

The last two tests performed, were to show the effect in cost per metre of differing bit costs with constant rig costs (one at low rig cost £100, the other high £10000), and constant tripping times, again plotted against depth. The two bit cost used were £500 and £1500.

4.4.2.1 Low Rig Costs.

Figure 4.6 shows that as with the test shown in Figure 4.3, it is essential that when bit costs are greater that rig costs, wear rates should be kept to a minimum, otherwise the cost per metre increases dramatically. This is highlighted further by the higher of the bit cost graphs, where the cost per metre would be tripled is high wear rates were to occur.

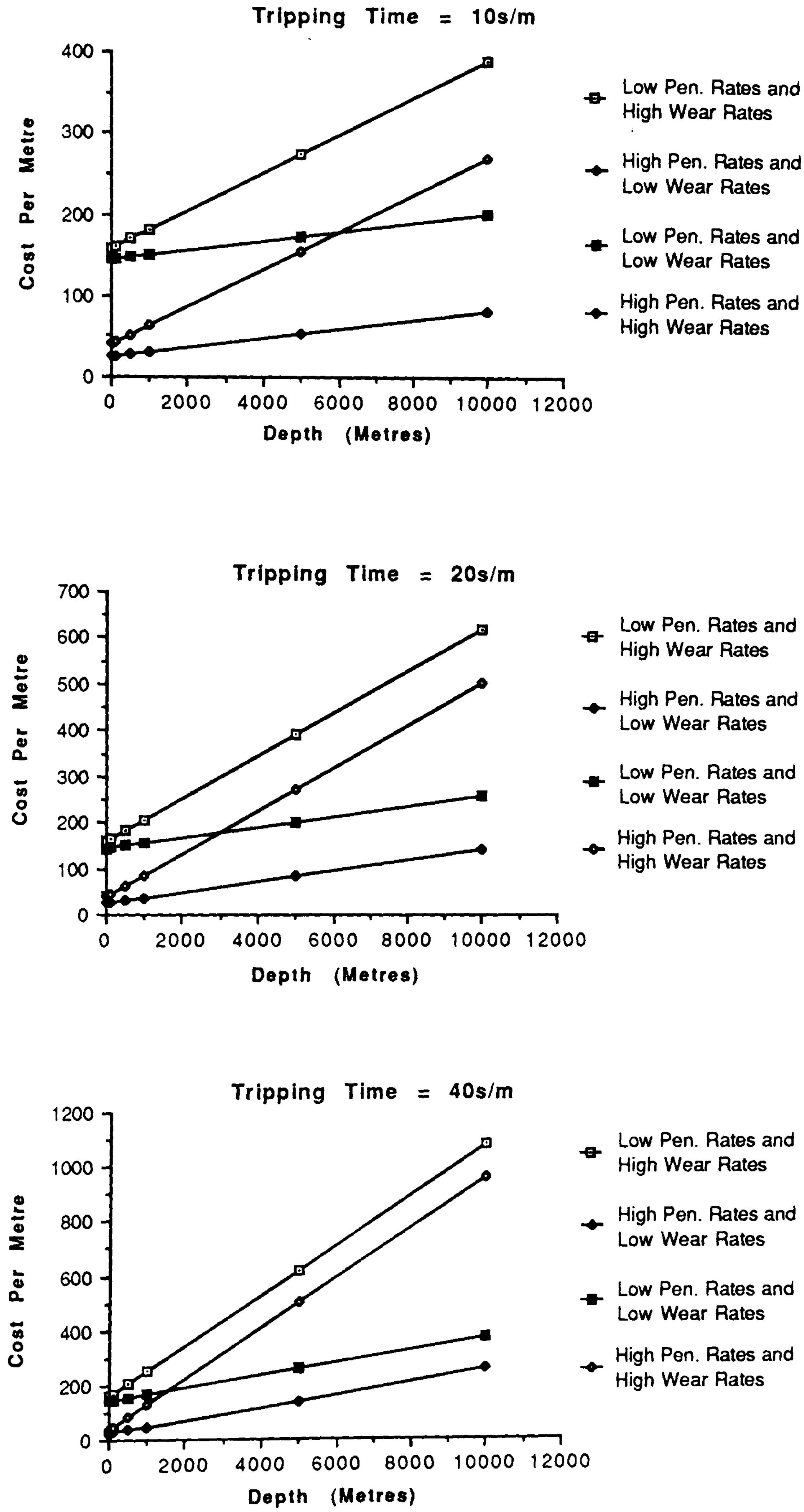
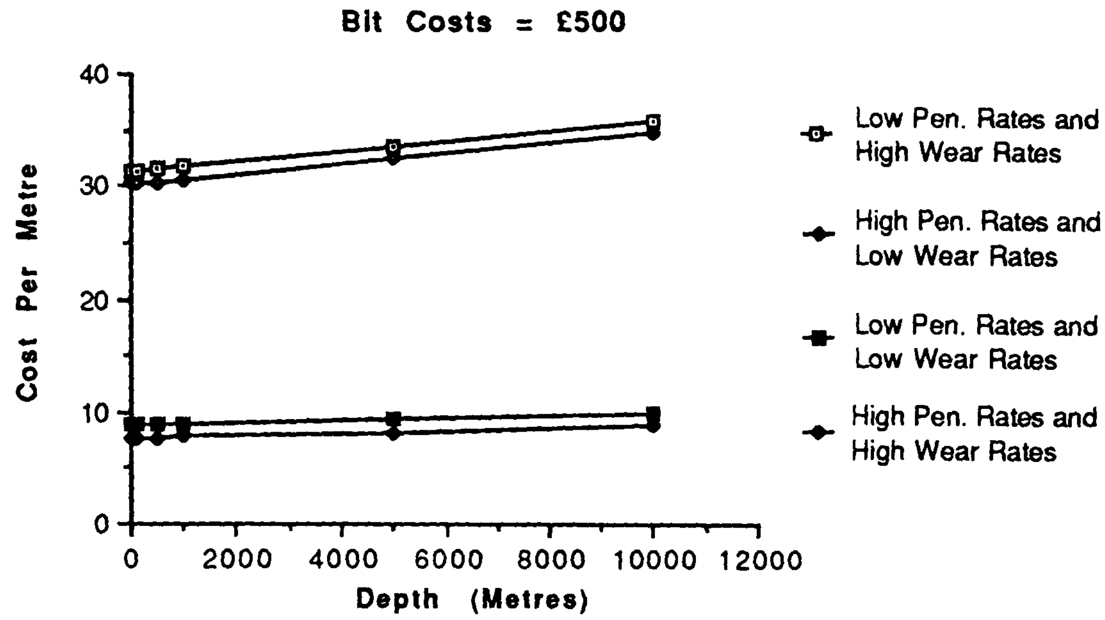


Figure 4.5 The Influence of Tripping Time when Bit Costs (£1000) are Less than Rig Costs (£10000)



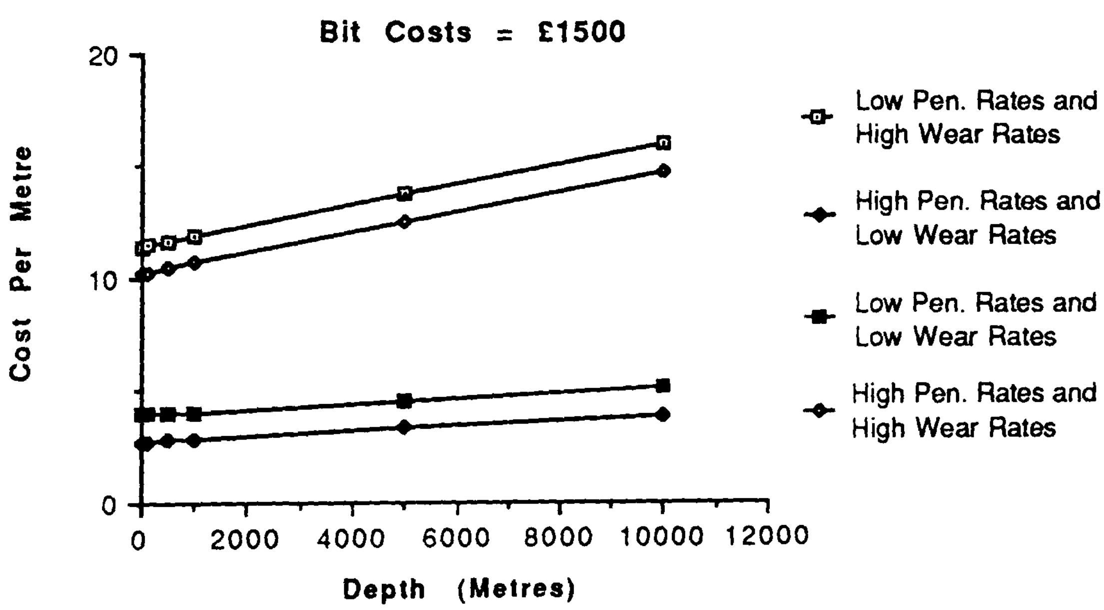


Figure 4.6 The Influence of Bit Costs Compared to Constant Rig Costs (£100) and Constant Tripping Time (20 s/m)

4.4.2.2 High Rig Costs

Figure 4.7 illustrates that when rig costs are much higher than bit costs, that the influence of bit costs on the cost per metre is negligible. This is shown aptly by the superimposed graph at the bottom.

4.4.3 Conclusions of the Sensitivity Analysis

From the analysis, we can draw several conclusions :-

i) With rig costs less or equal than bit costs, emphasis is placed on low wear rate, as the effect of higher wear values dramatically increase the cost per metre. This is increasingly important with high bit costs. Tripping time has very little effect of the cost per metre.

ii) With Rig costs higher than bit costs, bit costs have very little effect on the overall cost per metre. Tripping times however, significantly effect the cost per metre. Increase tripping time, cause increases in the cost per metre, especially if high wear rates are seen. The effect is much less with low wear rates. A cross over point is also seen where, after an initial requirement of maximising penetration rates, the emphasis is change to low wear rates. The depth at which this interchange occurs is effected by the tripping time, being dramatically reduced by increasing tripping times

4.5 Conclusion

In concluding, to achieve optimisation of a process, a governing parameter and its relation to that process must be developed. In selecting the optimum parameter, it is beneficial to select one that eliminates as many variables as possible, to enhance the development of the optimisation system. In this case, a trade off between penetration rates and wear rates was selected as the rational for drill optimisation. Several parameters were examined e.g maximised penetration rate, time per bit run, total time to completion, but most were disregarded, due to non-practicality, and / or the inflexibility of the likely optimisation system.

Optimisation by cost per metre was selected as the governing parameter and a well established cost equation was used. By mathematical manipulation of this equation, parameters directly related to the drilling operation were derived to establish the rule base for the optimisation system.

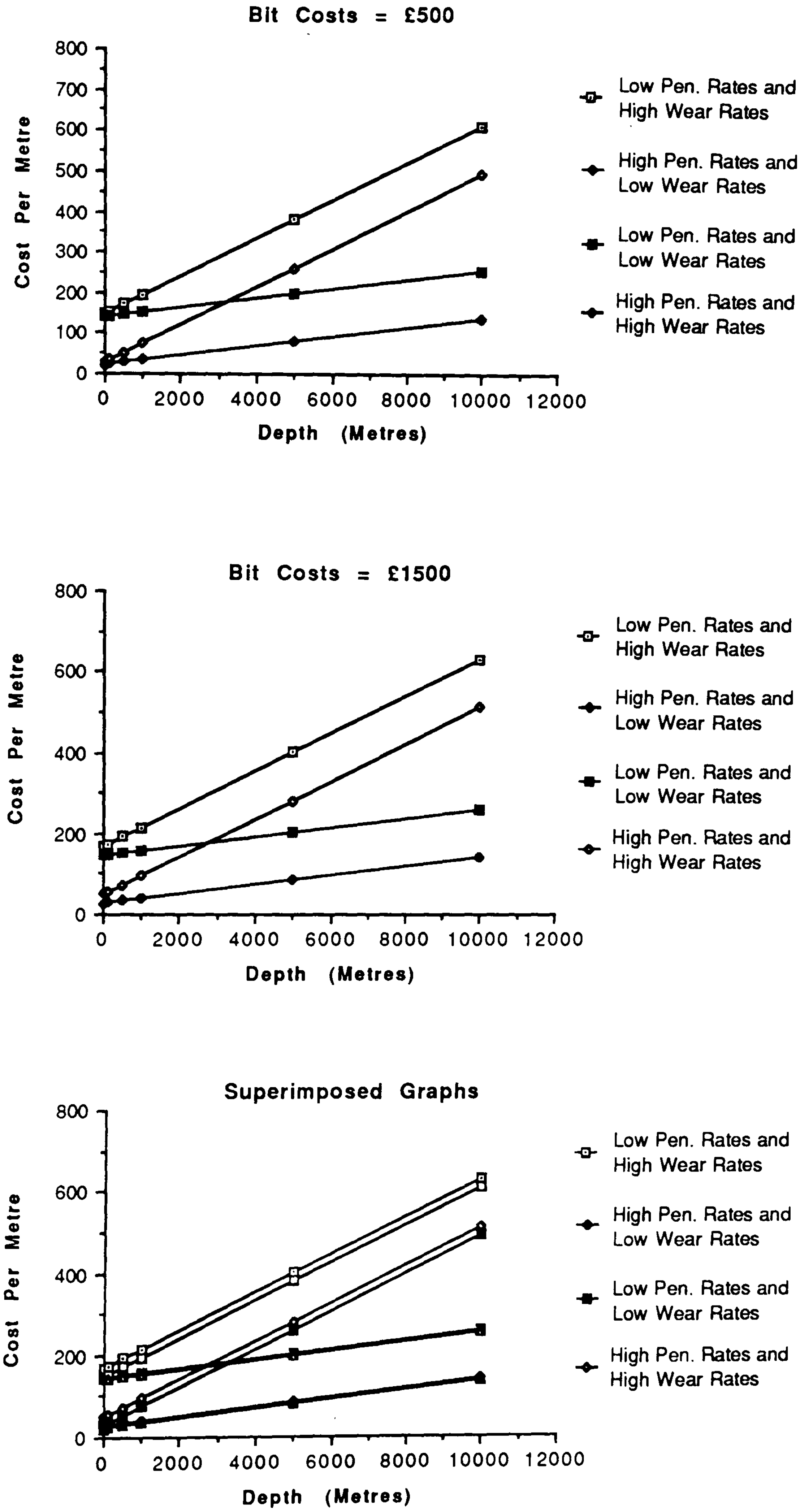


Figure 4.7 The Influence of Bit costs Compared to Constant Rig Costs (£10000) and Constant Tripping Time (20 s/m)

To develop general understanding of this equation, a sensitivity analysis was performed on this equation to indicate the trends etc, associated with it. This highlighted several points when dealing with differing rig costs, tripping times etc, which were useful when developing the minimum cost optimisation system.

Chapter 5 - Bit Wear and Wear Prediction

5.1 Introduction

The monitoring of most drill parameters in the laboratory is relatively easy. In the field however, difficulties do arise as a result of current technology limitations and engineering constraints. As a consequence, drill parameter monitoring becomes difficult. Furthermore when considering deep holes, the surface monitored data may not depict the true down hole conditions. Despite this however, it is in the authors opinion that with increased exploitation of Measurement While Drilling Tools (MWD) and other techniques, accurate and reliable data will be available for most parameters in the future. The one exception to this is possibly bit wear.

Bit wear is a complex subject involving many different processes, which determine the type and extent of bit wear. Different bits wear in different ways, but some processes are common to all such as abrasion. The correct selection of bit type, may play the most crucial part in minimising bit wear and enhancing performance. Despite correct selection, wear and damage will always occur, and therefore it is important that research is conducted into bit wear to understand the processes that govern it. This is not only important to the bit manufacturer, for improving cutting performance and reducing wear characteristics, but also to the driller who needs to know when the bits life is exhausted and thus reduce the chance of pulling a green bit.

Throughout drilling history, research has been conducted into bit wear, and consequently many schemes and systems have been produced to minimise wear each having differing degrees of success *(2,5,9,11,13,14,19,25,28,72)*. Tri-cone roller bits have probably been the most extensively researched. They were originally regarded as the work horse of the oil drilling industry, still extensively used but now being surpassed by PDC bits. Tri-cones are also predominantly used for large diameter blast-hole production for surface mining operations.

Prediction of the bit wear mechanism for a tri-cone bit is complicated having both a wear mechanism common to all types of bits, as well as a bearing failure mode. However previous research, has lead to a good understanding of the wear modes and prediction of failure. Consequently several formulas and prediction methods are in current use with both the oil industry and surface mining industries.

Research at the university, has focused just on two types of bits, primarily diamond impregnated core bits, and latterly polycrystaline diamond bits for use in roof bolting. Diamond impregnated bits are generally thought of as having fairly uniform wear characteristics *(11,70,73)*, the cutting matrix wearing away to expose new diamonds at a relatively constant rate, for constant drill parameters. This enables wear characteristics to be determined fairly easily. Much of the work into diamond bit wear was conducted by Ambrose. The author continued some of this work, mainly in the improvement of the accuracy of the wear measurement jig. Determination of further wear characterises were not undertaken due to time constraints. Research on the PDC side is fairly new and the author has had no direct involvement. PDC itself, has good wear characteristics being comprised of sintered diamond, but it is prone to impact damage and is intolerant of maltreatment. Its introduction into the drilling industry has been fairly recent. Consequently the wear mechanisms are still under investigation to determine modes of wear and best performance scenarios *(9,68)*.

Attaining wear data in the laboratory is relatively easy. However to measure real field wear data and to construct and validate wear models is very difficult as in a commercial operation, the tripping of the bit every set distance to measure the incurred wear is highly impractical. The actual measurement of the wear is also complicated and often prone to subjective interpretation, such as in the case of the IADC wear code for tri-cone roller bits.

Furthermore, having attained a wear value, how do we depict what parameters, have influenced the wear which has occurred. Obviously in the field, this is very difficult as we do not know exactly what bottom hole conditions are. The laboratory environment, while not imitating the real situation fully, does enable controlled experiments to be performed, and wear characteristics to be taken with relative ease. Once adequate data has been gathered and a wear theory developed, comparisons can be made with those from the field and validation made.

5.2 The Wear Predictor

The aim of this research project was not to enhance knowledge about the mechanism of wear for a particular bit, but to develop a system which would enhance the data already available and predict likely wear values for any type of bit.

Most current wear predictors work on a formula bases, or use rules established from data bases. A typical example is shown below for Tri-cone bit wear, F.S.Young *(74)*.

Rate of Bit Bearing Wear

$$\frac{dB}{dt_r} = \frac{1}{B} .N.W^{\sigma} \quad \text{---} \quad (5.1)$$

Rate of Bit Tooth Wear

$$\frac{dH}{dtr} = \frac{A_f\,(PN + QN^3)}{(-D_1.W+D_2)(1+C_1.H)} \quad \text{---} \quad (5.2)$$

where B = Normalised bit wear
t_r = Rotating time
N = Rotary Speed (r.p.m)
W = Bit Weight, (pounds)
σ = Weight exponent in bearing rate equation
H = Normalised tooth wear height
P & Q & C_1 = Constants dependent on bit type
D_1 and D_2 = Constants dependant upon bit size
A_f = Formation abrasiveness factor

By entering the required values, an estimation can be made of the extent and type of wear / failure likely to occur. However these equation are rigid, and if inaccurate will always remain so.

The emphasis placed on this predictor was not to be tied to any particular formula or rule base, but to predict solely on data collected previously, from other holes. An analogy can de drawn, to a brain learning a process for itself. With the large number of possible influences on wear, a system that could be expanded to accept these is also desirable.

To produce such a system data points must be stored with distinct set of reference parameters, and stored in such a way as to allow the inclusion of additional reference parameters. This is best done in a matrix format. For different combinations of parameters, each has a unique accessible data point. Additional parameters can be accommodated by adding another dimension to the matrix. These matrix tables were named S.L.P.M.'s (Self Learning Prediction Matrices), the self-learning aspect is described later in this chapter. Therefore, by measuring wear values, these can be loaded into the S.L.P.M.'s with respect to their reference parameters. They may be either historical data or from on line measurements.

5.2.1 Data Validity

With progressive use of the predictor it is likely that over time several values will be generated for one particular point. Therefore, some sort of averaging process is necessary. One of the more common methods for continual data streams is the running average given by :-

$$\text{Running Average} = \frac{\text{New Reading} + \text{Previous Average}}{2} \quad \text{--- (5.3)}$$

This method can also be used to generate more a general average by using say the sum of the previous five or ten readings. However this method does not give a true average, and more importantly, it does not give any indication of the accuracy/ range of the data such as given by the standard deviation. To calculate the mean and standard deviation, requires the storage of all the previous data values. With the matrix system proposed, this would be undesirable, as over time the amount of data stored would be colossal. Therefore ways were investigated to reduce the number of values or variables which would be required for each point.

The Mean is given by

$$\bar{x} = \frac{\text{Sum of all values}}{\text{Number of values}} \quad \text{--- (5.4)}$$

$$\bar{x} = \frac{\text{Sum of previous values} + \text{New value}}{\text{Number of values}} \quad \text{--- (5.5)}$$

$$\bar{x} = \frac{(N_o \cdot \bar{x}_o) + \text{New value}}{N_o + 1} \quad \text{--- (5.6)}$$

where N_o = Previous number of values
$\bar{x}_o$ = Previous mean

It can be seen that to calculate the mean, only two values have to be stored, i.e. the mean and the number of data points entered. Small errors do occur from progressive multiplication of the mean value but these are negligible. The standard deviation may be calculated in a similar fashion.

$$\text{Standard Deviation} = \sqrt{\text{Variance}} \quad \text{---}\ 5.7$$

$$\text{Variance} = \frac{\sum(x - \bar{x})^2}{n} \quad \text{---}\ 5.8$$

By multiplying out and reducing,

$$\text{Variance} = \frac{\sum x^2}{n} - (\bar{x})^2 \quad \text{---}\ 5.9$$

From this it can be seen that we need to store the 'sum of the squares' of each point along with the mean and the number of data points. Thus to calculate both the true mean and the standard deviation, we need only need store three values.

The mean
The number of data Values
The sum of the squares

Compared to the original suggestion of storing every data point, this method provides a usable and accurate means for determining data reliability.

Summarising what has be proposed so far; as wear is a difficult parameter to measure, we require some sort of prediction mechanism to provide estimation of wear for the optimisation scheme. This predictor has been developed in the form of a matrix system (S.L.P.M.) which may be readily expanded to multi dimensions for the various parameters required. To provide some indication of the accuracy of the data, the Mean and standard deviation are calculated for each point, but only necessitating three storage variable for each point.

5.2.2 Data Enhancement by Interpolation

When using the predictor, to start with data values will be sparse, and consequently predicted values will be inaccurate but with progressive use the predictor becomes more and more accurate. However as the reader has probably already questioned, for a large matrix, there are a large number of data points to fill. For example a 20 by 20 has 400 points! This is clearly impractical to fill both in the laboratory and in the field. Therefore we need some way of enhancing the data which we load into the S.L.P.M.'s, i.e. a self-learning capability, such that we can estimate values for unknown points. This can be achieved by interpolation.

Interpolation of data is always subject to risk as the interpolated values may generate totally meaningless data which does not represent the true process. However with the S.L.P.M.'s having a continual learning process i.e. data will be continually entered, it is felt that if interpolation takes place after each addition, a reliable system will be produced.

5.2.2.1 Two Dimensional Interpolation

There are many ways in which we could 'interpolate' the data with in the matrix. A simple system could give every unknown point the average value of all the known points. This however, would give unrealistic values as no account is taken of the trend / surface variation of the data. This is shown in Figure 5.1.

Therefore some sort of curve fitting or general averaging method is required. As an averaging process is more readily applied and easier to develop, initial work concentrated on this type, with the idea of investigating curve fitting etc, at a later date once the main optimisation system had been developed.

For each value with in the matrix if the point was an unknown, the four values directly adjacent to the selected value, were averaged. This value then replaced the original selected value, as shown below.

$$\begin{array}{ccccc} & & 2 & & \\ & & | & & \\ 3 & — & ? & — & 8 \\ & & | & & \\ & & 5 & & \end{array} \qquad\qquad \begin{array}{ccccc} & & 2 & & \\ & & | & & \\ 3 & — & 5 & — & 8 \\ & & | & & \\ & & 5 & & \end{array}$$

Using this as the bases of the averaging process. The original method of applying this technique was to interpolate the whole matrix starting from one corner and ending in the opposite corner. The process would continue until no change was seen in the matrix.

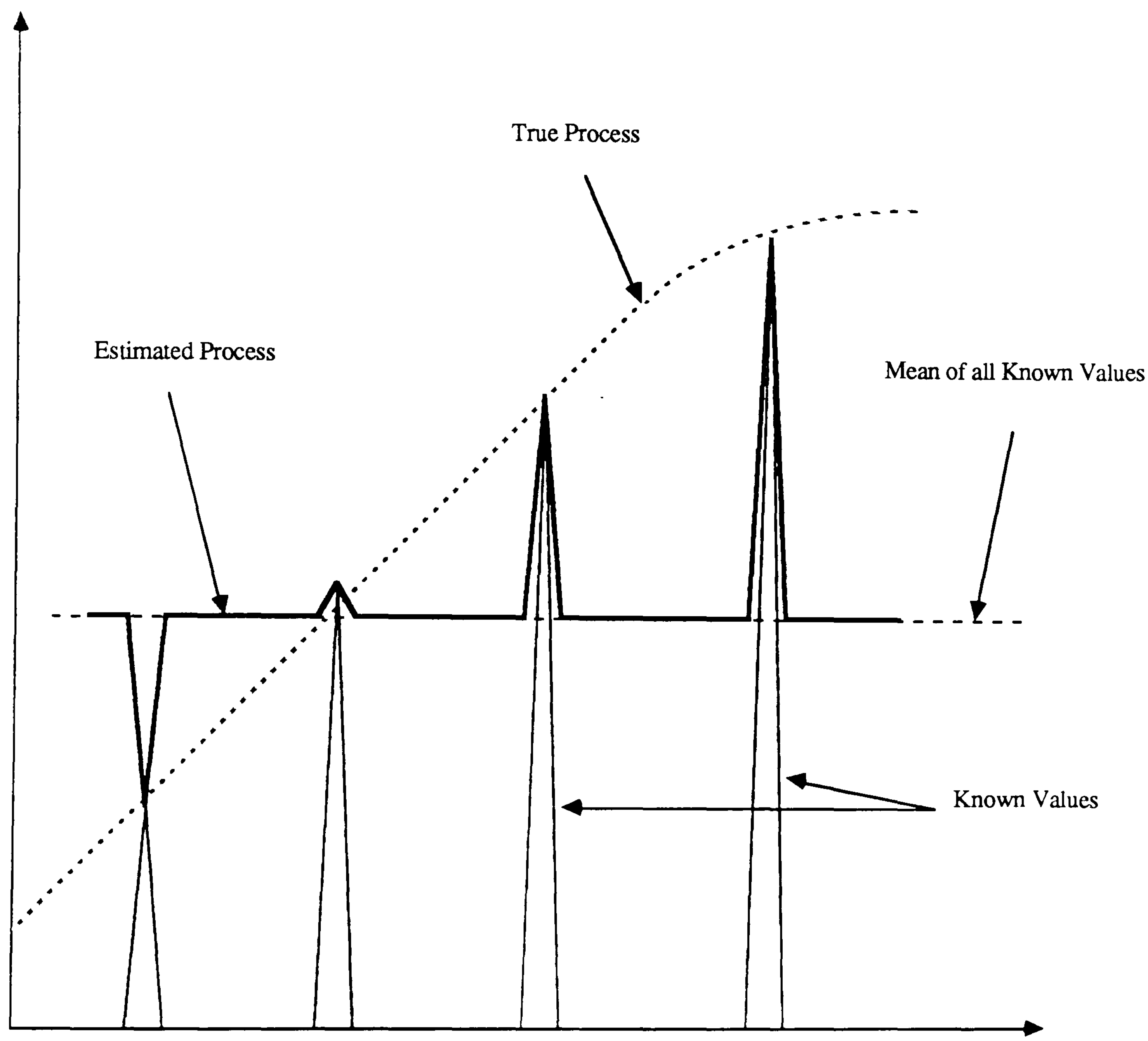
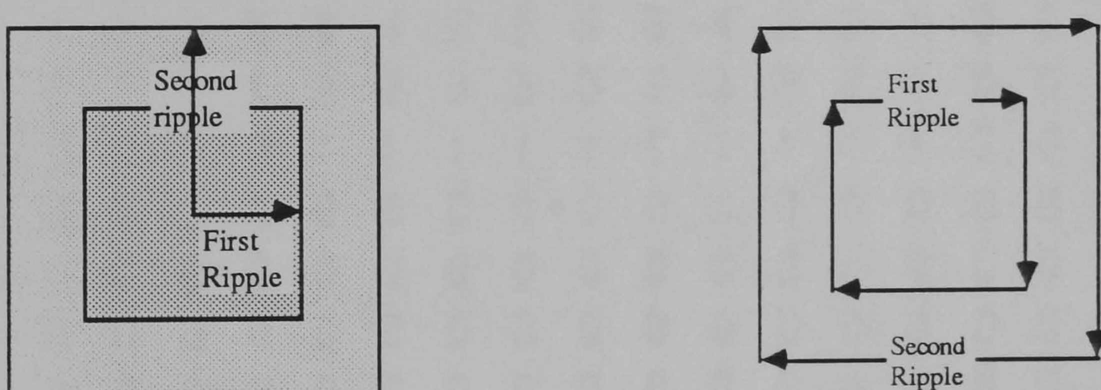


Figure 5.1 An Illustration to Show the Effect of Giving the Mean Values to Unknown Points

This however is extremely wasteful of processing time as generally the influence of the new value was restricted to a small part of the matrix, and therefore did not require the whole matrix to be interpolated.

To improve the efficiency of the interpolation system, a technique which later became known as the ripple technique was developed. When a new value was entered into the matrix, the averaging process, would radiated outwards in concentric squares (if 2 dimensional) until the effects were minimal. This would repeat itself starting from the new value once again, until no change was seen.

The original method was to interpolate the whole of each growing square. However, as the squares radiate outwards the inner average values would never change, and thus computing time would be wasted. Therefore only the periphery values of each square would be used as shown.



Old Method

New Method

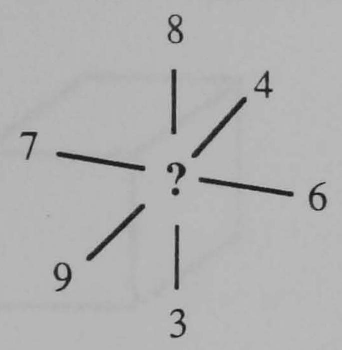
A similar action is seen by ripples (hence the name) radiating outward from its disturbance point in water. Figure 5.2 shows a small two by two matrix undergoing rippling. It can be seen from this that the closer the points are effected to a greater extent, than those further away.

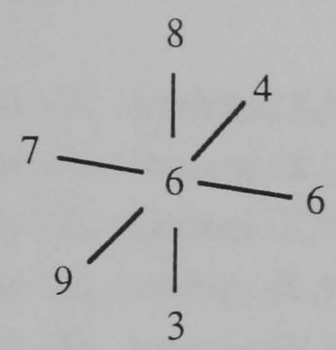
5.2.2.2 Three Dimensional Ripple.

The ripple method described so far has only been for two dimensions and is thus easy to visualise and develop. For three dimensions, a cubic like structure is see. Therefore an average of the six adjacent values to the selected point must be taken forming a three dimensional cross, as shown overleaf.

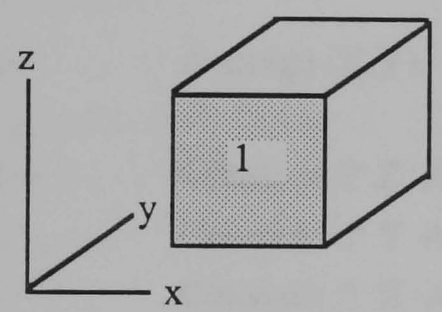
0	0	0	1	2	3	4	5	6	6	6	5	4	4	3	2	1	0	0	0
0	0	0	1	2	3	5	6	7	7	7	6	5	4	3	2	1	0	0	0
0	0	0	1	3	4	6	8	9	9	9	7	5	4	3	2	1	0	0	0
0	0	1	2	3	5	8	10	12	13	12	9	7	5	4	3	1	0	0	0
0	0	1	2	4	7	10	13	17	19	17	13	9	7	5	3	1	0	0	0
0	0	1	3	5	8	12	17	24	31	24	17	11	8	5	3	1	0	0	0
0	0	1	3	5	8	13	19	31	58	31	19	12	8	5	3	1	0	0	0
0	0	1	3	5	8	12	17	24	31	24	17	11	7	5	3	1	0	0	0
0	0	1	3	5	7	10	13	17	19	17	13	9	6	4	2	1	0	0	0
0	0	1	3	4	5	7	9	11	12	11	9	7	5	3	2	1	0	0	0
0	0	1	2	3	4	5	6	7	8	8	7	5	4	3	1	0	0	0	0
0	0	1	2	2	3	3	4	5	5	5	5	4	3	2	1	0	0	0	0
0	0	1	1	1	1	2	2	3	3	3	3	3	2	2	1	0	0	0	0
0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 5.2 A Two by Two Matrix which has Undergone Rippling After a Value has Been Entered





The actual mode of rippling will take a cuboidal shell. However, this may be split down into six two dimensional squares similar to those of the two dimensional ripple. However unlike the 2-D ripple where just the periphery is averaged, the whole square must be averaged.

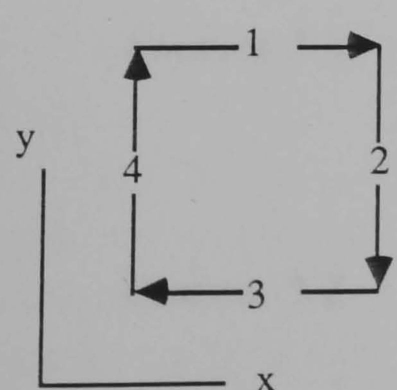


e.g Side 1 = Constant -Y, Average (X,Z)

5.2.2.3 Multi- Dimensional Interpolation

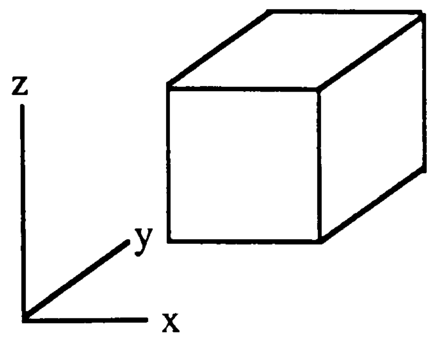
It may be necessary for dimensions greater than three, but these are beyond the capacity of the human brain. Therefore a pattern must be established which links the addition of extra dimensions.

Considering the two dimensional ripple, rippling occurs in a square like function, with the respective areas being held either constant or rippled. This is summarised below:-



1. Constant +Y, Ripple -X to +X
2. Constant +X, Ripple +Y to -Y
3. Constant -Y, Ripple +X to -X
4. Constant -X, Ripple -Y to +Y

In the three dimension ripple, the steps are listed below.



1. Constant -Y, Average (X,Z)
2. Constant +Y, Average (X,Z)
3. Constant -Z, Average (X,Y)
4. Constant +Z, Average (X,Y)
5. Constant -X, Average (Y,Z)
6. Constant +X, Average (Y,Z)

From the two dimension case, it looks as though no pattern exists. However as mentioned previously, in the 2D version only the peripheral values were used, as averaging the whole of each growing square was inefficient. However if this method was used a pattern could be established.

2D :-	Average (X,Y)
3D :-	Constant $\pm$ Z Average (X,Y)
	Constant $\pm$ Y Average (X,Z)
	Constant $\pm$ X Average (Y,Z)

Thus for a four dimensional ripple, the selected would require the average of the eight adjacent values, W $\pm$1 , X $\pm$1, Y $\pm$1, Z $\pm$1, and ripple in a fashion shown below.

Constant $\pm$ W	Constant $\pm$ Z	Average (X,Y)
	Constant $\pm$ Y	Average (X,Z)
	Constant $\pm$ X	Average (Y,Z)
Constant $\pm$ X	Constant $\pm$ Z	Average (W,Y)
	Constant $\pm$ Y	Average (W,Z)
	Constant $\pm$ W	Average (Y,Z)
Constant $\pm$ Y	Constant $\pm$ Z	Average (X,W)
	Constant $\pm$ W	Average (X,Z)
	Constant $\pm$ X	Average (W,Z)
Constant $\pm$ Z	Constant $\pm$ W	Average (X,Y)
	Constant $\pm$ Y	Average (X,W)
	Constant $\pm$ X	Average (Y,W)

5.3 Testing of the Predictor

For the initial development of the predictors only two and three dimensional ripple methods were developed. To test the accuracy of prediction, the matrices were loaded with a set number of known points, with rippling occurring after each addition. To generate the known data points, random co-ordinates were fed into a known equation and the value calculated. Once the required number of points had been entered, using the known equation, the accuracy of the interpolation could be determined.

Several test were performed, by varying the number of entered values as well as the form of the equation. This allowed equations / surfaces of varying complexity to be tested.

5.4 Results

For a measure of the prediction accuracy a limit was set in which the data had to be within the ± 10 % of the real value, the greater number in this range, the greater the accuracy.

5.4.1 Two Dimensional Method.

Figure 5.3 shows a three dimensional plot of the equation / function which was used to perform the first series of tests. Table 5.1 shows the results of these tests, with Figures 5.4 - 5.6, giving typical examples. It can be seen that initially with only limited data in the S.L.P.M.'s, the predicted results are highly inaccurate. However after the S.L.P.M. is 5% full, there is a dramatic improvement in the accuracy, i.e. with the S.L.P.M. only 10% full, 77% of the data is acceptable, and with the S.L.P.M. 37.5% full, 97% is acceptable. This is also reflected in the time taken to ripple each of the tests, the majority of time taken with the first 5%, and only small increases there after. Therefore for simple surfaces, the ripple method proved a good predictor.

Figure 5.7 shows the three dimensional dome like structure generated by the equation for the second series of experiments. The results are shown in Table 5.2 and Figures 5.8 - 5.10. From these results it can be seen that the accuracy of the prediction method is reduced. Despite this, the predictor still performs adequately once 15-20% of the S.L.P.M. is full, with 70% of the data being with in the tolerance. As the surface changes more rapidly than in test one, the influence of each point to the matrix as a whole is reduced and hence the very low rippling times are seen.

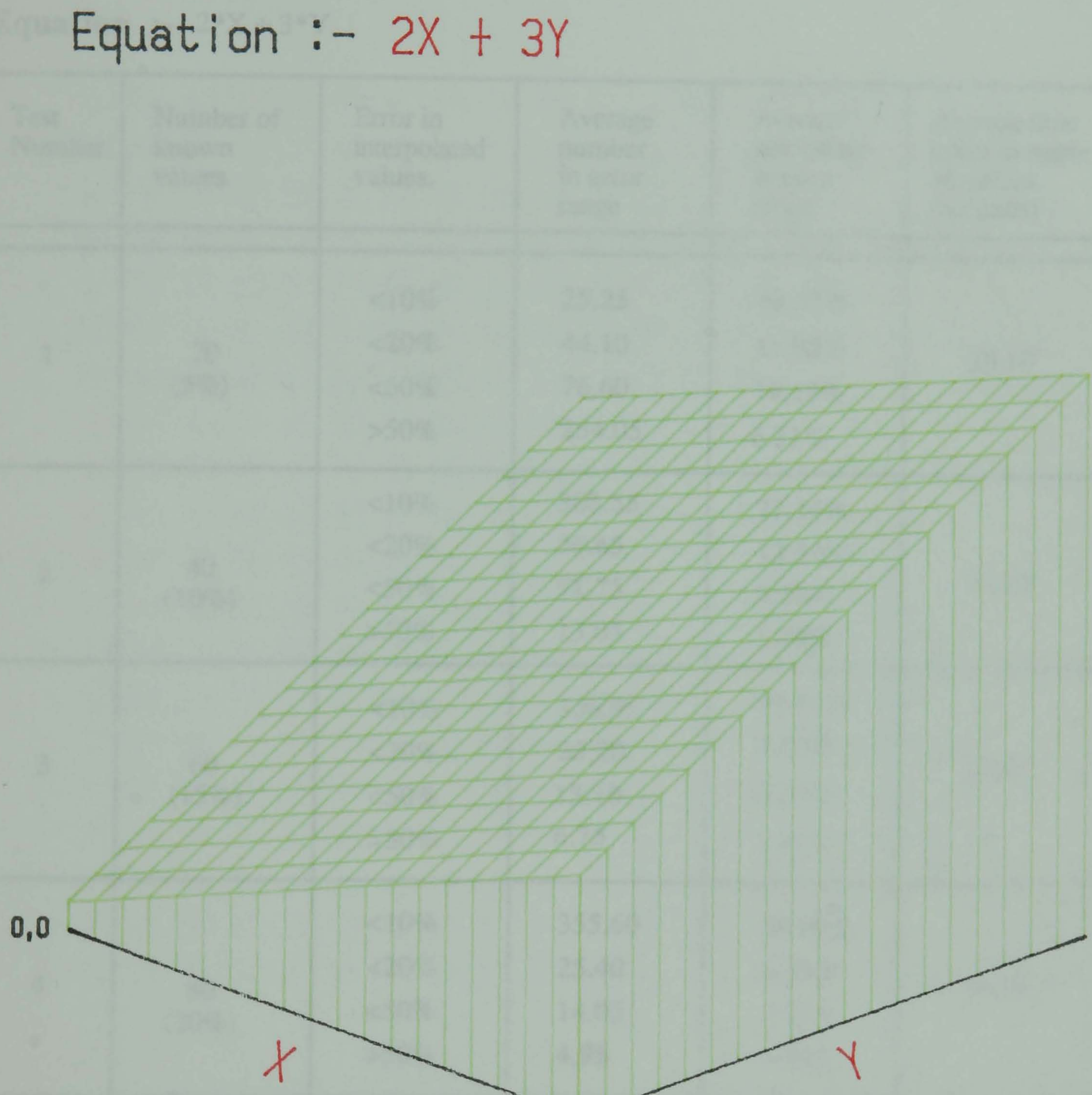


Figure 5.3 A 3-Dimensional Plot of the Equation Used for the First Set of 2-Dimensional Ripple Tests

Table 5.1 :- 2-Dimensional Ripple Test 1

Matrix Size :- 20*20 **Number of Runs per Test :-** 20

Equation :- 2*X + 3*Y.

Test Number	Number of known values	Error in interpolated values.	Average number in error range	Average percentage in error range.	Average time taken to ripple all values (seconds)
1	20 (5%)	<10% <20% <50% >50%	25.25 44.10 76.60 254.05	63.51% 11.02% 19.15% 6.31%	29.10
2	40 (10%)	<10% <20% <50% >50%	308.55 26.65 51.75 13.05	77.14% 12.94% 6.66% 3.24%	31.25
3	60 (15%)	<10% <20% <50% >50%	356.95 23.20 13.10 6.75	89.24% 5.80% 3.27% 1.67%	32.95
4	80 (20%)	<10% <20% <50% >50%	355.60 25.40 14.05 4.95	88.90% 6.35% 3.51% 1.24%	34.90
5	100 (25%)	<10% <20% <50% >50%	372.10 16.00 8.30 3.60	93.02% 4.00% 2.07% 0.90%	34.85
6	150 (37.5%)	<10% <20% <50% >50%	386.85 8.55 3.65 0.95	96.71% 2.14% 0.91% 0.24%	36.85

Equation :- 2X + 3Y

62	64	60	59	59	60	62	64	66	68	71	74	78	76	74	73	73	73	73	73
59	59	58	58	59	60	62	64	66	68	71	75	83	77	74	73	73	73	73	73
56	56	56	57	58	60	62	65	66	68	70	73	76	75	73	73	73	73	73	73
54	54	54	55	56	58	61	67	66	67	69	72	73	73	72	72	73	73	74	75
52	52	52	53	54	56	59	62	64	66	68	72	71	71	71	72	73	74	76	79
50	50	50	51	52	54	57	59	61	63	65	67	68	69	70	72	74	75	78	85
48	48	48	49	50	52	54	56	58	60	62	64	66	68	69	71	76	74	75	77
46	46	46	47	48	50	52	54	56	58	60	62	64	67	67	68	70	70	71	71
43	43	44	45	46	48	50	52	54	56	58	60	61	63	64	65	66	66	66	66
40	40	41	42	43	45	47	49	51	53	55	57	58	59	60	61	62	62	62	62
36	34	37	38	40	42	44	46	48	50	52	54	55	56	57	58	59	59	59	59
35	35	36	37	38	40	42	44	46	48	49	51	53	54	55	56	58	57	57	57
34	34	34	34	36	38	40	41	43	45	46	48	50	51	52	54	58	55	54	54
32	32	32	29	34	36	37	37	40	42	43	45	47	48	49	51	52	52	51	51
31	31	31	31	33	35	36	37	38	39	40	42	44	45	46	47	48	49	48	48
31	31	31	32	33	34	35	36	36	35	38	39	41	42	43	44	45	46	46	46
31	31	31	32	32	33	34	34	33	34	36	37	39	40	41	42	43	44	45	44
31	31	31	32	32	33	33	32	27	32	34	35	37	38	39	40	42	43	44	44
31	31	31	32	32	32	32	32	31	32	32	32	34	36	38	38	41	43	44	44
31	31	31	31	31	31	31	31	31	31	30	27	32	35	37	38	40	42	43	44

Random entered values = 20
Interpolated values with <10% error= 244
Interpolated values with 10-20% error= 75
Interpolated values with 20%-50% error= 33
Interpolated values with >50% error = 28

Figure 5.4 A Typical Result from the First 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 20 RandomValues have Been Entered

Equation :- 2X + 3Y

62	60	60	62	63	66	70	76	73	73	75	77	80	84	90	90	91	93	96	100
59	59	60	62	63	65	68	71	71	72	74	76	79	82	86	89	91	92	95	96
56	57	59	62	63	64	66	68	69	71	73	76	78	80	83	85	87	89	92	94
53	55	57	59	61	63	64	66	67	69	72	75	76	78	80	82	84	86	88	89
52	53	55	56	58	60	62	64	65	67	70	72	74	76	78	80	82	84	86	86
50	51	52	53	55	57	59	61	63	65	67	69	71	73	75	77	79	81	82	82
48	49	49	50	52	54	56	58	60	62	64	66	68	70	72	74	76	78	80	79
46	46	46	47	49	51	53	55	57	59	61	63	65	67	69	71	73	75	76	76
43	43	43	44	46	48	50	52	54	56	58	60	62	64	66	68	70	72	74	73
40	40	40	41	43	45	47	49	51	53	55	57	59	61	63	65	66	67	68	68
37	37	36	38	40	42	44	46	48	50	52	54	56	58	60	61	62	63	64	64
33	34	34	35	37	40	42	43	45	47	49	51	53	55	57	58	59	60	61	61
29	30	30	32	34	37	39	40	43	45	46	48	50	52	54	56	57	58	59	59
23	27	28	29	31	34	37	39	41	42	44	46	48	49	51	53	55	56	57	57
24	25	25	27	29	32	34	36	38	38	41	43	45	46	48	50	52	54	56	55
23	23	21	23	25	28	31	34	36	38	40	41	42	43	45	47	49	51	52	52
21	21	20	20	22	24	28	31	34	36	38	39	38	40	43	45	47	49	50	50
18	18	18	17	19	23	26	28	31	33	36	38	39	40	42	43	45	46	47	49
14	14	16	18	20	22	23	22	27	29	33	36	38	40	40	38	42	42	45	46
11	7	13	17	20	22	23	23	24	23	30	35	38	39	40	40	42	43	44	45

Random entered values = 60
Interpolated values with <10% error= 283
Interpolated values with 10-20% error= 34
Interpolated values with 20%-50% error= 17
Interpolated values with >50% error = 6

Figure 5.5 A Typical Result from the First 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 60 Random Values have Been Entered

Equation :- 2X + 3Y

62	64	65	68	70	72	74	74	76	80	82	82	83	86	90	89	90	91	90	90
59	61	63	65	67	69	71	73	75	77	79	80	82	85	87	88	91	93	90	89
57	58	60	62	64	66	68	70	72	74	76	78	80	82	84	86	88	90	88	87
54	55	57	59	61	63	65	67	69	71	73	75	77	79	81	83	85	86	86	85
50	52	54	56	58	60	62	64	66	68	70	72	74	76	78	80	82	83	83	83
49	50	51	53	55	57	59	61	63	65	67	69	71	73	75	77	79	80	81	81
46	47	48	50	52	54	56	58	60	62	64	66	68	70	72	74	76	78	80	80
41	44	45	47	49	51	53	55	57	59	61	63	65	67	69	71	73	75	77	79
38	41	42	44	46	48	50	52	54	56	58	60	62	64	66	68	70	72	74	76
35	38	39	42	44	45	47	49	51	53	55	57	59	61	63	65	67	69	71	72
32	35	37	39	41	42	44	46	48	50	52	54	56	58	60	62	64	66	68	70
29	31	33	35	37	39	41	43	45	47	49	51	53	55	57	59	61	63	65	67
26	28	30	32	34	36	38	40	42	44	47	49	50	52	54	56	58	60	62	64
25	26	27	29	31	33	35	38	40	42	44	46	47	49	51	53	55	57	59	61
22	23	24	26	28	30	32	35	36	38	41	42	44	46	48	50	52	54	56	58
17	19	21	23	25	27	29	32	34	36	38	40	42	43	45	47	49	51	53	55
14	16	18	20	23	24	27	29	31	33	34	36	39	41	43	44	46	48	50	52
11	13	15	18	21	23	24	25	28	30	31	33	36	38	40	41	43	45	47	49
8	10	12	15	18	20	21	23	24	26	28	31	33	34	37	39	40	43	45	46
9	9	9	11	16	18	17	21	23	23	27	29	29	32	33	36	37	41	44	45

Random entered values = 150
Interpolated values with <10% error= 242
Interpolated values with 10-20% error= 5
Interpolated values with 20%-50% error= 2
Interpolated values with >50% error = 1

Figure 5.6 A Typical Result from the First 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 150 RandomValues have Been Entered

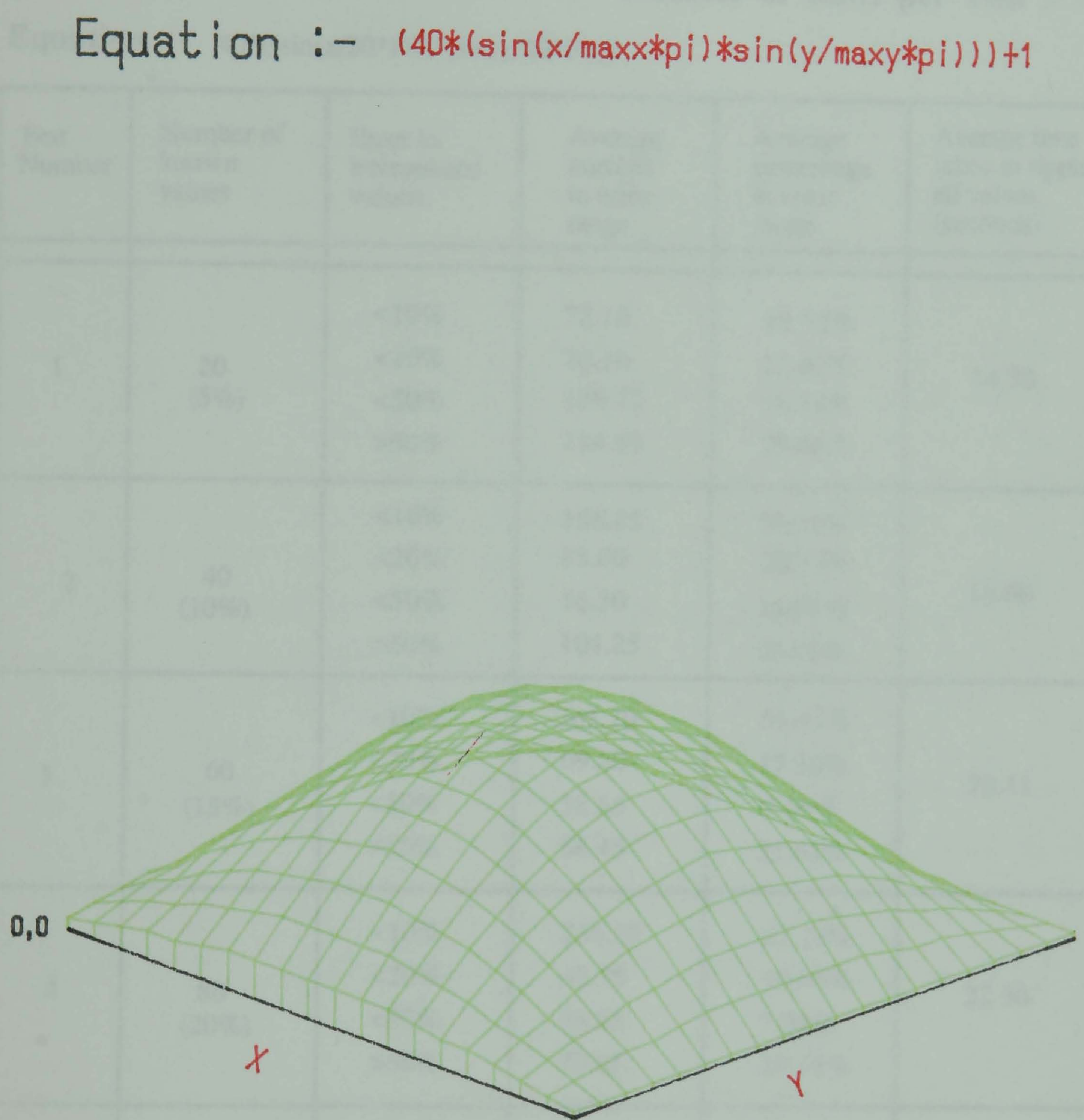


Figure 5.7 A 3-Dimensional Plot of the Equation Used for the Second Set of 2-Dimensional Ripple Tests

Table 5.2 :- 2-Dimensional Ripple Test 2

Matrix Size :- 20*20 **Number of Runs per Test :-** 20

Equation :- 40*((sin(x/20*Pi))*(sin(y/20*Pi)))

Test Number	Number of known values	Error in interpolated values.	Average number in error range	Average percentage in error range.	Average time taken to ripple all values (seconds)
1	20 (5%)	<10% <20% <50% >50%	78.10 70.50 136.75 114.65	19.52% 17.62% 34.19% 28.66%	14.20
2	40 (10%)	<10% <20% <50% >50%	156.45 83.00 56.30 104.25	39.11% 20.75% 14.07% 26.06%	18.60
3	60 (15%)	<10% <20% <50% >50%	205.70 69.20 38.65 86.45	51.41% 17.30% 9.66% 21.61%	20.11
4	80 (20%)	<10% <20% <50% >50%	246.95 43.75 31.65 77.65	61.74% 10.94% 7.91% 19.41%	22.30
5	100 (25%)	<10% <20% <50% >50%	276.40 33.45 29.65 60.50	69.10% 8.36% 7.41% 15.21%	23.65
6	150 (37.5%)	<10% <20% <50% >50%	318.90 18.20 21.00 41.90	72.22% 4.55% 5.25% 10.47%	26.05

Equation :- (40*((sin(X/20*Pi))*(sin(Y/20*Pi))))+1

6	6	7	8	9	10	11	11	11	10	12	13	13	12	11	10	9	9	9	9
5	6	7	8	9	10	11	12	11	7	12	14	14	13	12	11	9	8	9	9
3	6	8	8	10	11	12	13	13	13	15	16	15	14	13	11	9	5	8	8
7	8	10	11	12	13	14	15	16	17	19	18	17	16	14	12	10	8	8	8
9	10	12	15	15	15	16	17	18	19	20	20	19	18	16	14	12	10	9	9
10	11	13	15	16	17	18	19	20	22	23	24	22	20	18	16	13	10	10	10
11	12	14	16	18	19	20	21	22	24	27	32	26	23	20	17	14	11	11	11
12	13	15	18	20	22	23	23	24	25	27	29	27	25	22	19	16	14	12	11
13	14	16	19	23	26	26	25	26	27	28	28	28	28	24	21	18	15	13	12
14	15	17	20	25	33	28	27	27	28	28	28	29	33	26	21	18	15	13	12
14	15	17	20	24	27	27	27	28	29	29	28	28	27	24	20	17	15	13	12
14	15	17	20	22	24	26	27	30	32	30	28	26	25	22	19	16	14	12	10
14	15	17	19	21	23	25	27	31	39	31	27	25	23	21	18	15	13	10	7
13	14	16	18	20	22	24	25	28	30	28	25	23	21	19	17	15	12	8	1
12	13	15	18	20	21	22	23	25	25	24	23	21	20	18	16	14	12	10	7
11	10	14	17	21	21	21	21	22	22	21	20	19	18	17	15	14	13	11	10
10	11	13	16	18	20	19	19	19	19	19	18	18	17	16	14	14	13	12	11
9	10	12	14	15	16	16	16	16	16	16	16	16	16	15	12	13	13	12	12
6	7	10	12	13	14	14	14	14	14	14	14	14	14	14	13	13	13	12	12
2	3	8	11	12	13	13	13	13	13	13	13	13	13	13	13	13	13	12	12

Random entered values = 20
Interpolated values with <10% error= 51
Interpolated values with 10-20% error= 100
Interpolated values with 20%-50% error= 119
Interpolated values with >50% error = 110

Figure 5.8 A Typical Result from the Second 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 20 Random Values have Been Entered

Equation :- (40*((sin(X/20*Pi))*(sin(Y/20*Pi))))+1

9	8	6	6	5	1	4	1	6	8	6	1	4	1	8	11	11	11	10	8
9	8	4	7	8	8	9	9	10	11	10	8	9	9	11	12	12	11	9	6
9	9	8	9	10	12	13	14	14	14	13	13	13	13	13	13	13	12	9	1
10	10	9	12	13	15	17	18	18	18	17	17	17	16	14	14	14	13	11	8
11	11	12	14	16	18	20	23	22	22	21	21	20	19	17	16	15	13	12	11
11	12	14	16	18	20	22	24	25	25	25	25	24	24	20	18	15	10	12	12
11	13	16	19	20	22	25	27	29	29	29	29	27	25	22	19	16	11	12	12
10	13	17	22	22	24	27	31	36	34	34	35	31	28	25	21	17	14	13	12
7	13	17	21	23	26	29	33	39	37	36	35	33	32	28	22	18	15	13	12
11	14	18	21	24	27	30	34	37	38	38	37	34	32	27	22	18	15	13	12
11	15	19	22	26	29	31	34	37	41	41	39	35	33	27	22	18	15	13	12
7	14	19	23	29	31	32	34	37	39	38	36	33	30	26	22	18	15	13	12
12	15	18	22	27	32	33	34	36	39	36	34	32	29	25	21	17	13	13	12
13	15	18	21	25	29	33	33	34	37	34	33	33	28	24	20	16	13	12	12
12	13	16	19	23	27	30	30	31	32	31	30	28	25	22	19	15	11	11	11
10	10	14	17	21	24	25	26	27	28	29	28	25	22	20	18	14	10	9	9
8	10	12	15	18	20	21	22	23	24	24	23	21	19	18	15	12	9	5	7
4	8	10	12	14	16	17	18	19	19	19	18	17	16	15	12	10	8	7	7
7	8	9	9	10	12	13	15	16	16	15	14	14	14	13	11	8	5	6	7
8	8	7	5	5	8	7	12	14	14	12	7	11	12	12	10	7	3	5	6

Random entered values = 60
Interpolated values with <10% error= 157
Interpolated values with 10-20% error= 68
Interpolated values with 20%-50% error= 21
Interpolated values with >50% error = 94

Figure 5.9 A Typical Result from the Second 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 60 Random Values have Been Entered

Equation :- (40*((sin(X/20*Pi))*(sin(Y/20*Pi))))+1

2	1	4	6	5	1	4	4	1	4	4	1	4	4	1	1	3	3	2	2
2	3	6	8	8	6	7	8	7	8	7	7	7	7	6	5	4	4	2	1
3	5	7	10	11	11	12	13	13	13	13	13	12	11	10	9	7	6	4	3
5	7	9	12	14	15	16	17	18	19	19	18	17	16	14	12	10	7	5	3
6	8	12	15	18	20	20	21	22	23	24	23	22	20	17	15	12	8	5	1
5	10	14	18	21	24	24	25	26	27	29	28	26	24	20	17	14	10	5	4
6	12	16	20	23	26	27	29	30	31	33	32	30	27	23	20	16	11	6	6
11	14	18	22	25	28	30	33	34	35	35	35	33	30	26	22	17	12	9	7
12	14	18	23	28	31	33	37	39	39	38	37	35	31	28	23	18	14	10	6
11	13	19	24	29	33	35	38	40	41	39	37	35	32	29	24	19	14	9	1
7	13	19	25	29	33	35	38	41	41	39	37	35	33	29	24	19	13	10	6
10	13	19	24	28	32	35	37	39	40	40	37	36	32	29	24	19	14	10	8
11	13	18	23	27	31	35	36	37	39	39	36	34	31	28	23	18	13	7	8
10	13	17	22	26	30	33	34	35	37	36	35	33	30	26	22	17	13	9	8
6	11	16	20	24	27	29	31	32	33	32	31	30	27	24	20	16	11	6	6
7	10	14	18	21	24	26	28	29	29	28	28	26	23	20	17	14	10	5	5
5	8	12	15	18	20	22	23	24	24	24	23	22	20	17	15	12	9	5	4
5	7	9	12	14	16	17	19	19	19	19	18	17	16	14	12	10	8	5	1
3	6	8	9	10	12	14	15	14	14	13	13	13	11	10	8	7	6	5	3
2	5	6	5	5	6	10	11	7	9	7	7	9	6	5	6	4	3	4	4

Random entered values = 150

Interpolated values with <10% error= 169

Interpolated values with 10-20% error= 21

Interpolated values with 20%-50% error= 19

Interpolated values with >50% error = 41

Figure 5.10 A Typical Result from the Second 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 150 Random Values have Been Entered

Figure 5.11 shows the last two dimensional surface tested, and as it is a fairly complex one. The results in Table 5.3 and Figures 5.12 - 5.14 reflect this fact, with the accuracy of the prediction method dropping dramatically. Only when the S.L.P.M. is 37.5% full are the predictions acceptable i.e. 60% are within tolerance. This implies that for more complex surfaces, other methods of interpolating must be used in conjunction or instead of this method.

5.4.2 Three Dimensional Method

Table 5.4 gives the results of interpolation of a three dimensional simple equation. As with the two dimensional simple equation, a good correlation between predicted and actual values is seen (with the S.L.P.M. 20% full, 90% of the data is $\pm 10\%$). The time taken however, has increased dramatically, being some 6-7 time greater than for the two dimensional ripple.

The results of a complex three dimensional surface ripple are shown in Table 5.5. It can be seen that for this type of surface, other methods must be used such as curve fitting in conjunction with rippling, as the prediction method is inaccurate i.e with the S.L.P.M. 30% full, only 46.55% is with in the tolerance range.

5.5 Conclusion

In concluding this chapter, wear is a complex subject with many different parameters effecting the type and extent of wear. It is also a difficult parameter to measure, both physically and practically. Therefore, the prediction of likely scenarios is required to aid drilling performance. There are many equations which have been produced calculating wear rates etc, some in every day use. However in using these equations, improvements to prediction will never occur unless the equation is re-calibrated with field results.

The wear predictor used for the drill optimisation system was designed to eliminate this problem, and to learn the wear process, therefore continually improving its prediction performance. To do this data was stored in a matrix format (named Self Learning Prediction Matrices), in which wear or penetration rates could be referenced by specific parameters. As wear results are hard to generate, on each addition of a new value, the S.L.P.M. would be interpolated to estimate unknown data points. The interpolation system used the "ripple" technique, which performs an averaging process within the S.L.P.M. The test results of the predictor are encouraging, especially for

Equation :- 20*(sin(x/7*pi)*sin(y/12*pi))

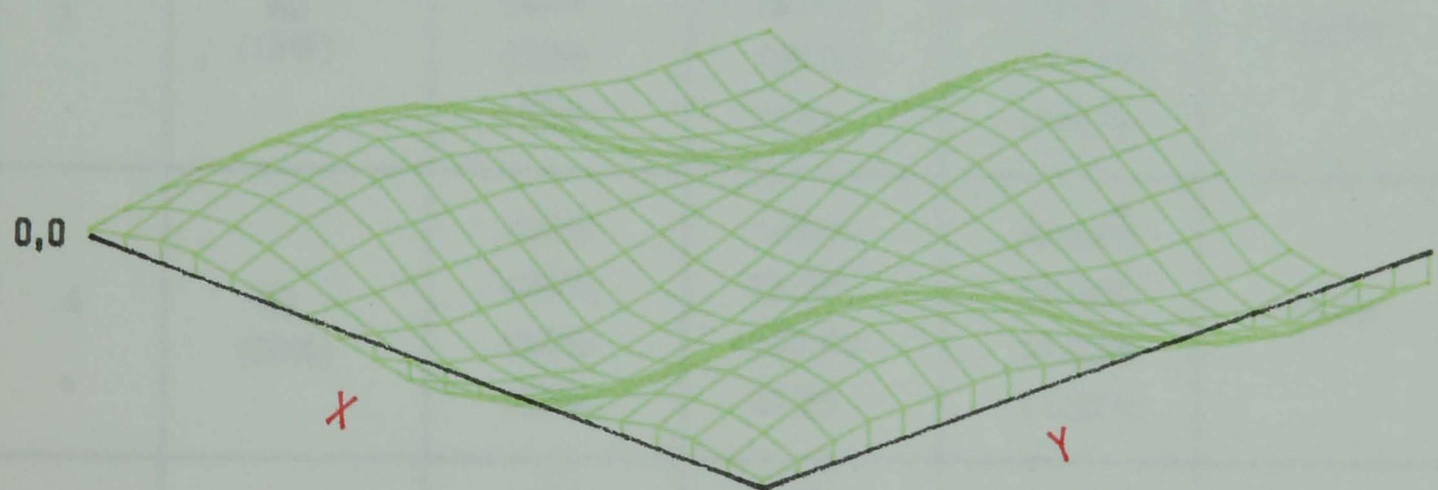


Figure 5.11 A 3-Dimensional Plot of the Equation Used for the Third Set of 2-Dimensional Ripple Tests

Table 5.3 :- 2-Dimensional Ripple Test 3

Matrix Size:- 20*20 **Number of Runs per Test :-** 20

Equation :- 20*((sin(x/7*Pi))*(sin(y/12*Pi)))

Test Number	Number of known values	Error in interpolated values.	Average number in error range	Average percentage in error range.	Average time taken to ripple all values (seconds)
1	20 (5%)	<10% <20% <50% >50%	89.05 16.50 85.45 209.00	22.26% 4.13% 21.36% 52.25%	5.00
2	40 (10%)	<10% <20% <50% >50%	115.70 31.15 117.90 135.25	28.92% 7.95% 29.47% 33.81%	7.95
3	60 (15%)	<10% <20% <50% >50%	135.55 39.20 150.60 74.65	33.89% 9.80% 37.65% 18.60%	10.30
4	80 (20%)	<10% <20% <50% >50%	162.55 53.20 137.00 47.25	40.64% 13.30% 34.25% 11.81%	11.95
5	100 (25%)	<10% <20% <50% >50%	183.60 64.60 126.75 25.05	45.90% 16.15% 31.65% 6.29%	13.45
6	150 (37.5%)	<10% <20% <50% >50%	238.80 77.30 72.55 11.35	59.70% 19.32% 18.14% 2.84%	16.70

Equation :- 20*(sin(x/7*pi)*sin(y/12*pi))

-6	-5	-4	-3	-2	-1	0	1	2	3	4	4	3	1	-2	-6	-10	-14	-13	-12
-6	-6	-5	-4	-3	-2	0	1	2	3	4	5	5	2	-2	-6	-11	-19	-14	-12
-7	-7	-7	-6	-4	-2	0	2	3	4	5	6	9	4	-1	-6	-10	-13	-12	-9
-8	-9	-10	-8	-5	-2	1	4	5	5	6	6	6	3	-1	-6	-11	-11	-10	-9
-9	-11	-17	-10	-6	-3	2	8	6	6	6	6	5	3	-1	-7	-17	-11	-9	-8
-8	-9	-10	-8	-6	-6	0	4	5	6	7	6	5	3	0	-4	-8	-8	-7	-6
-5	-6	-6	-6	-5	-4	-1	2	4	6	10	6	4	3	1	-2	-4	-5	-5	-4
-3	-3	-3	-3	-3	-2	-1	1	2	4	5	4	3	3	2	0	-2	-3	-3	-2
0	0	-1	-1	-1	-1	0	1	0	2	3	3	2	2	2	1	-1	-1	-1	-1
3	4	2	1	1	0	0	1	1	1	1	1	1	1	1	1	0	0	0	0
6	6	5	3	2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	11	7	5	4	2	0	-1	-1	-1	-1	-1	-1	-1	-1	0	0	0	0	0
7	8	7	6	5	3	0	-2	-3	-3	-3	-3	-3	-2	-1	0	0	0	0	0
6	7	7	8	8	4	0	-3	-5	-6	-6	-5	-4	-3	-1	0	0	0	0	0
5	6	7	10	16	5	-1	-5	-7	-9	-11	-8	-5	-3	-1	0	0	0	0	0
4	5	6	7	7	2	-3	-8	-8	-11	-19	-10	-6	-3	-1	0	0	0	0	0
3	4	4	4	3	0	-3	-6	-7	-9	-11	-8	-5	-3	-1	0	0	0	0	0
2	2	2	2	2	-1	-3	-5	-6	-7	-7	-6	-4	-3	-1	0	0	0	0	0
2	2	2	2	2	-1	-3	-4	-5	-5	-5	-4	-3	-2	-1	0	0	0	0	0
1	1	1	2	4	0	-2	-3	-4	-4	-4	-3	-2	-2	-1	0	0	0	0	0

Random entered values = 20
Interpolated values with <10% error= 67
Interpolated values with 10-20% error= 10
Interpolated values with 20%-50% error= 69
Interpolated values with >50% error = 234

Figure 5.12 A Typical Result from the Third 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 20 Random Values have Been Entered

Equation :- 20*(sin(x/7*pi)*sin(y/12*pi))

-10	-12	-13	-13	-12	-8	-3	1	4	4	3	1	0	-2	-5	-8	-10	-11	-12	-13
-8	-12	-14	-15	-15	-9	-3	3	7	5	3	1	0	-2	-6	-10	-11	-12	-13	-13
-9	-13	-16	-19	-14	-9	-2	6	16	7	3	1	0	0	-7	-16	-13	-13	-16	-13
-8	-15	-17	-19	-13	-8	-2	5	8	5	2	0	-1	-3	-6	-10	-11	-11	-12	-12
-11	-14	-17	-15	-11	-8	-1	8	5	3	1	-1	-2	-3	-5	-8	-9	-10	-10	-10
-10	-11	-12	-11	-9	-6	0	2	1	0	-1	-2	-2	-3	-4	-6	-8	-9	-9	-8
-8	-9	-9	-8	-8	-6	-3	-2	-2	-2	-2	-2	-2	-2	-3	-4	-6	-10	-7	-6
-5	-6	-6	-5	-5	-5	-4	-3	-3	-3	-2	-1	-1	-1	-1	-1	-2	-4	-3	-3
0	-2	-2	0	-3	-4	-4	-3	-4	-4	-3	0	0	0	1	2	2	1	1	0
2	1	1	1	-1	-2	-3	-2	-5	-6	-6	-4	-2	0	2	4	5	5	4	3
4	4	4	4	2	1	-2	-4	-7	-10	-10	-7	-4	-1	3	8	9	9	8	4
6	7	9	7	6	6	-1	-5	-8	-11	-12	-10	-6	-2	3	8	14	14	11	6
8	10	17	10	7	5	-1	-8	-10	-13	-17	-14	-8	-2	3	7	10	11	10	8
8	9	11	9	7	8	-1	-7	-10	-12	-14	-15	-8	-2	3	7	9	10	9	8
8	8	9	8	6	4	-2	-9	-10	-11	-12	-11	-7	-1	5	9	9	9	9	8
9	9	9	7	5	3	0	-6	-9	-11	-13	-10	-6	0	8	15	10	9	9	8
10	10	10	8	5	2	-1	-5	-8	-12	-17	-10	-5	0	5	9	9	9	9	8
10	11	14	10	6	2	-1	-4	-7	-10	-11	-8	-4	0	3	6	7	8	8	8
10	10	11	10	6	2	-1	-4	-7	-10	-8	-6	-4	-1	2	5	6	7	8	8
10	9	9	8	5	2	0	-3	-5	-5	-5	-5	-3	-1	2	4	5	6	7	8

Random entered values = 60
Interpolated values with <10% error= 80
Interpolated values with 10-20% error= 34
Interpolated values with 20%-50% error= 116
Interpolated values with >50% error = 110

Figure 5.13 A Typical Result from the Third 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 60 Random Values have Been Entered

Equation :- 20*(sin(x/7*pi)*sin(y/12*pi))

-14	-15	-16	-15	-14	-7	0	7	14	16	15	14	8	0	-8	-11	-14	-17	-14	-8
-13	-15	-19	-16	-13	-8	0	8	15	19	15	12	7	0	-7	-12	-15	-16	-15	-12
-9	-14	-17	-16	-13	-7	1	9	14	16	14	12	9	0	-9	-13	-19	-18	-16	-13
-11	-14	-17	-19	-15	-7	1	8	15	15	14	11	8	1	-6	-12	-19	-19	-15	-12
-11	-13	-17	-17	-12	-8	0	6	12	15	17	11	6	1	-5	-10	-15	-17	-13	-8
-9	-11	-14	-12	-9	-5	0	5	11	14	13	9	5	0	-6	-9	-12	-14	-11	-8
-4	-7	-9	-8	-8	-4	0	4	7	10	10	8	4	0	-4	-7	-10	-10	-7	-4
-2	-4	-5	-4	-4	-2	0	2	4	5	5	4	2	0	-2	-3	-4	-4	-4	-3
1	0	0	0	0	0	0	0	0	1	0	1	1	0	0	1	1	1	0	0
5	5	4	4	4	2	0	-2	-3	-3	-3	-2	-1	0	2	4	5	5	4	2
8	8	8	8	8	4	0	-4	-8	-7	-7	-6	-3	0	4	8	9	9	8	5
11	11	12	11	11	6	0	-6	-9	-11	-14	-10	-6	0	6	11	14	12	11	6
13	14	17	14	11	8	1	-6	-10	-14	-17	-14	-8	0	8	13	17	15	13	10
14	15	19	16	12	7	0	-8	-12	-19	-19	-13	-7	0	8	15	19	19	15	11
15	16	18	19	12	6	0	-6	-11	-15	-15	-11	-6	0	9	14	18	19	16	9
14	15	19	16	11	6	0	-6	-11	-14	-14	-11	-6	0	7	14	19	17	15	8
13	14	15	13	10	8	0	-7	-14	-15	-17	-14	-8	-1	6	14	15	14	13	10
11	12	14	11	8	5	-1	-6	-11	-14	-13	-11	-6	-1	5	10	12	12	11	10
9	9	9	8	6	3	-1	-4	-8	-10	-10	-8	-4	0	4	8	10	10	8	8
8	7	5	5	4	2	-1	-4	-6	-7	-5	-5	-2	0	4	7	8	7	4	6

Random entered values = 150
Interpolated values with <10% error= 86
Interpolated values with 10-20% error= 73
Interpolated values with 20%-50% error= 63
Interpolated values with >50% error = 28

Figure 5.14 A Typical Result from the Third 2-Dimensional Test Showing the Resulting S.L.P.M. Values after 150 Random Values have Been Entered

Table 5.4 :- 3-Dimensional Ripple Test 1

Matrix Size :- 10*10*10 **Number of Runs per Test :-** 20

Equation :- 2*X + 3*Y.+2*Z

Test Number	Number of known values	Error in interpolated values.	Average number in error range	Average percentage in error range.	Average time taken to ripple all values (seconds)
1	50 (5%)	<10% <20% <50% >50%	567.90 311.05 98.45 22.60	56.79% 31.10% 9.84% 2.26%	167.30
2	100 (10%)	<10% <20% <50% >50%	793.05 137.45 53.74 15.75	79.30% 13.74% 5.38% 1.57%	196.40
3	200 (20%)	<10% <20% <50% >50%	907.65 63.10 25.35 3.90	90.76% 6.31% 2.53% 0.39%	231.40

Table 5.5 :- 3-Dimensional Ripple Test 2

Matrix Size :- 10*10*10 **Numberof Runs per Test :-** 20

Equation :- 80*(sin(x/10*pi)*sin(y/10*pi)*sin(z/10*pi))

Test Number	Number of known values	Error in interpolated values.	Average number in error range	Average percentage in error range.	Average time taken to ripple all values (seconds)
1	50 (5%)	<10% <20% <50% >50%	137.80 99.10 311.85 451.25	13.78% 9.91% 31.18% 45.12%	126.65
2	100 (10%)	<10% <20% <50% >50%	202.90 125.95 270.70 400.45	20.29% 12.59% 27.07% 40.04%	182.35
3	200 (20%)	<10% <20% <50% >50%	342.35 174.60 180.15 302.90	14.23% 17.46% 18.01% 30.29%	241.90
4	300 (30%)	<10% <20% <50% >50%	465.50 182.60 120.95 230.95	46.55% 18.26% 12.09% 23.09%	267.20

simple functions. However as the functions become more complex, the accuracy of prediction drops. This indicated that some sort of polynomial curve fitting technique should also be developed to aid the rippling technique. In view that the predictor worked fairly well on moderately complex surfaces, work on the polynomial fitter was left, to return to once the initial optimisation system had be developed and was running.

Chapter 6 - The Control Algorithm

6.1 Introduction

In Chapter 1, an introduction was given to drilling optimisation and an indication of the requirements for the development of such a system. This concept was shown by Figure 1.2, where drilling parameters were fed to an Intelligent Knowledge Induction System, which was used to model the current drilling environment. It then selected and manipulated those parameters required to bring about an improvement to the current situation.

To enable an optimisation system to make such judgements, a decision has to be made on what is the requirement of the optimisation system, and through which controlling parameter or parameters, this can be achieved. Its relationship with other drilling parameters must also be considered, to ensure that they do not conflict with the overall optimisation scheme. This selection process was developed in Chapter 4. The optimisation criteria had previously been defined as achieving optimum operating performance through the trade off between penetration rates and wear rates. Many drilling parameters were proposed for the controlling parameter, but most were rejected. Cost per metre was selected, as it enabled both a relatively simple and flexible system to be developed. A simple cost equation was used incorporating running costs such as bit costs and rig charges. However, as this equation contained no parameters directly relating the drilling operation, it was manipulated to produce such an equation, with parameters more specific to the drilling operation. This equation 4.27 (shown below) would form the basis for the optimisation scheme.

$$C = \frac{(B + R \cdot T_m \cdot D) \cdot W}{K} + \frac{R}{P} \quad \text{---- (6.1)}$$

To use this equation however, data must be readily available for both penetration rates and wear rates. While penetration rates may generally be measured on line, wear rates are difficult to measure and often require extensive laboratory testing to obtain. A method for storing and enhancing known data was described in Chapter 5, where the concept of S.L.P.M.'s was developed and used to progressively learn and predict a process such as bit wear. Utilising these S.L.P.M.'s in the cost optimisation scheme, enables reliable and readily available data to prime the cost optimisation equation.

However, how is this data and the cost optimisation equation used, and by what process can the minimum cost operating point be determined? Once the optimum point has been established, can the system cope with a changing environment such as changing lithology? The answers to these questions forms the basis for this chapter and it describes the various methods which have been developed to locate the minimum cost operating point and overcome problems likely to be encountered by the optimisation system.

6.2 Establishing the Minimum Cost Operating Point

6.2.1 Maxima and Minima Theory.

In any process requiring either a maximum or minimum value to be found, one of the most simple and direct methods is that of maxima and minima theory. This states that when the first derivative is equal to zero, then a maximum, minimum or inflection is found. By substituting values back into the equation, the type of feature found may be established.

To apply this, the first derivative of equation 6.1 must be found. However it can be seen that there are two independent variables with respect to cost, that of penetration rate and wear rate. Therefore, substitution is required to eliminate one of them, i.e. a relationship between wear rate and penetration rate must be found such that :-

$$W = f(P) \quad \text{---} \quad (6.2)$$

Substituting this into equation 6.1 ,gives

$$C = \frac{(B + R \cdot T_m \cdot D) \cdot f(P)}{K} + \frac{R}{P} \quad \text{---} \quad (6.3)$$

and differentiating gives,

$$\frac{dC}{dP} = \frac{B + (R \cdot T_m \cdot D) \cdot f'(P)}{K} - \frac{R}{P^2} \quad \text{---} \quad (6.4)$$

To find the minimum, the equation is equated with zero, such that,

$$0 = \frac{B + (R \cdot T_m \cdot D) \cdot f'(P)}{K} - \frac{R}{P^2} \quad \text{----} \quad (6.5)$$

and thus

$$f'(P) \,.\, P^2 = \frac{R \,.\, K}{(B + R \,.\, T_m \,.\, D)} \quad \text{--- (6.6)}$$

However, to be able to solve this, the relationship $W=f\,(P)$ must be found.

The work reported by Ambrose, gave a series of relationships between varying rotational speeds and weight on bit values, with corresponding penetration rates and wear rates. For each rock type tested, values were entered into a database, allowing retrieval and also subsequent addition in the event of new values being generated. A curve fitting routine utilising least squares method was used on each set of data (i.e. for each different rock type) to determine a polynomial equation. The best fit was determined by visual observation. For simplicity the equations were kept to forth order or below. The resulting polynomial equation 6.7, thus gave the desired relationship between wear rates and penetration rates.

$$W = f\,(P) = E \,.\, P^4 + D.\, P^3 + C.\, P^2 + B \,.\, P + A \quad \text{---(6.7)}$$

where A,B,C,D,E are constants of the polynomial equation.

The resulting polynomial can be readily differentiated such that,

$$f'(P) = 4.\, E.\, P^3 + 3 \,.\, D.\, P^2 + 2 \,.\, C \,.P + B \quad \text{---(6.8)}$$

Substituting this back into equation 6.7, gives

$$(4.E.\, P^3 + 3 \,.\, D.\, P^2 + 2 \,.\, C \,.P + B).\, P^2 = \frac{R \,.\, K}{(B + R \,.\, T_m \,.\, D)} \quad \text{---(6.9)}$$

Hence by solving this, a minimum can be determined. This can be achieved using an iterative technique such as Newton Raphson.

The method described, formed the bases of a computer programme, which was developed at an early stage in the research project. It was developed to test the idea of cost optimisation and to learn and generate ideas which would aid the design of the main cost optimisation system.

From the work performed by Ambrose, four rock types had been tested, and thus penetration rates and associated wear rates from this work, were used to generate the polynomial relationship described. However, it should be noted that these relationships only hold for the data shown. They are not general rules or laws, but are solely used to show how such a relationship could be developed with progressive testing, and how these relationships may be used for minimum cost prediction.

The relationships developed are shown in Figures 6.1 - 6.4. Using these relationships, tables could be generated giving the cost per metre for differing values of the parameters in the cost equation, as shown in Table 6.1. It can be seen from this table that the penetration rates have been evenly space, having ten values ranging from maximum penetration rate to zero. The wear rates have been derived from the polynomial expression and these penetration rate values. From the minimum cost values for each depth (highlighted in the table), it can be seen that in certain cases as depth increases, the required penetration rate and wear rate change.

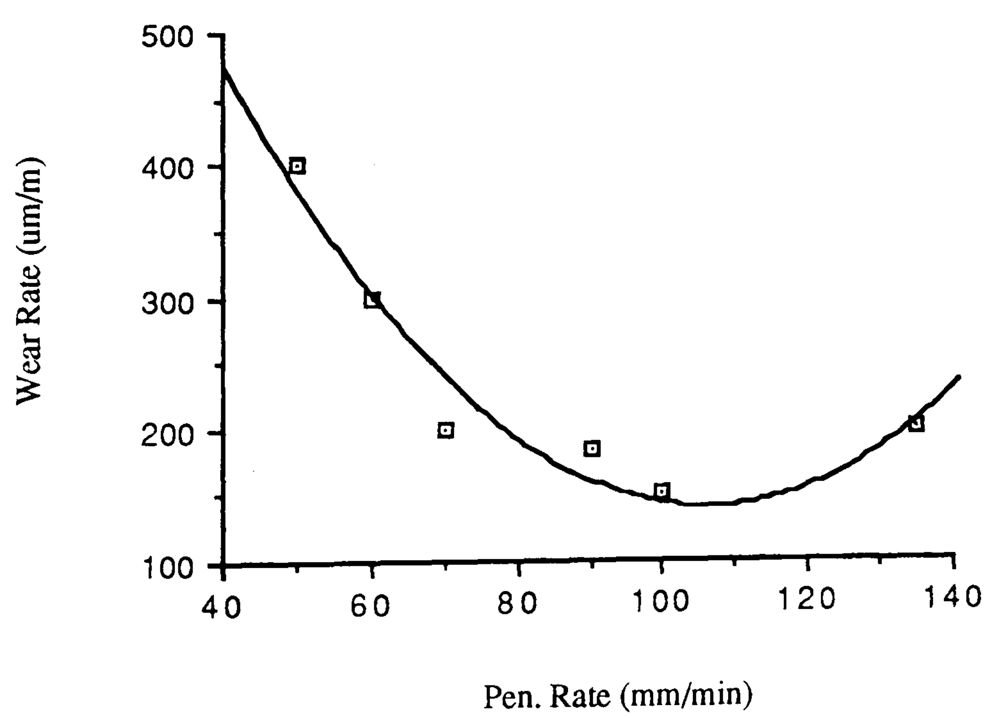
By utilising the principle of maxima and minima, and the substitution via the polynomial relationship, all previously described, the computer programme can be made to determine the best wear rates and penetration rates for a particular drill rig scenario, at any depth. Furthermore, as polynomial relationships have been derived for four rock types, the programme was developed to allow differing combinations and thickness of the rocks, hence giving self-designer bore holes.

Figure 6.5 shows the results of such a test on a hypothetical hole with the same rig conditions as shown in Table 6.1. It can be seen that on several occasions, changes of penetration rate and wear rate have been made within a particular lithology. Tripping depths and the cost per metre at the start and finish of each horizon are shown. Therefore by using this format, the proposed hole could be drilled at minimum cost.

However, while this method does give an easy solution, it should be remembered that penetration rates and wear rates are not truly interdependent, but there are many other variables which effect either one or both. For this reason, the assumption that $W = f(P)$ is invalid, and therefore this method was not persued any further. This method also has another disadvantage when considering development of a versatile optimisation system. To enable differentiation, the exact process must be known, either by a

Rock Type :- Gniess

Penetration Rate (mm / min)	Wear Rate (um / m)
50	400
60	300
70	200
90	185
100	150
135	200



$y = 1003.3038 - 16.2692x + 0.0767x^2 \quad R = 0.97$

Figure 6.1 Wear Rates Vs Penetration Rate Data, Graph and Polynomial Fit for Gniess

Rock Type :- Sandstone

Penetration Rate (mm / min)	Wear Rate (um / m)
50	180
100	150
150	110
200	100
250	95
350	90

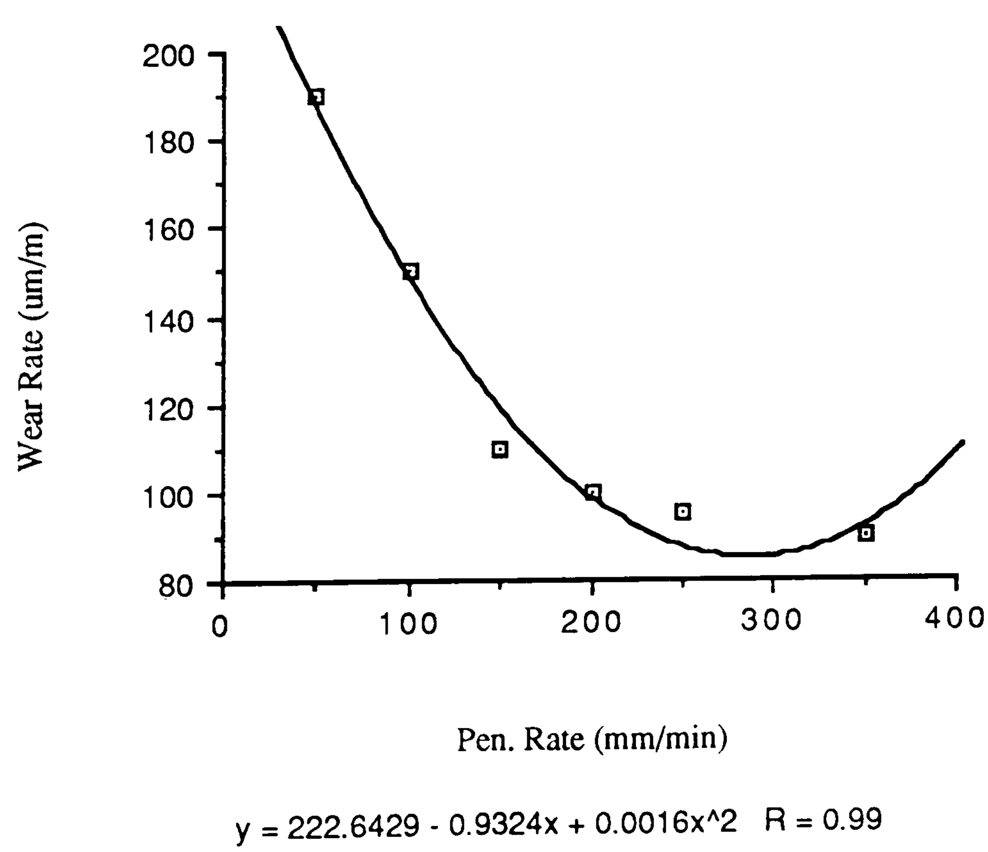
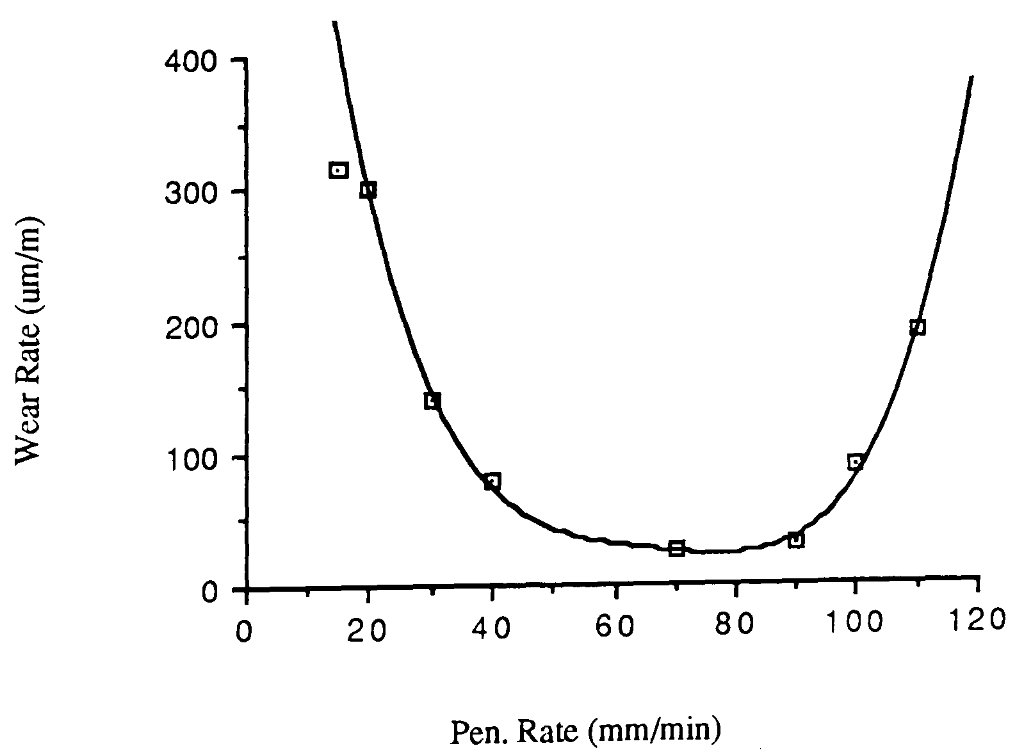


Figure 6.2 Wear Rates Vs Penetration Rate Data, Graph and Polynomial Fit for Sandstone.

Rock Type :- Limestone

Penetration Rate (mm / min)	Wear Rate (um / m)
20	300
30	140
40	80
70	25
90	30
100	90
110	190



y = 1017.9478 - 55.8907x + 1.2155x^2 - 0.012x^3 + 0.000e+0x^4 R = 1.00

Figure 6.3 Wear Rates Vs Penetration Rate Data, Graph and Polynomial Fit for Limestone

Rock Type :- Fine Grained Sandstone

Penetration Rate (mm / min)	Wear Rate (um / m)
100	40
150	41
200	42
300	45
350	50
380	70

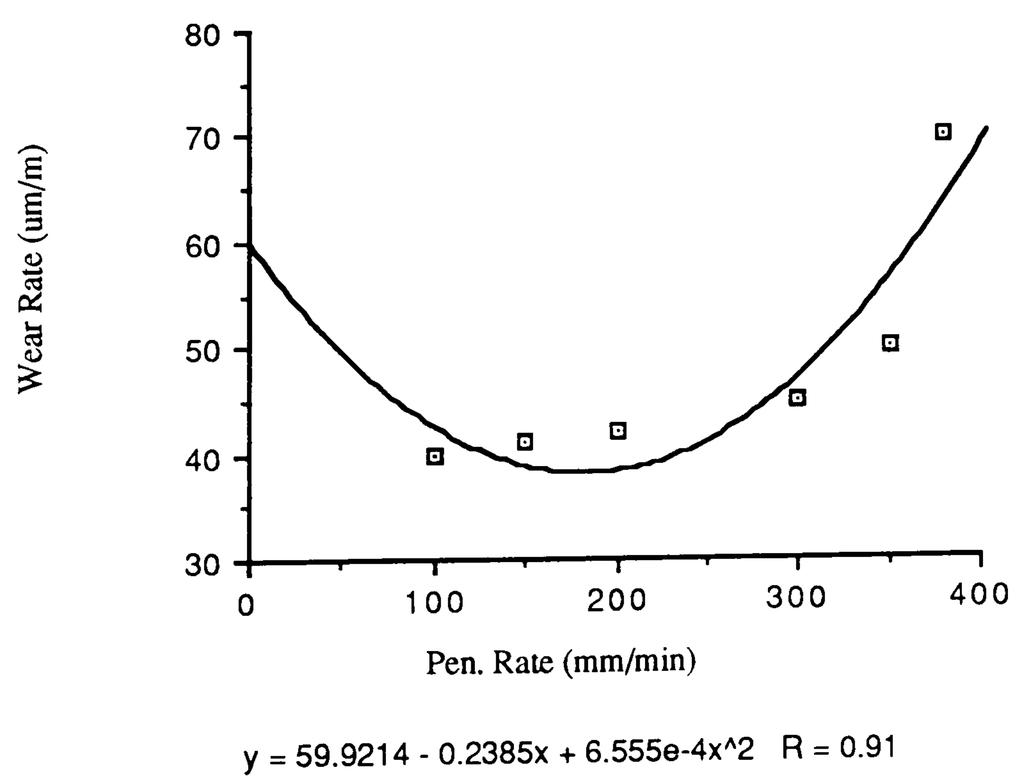


Figure 6.4 Wear Rates Vs Penetration Rate Data, Graph and Polynomial Fit for Fine Grained Sandstone.

Bit Costs = £1500

Rig Cost Per Day = £5000

Average Round Trip Time Per Metre = 20 seconds

Rock Type :- Gniess

Penetration Rate (mm/s)	Wear Rate (mm/m)	Depth (Metres)				
		10	100	500	1000	1500
2.250	0.205	56.71	58.84	68.33	80.20	92.06
2.025	0.159	**52.61**	**54.27**	61.63	70.83	80.03
1.800	0.141	53.46	54.93	**61.46**	**69.62**	**77.78**
1.575	0.151	59.57	61.14	68.13	76.87	85.61
1.350	0.189	71.44	73.40	82.15	93.09	104.03
1.125	0.255	85.45	87.79	98.21	111.23	124.25
0.900	0.349	117.05	120.69	136.85	157.04	177.24
0.675	0.470	156.78	161.67	183.43	210.63	237.83
0.425	0.620	229.88	263.34	265.05	300.92	336.80
0.225	0.798	377.83	386.14	423.08	469.26	515.44

Rock Type :- Sandstone

Penetration Rate (mm/s)	Wear Rate (mm/m)	Depth (Metres)				
		10	100	500	1000	1500
5.833	0.092	**23.83**	**24.79**	**29.05**	34.37	39.69
5.250	0.087	24.17	25.08	29.11	**34.14**	**39.18**
4.667	0.087	25.55	26.46	30.48	35.52	40.55
4.083	0.090	27.78	28.72	32.88	38.09	43.30
3.500	0.097	31.20	32.21	36.70	42.31	47.92
2.917	0.108	36.16	37.29	42.29	48.54	54.79
2.333	0.123	43.40	44.68	50.37	57.49	64.61
1.750	0.142	54.53	56.01	62.59	70.80	79.02
1.167	0.165	74.53	76.25	83.89	93.44	102.98
0.583	0.192	128.29	130.29	139.17	50.29	161.40

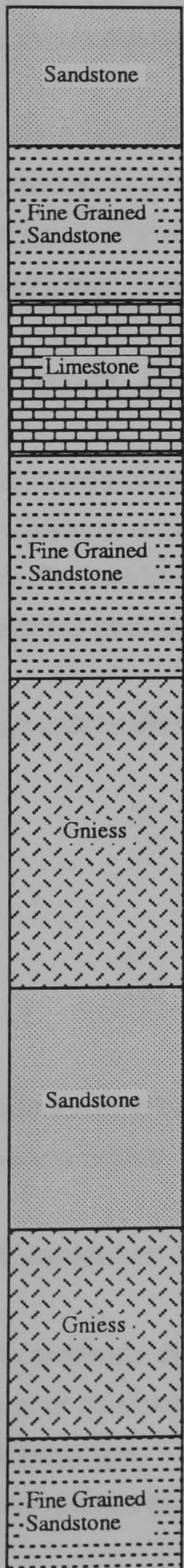
Rock Type:- Limestone

Penetration Rate (mm/s)	Wear Rate (mm/m)	Depth (Metres)				
		10	100	500	1000	1500
1.833	0.135	51.98	53.38	59.63	67.45	75.26
1.650	0.070	45.46	46.38	49.62	53.67	57.73
1.467	0.040	**45.49**	**45.91**	**47.76**	**50.08**	**52.39**
1.283	0.027	49.19	49.47	50.72	52.28	53.84
1.110	0.022	55.46	55.69	56.71	57.98	59.25
0.917	0.027	67.19	67.47	68.72	70.28	71.85
0.733	0.054	87.11	87.68	90.18	93.30	96.43
0.550	0.121	123.51	124.77	130.37	137.37	144.38
0.367	0.260	196.99	199.69	211.73	226.78	241.82
0.183	0.511	393.47	398.80	422.45	452.03	481.60

Rock Type :- Fine Grained Sandstone

Penetration Rate (mm/s)	Wear Rate (mm/m)	Depth (Metres)				
		10	100	500	1000	1500
6.333	0.064	18.81	19.48	22.44	26.15	29.85
5.700	0.055	**18.47**	**19.04**	21.59	24.77	27.95
5.067	0.048	18.68	19.18	**21.40**	**24.18**	**26.95**
4.433	0.043	19.55	20.00	21.99	24.48	26.97
3.800	0.040	21.28	21.69	23.54	25.86	28.17
3.167	0.038	24.02	24.41	26.17	28.37	30.57
2.533	0.039	28.74	29.15	30.95	33.21	35.47
1.900	0.041	36.66	37.08	38.98	41.35	43.73
1.267	0.046	52.63	53.11	55.24	57.90	60.56
0.633	0.052	99.28	99.82	102.23	105.24	108.25

Table 6.1 The Cost per Metre for Varying Penetration and Wear Rates, for the Rig Parameters and Rock Types Shown



Depth (Metres)	Crown Hieght (mm)	Comments	Cost per Metre	Penetration Rate (mm/s)	Wear Rate (mm/m)
0	10.00		£23.73		
				5.833	0.092
50	5.4		£24.25		
			£18.72		
				5.700	0.055
120	1.55		£19.17		
			£46.00		
159	10.00	Trip		1.467	0.040
220	7.56		£46.47		
			£19.80		
		Penetration Rate Change		5.700	0.055
270	4.81		£20.12		
				5.067	0.048
350	0.97		£20.57		
			£58.89		
356	10.00	Trip		2.025	0.159
415	0.62	Penetration Rate Change	£60.07		
420	10.00			1.800	0.141
492	10.00				
500	8.87		£61.46		
			£29.05		
596	10.00	Trip		5.833	0.092
610	8.712	Penetration Rate Change	£30.32		
				5.250	0.087
700	0.88		£31.12		
			£64.72		
706	10.00	Trip		1.800	0.141
777	10.00	Trip			
800	6.76		£66.36		
			£23.07		
941	10.00	Trip		5.067	0.048
1000	7.168		£24.18		

Figure 6.5 The Minimum Cost Results Obtained for Maxima and Minima Cost Optimisation

pre-defined equation or by data to which one can be fitted. Therefore, by using this method, an optimisation system could never start form a null state, thus would require test programmes from which the relevant data could be learnt. In an optimisation process, this is not desirable.

Despite these limitations however, the method of substitution and applying maxima and minima theory, is extremely useful and could be applied to aid the search algorithm for locating areas of minimum cost, especially when multi-slope surfaces are seen. This will be expanded later in Chapter 9.

6.2.2 Partial Differentiation

As the cost optimisation equation has two independent variables i.e. penetration rate and wear rate, it is possible to partially differentiate the equation with respect to each variable. The resulting equations may be solved in a similar way to find a minimum as that described previously.

The two partial differential equations of equation 6.1 are shown below.

$$\frac{\delta C}{dP} = \frac{(B + R \cdot T_m \cdot D)}{K} \cdot \frac{\delta W}{dP} - \frac{R}{P^2} \quad \text{---- (6.10)}$$

$$\frac{\delta C}{dW} = \frac{(B + R \cdot T_m \cdot D)}{K} - \frac{R}{P^2} \cdot \frac{\delta P}{dW} \quad \text{---- (6.11)}$$

A solution to these equations was sought, but none were found due to the large number of unknowns which make any solutions complex if not impossible.

6.2.3 Computer Search Methods

The two methods described above provide a direct method with which to locate a maximum or minimum position. However both these methods were ruled out for use in drill optimisation. Therefore a different way in which to use this equation to achieve optimisation must be found.

Developing technology has produced computers with ever increasing memory capacity and more importantly increased processor speed. This allows a large number of calculations to be performed in a short space of time. Consequently it is now possible to develop computer search methods which can cope with the large numbers of repetitive calculations required to find the optimum value or position.

Applying this to a drill optimisation scheme, associated combinations of penetration rates and wear rates could be fed through the cost equation and the combination yielding the minimum cost, used to set the drill parameters. However to do such calculations, the system requires the ready access of both penetration rate and associated wear rate data. Such a storage method was described in Chapter 5, where penetration rates and wear rates were stored by set reference parameters in S.L.P.M.'s. By accessing parameters common to both, a means of inter-relating the two can be established.

Therefore, the various combinations of wear rates and penetration rates can be fed through the cost equation to yield a minimum cost. Furthermore, as drilling progresses, the two S.L.P.M.'s will progressively learn their respective process and hence enhance the prediction of the minimum cost position. This process is shown in Figure 6.6.

However, by using this method, it has to be remembered that the process of wear rate and /or penetration rate may not be fully understood ie the S.L.P.M.s may only be partially full. Furthermore, if the system is starting from the null state, then they will contain no information. Therefore, as the computer searching method can only predict the minimum cost based on the information it contains, and hence the predicted minimum cost per metre may not necessarily be the true minimum cost per metre. This may be hidden in an area where information is sparse or unknown, and consequently not revealed by the S.L.P.M.'s interpolation method.

The control algorithm therefore, also has to be able to search for the true minimum cost position starting from that given by the predictors. This may be achieved by manipulating the drill's parameters and monitoring the response.

6.2.3.1 The Search Algorithms

The search algorithm has to be able to manipulate the drill parameters in such a way as to bring about an improvement to the current situation. Several methods were tried, each having a varying degrees of success. The results of the search methods are contained in the next chapter, but the theory of each is described below.

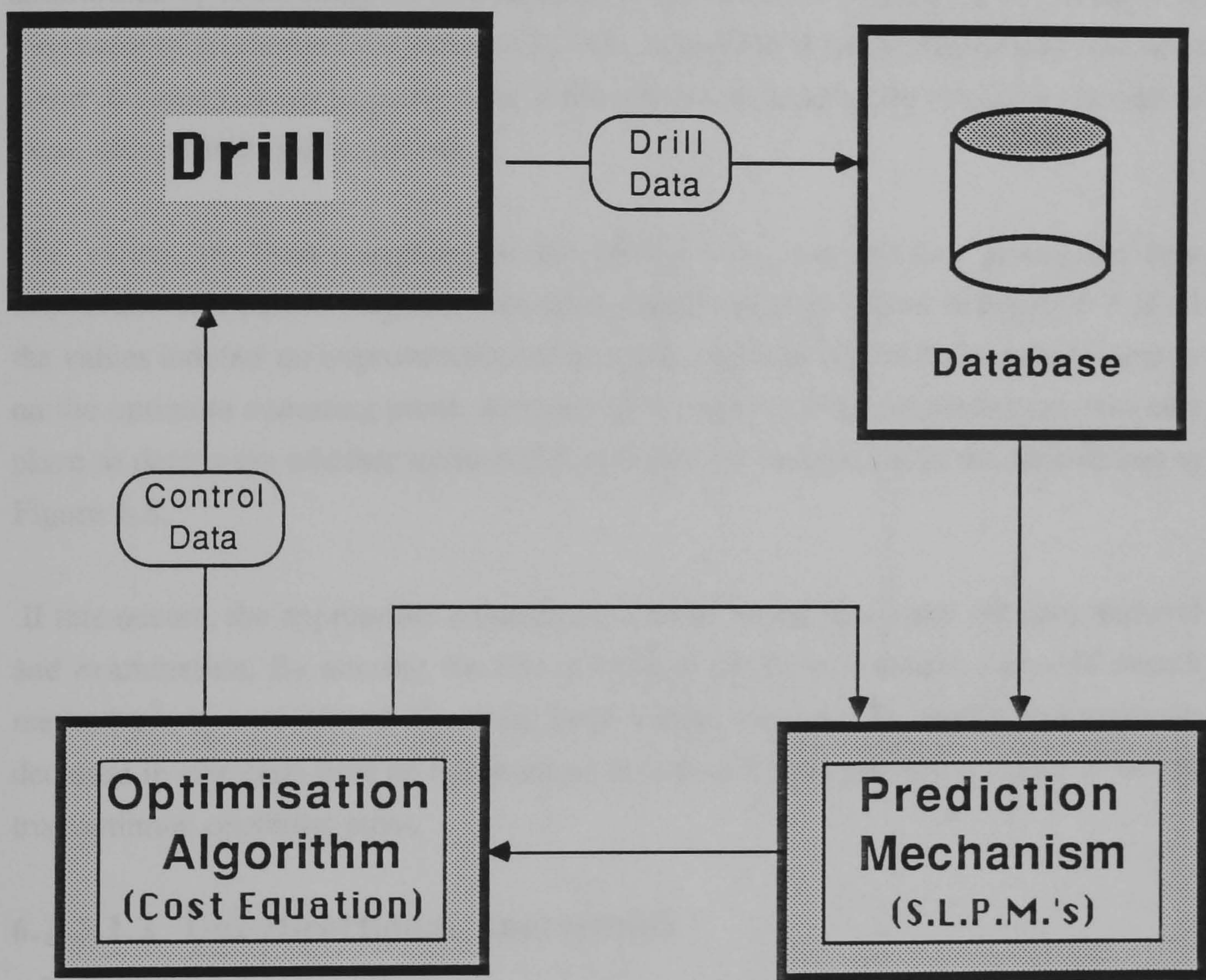


Figure 6.6 A Simplified Control Scheme with the Prediction Mechanism Included

6.2.3.1.1 Vector Method

This method was designed as an initial starting process, which would determine the best direction in which to manipulate the drilling parameters to bring about the greatest improvement over the current situation. From the selected starting point, four data points are established by manipulating the required parameters in a cross format and their differences compared to the central point established. The diagonal values are determined by summating the two adjacent cross values, if the point is an unknown. If the vector of this value falls between 30 - 60 degrees of the two cross values and has a positive value (i.e. an improvement in the current situation), the vector is deemed to exist, otherwise it is disregarded.

The values are then compared to the central one, and the one giving the best improvement selected, diagonal ones taking preference, as shown in Figure 6.7. If all the values indicate no improvement can be made, then the central point must be near or on the optimum operating point. Analysis of the other values calculated can also take place to determine whether multi-hump surfaces are present, as in the case shown in Figure 6.8.

If this occurs, the appropriate co-ordinates can be stored to a stack for later retrieval and examination. By altering the size of each of the crosses tested, a general search method can be established. By using large values to start with, which progressively decrease in size each time an optimum point is found, the system can 'home in' on the true optimum operating point.

6.2.3.1.2 Uni-Directional Increments

This is a very simple method and involves the manipulation of only one drill parameter at a time. Starting at the predicted minimum point, and either using a random starting direction or one selected by the vector method, an increment in this direction is taken e.g. an increase in rotational speed. The response of the drilling system is noted. Progressive increments are added until such time that a deterioration is experienced. The direction is then reversed, and backtracked until the optimum value for that parameter established. The search algorithm then selects another parameter, and optimises it in the same way. The parameter selection continues in a rotational fashion until no improvements are seen, indicating the optimum operating point has been reached.

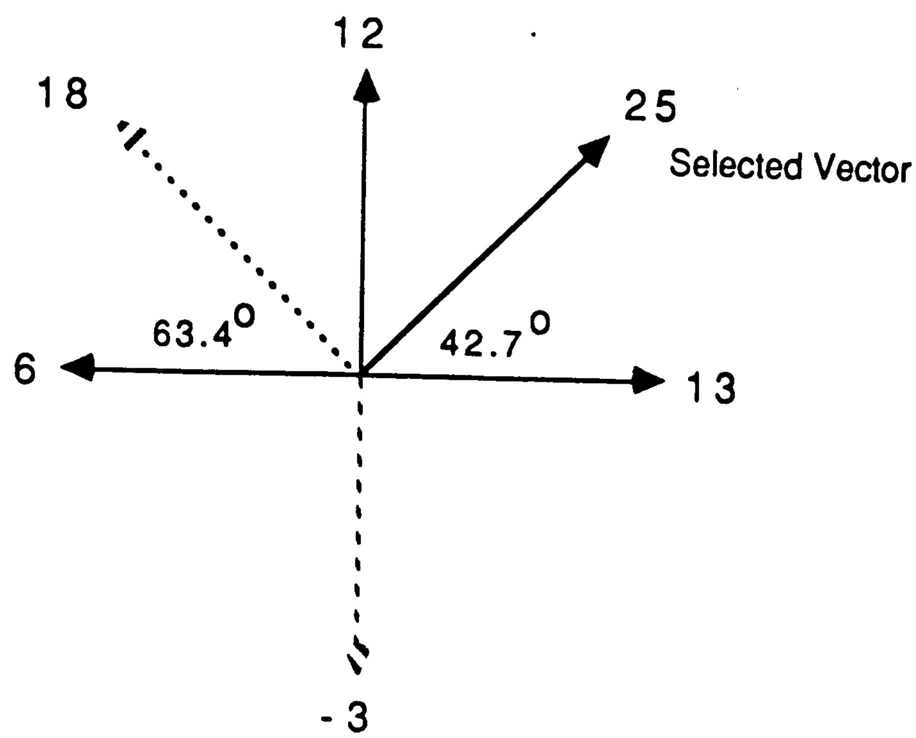


Figure 6.7. An Illustration of the Vector Selection Method

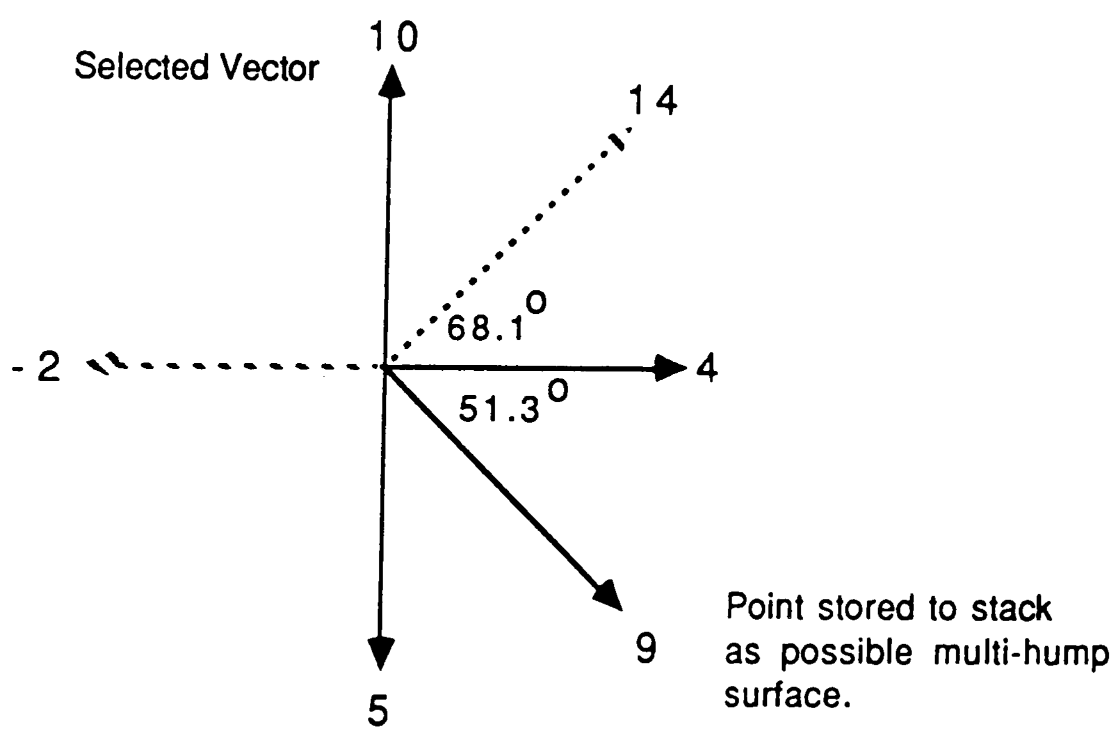


Figure 6.8. A Diagram to Show How the Vector Method May be Used to Aid Detection of Multi-Hump or Multi-Trough Surfaces.

6.2.3.1.3 Multi Directional Method

This method is similar to the uni-directional method but all parameters are searched at the same time. This is performed on a rotational bases. In turn, each of the parameters is manipulated in its respective direction and the response determined. If an improvement is seen the search algorithm moves to the new optimum point. If not, the search algorithm stays at the original position, and the direction of manipulation is changed. The parameter is not manipulated further until all the other parameters have been manipulated.

6.3 The Complete Cost Optimisation System

The complete optimisation system is summarised in Figure 6.9, which shows the main parts of the control scheme. Information about the drilling operation is fed directly via transducers on the rig etc, to a central data base. The information within this data base, along with external data such as wear rates, geology, etc is used to load two S.L.P.M., one for penetration rate, and the other for wear rate. The optimisation algorithm uses the cost equation to predict the estimated minimum cost position, from the data contained within these two S.L.P.M's. This estimated minimum cost may not necessarily be the true minimum cost, as the penetration rate and wear rate processes may not be fully understood i.e. the S.L.P.M.'s may only be partially full. Therefore, a search algorithm is used to manipulate the drill parameters in an effort to improve the current operating point and establish a lower minimum cost. This manipulation continues until no improvements are seen, whereby the true minimum cost operating point has been established.

As the cost optimisation scheme is running, new penetration rate and wear rate values will be generated, both from attaining the initial minimum cost predicated point and subsequent drill parameter manipulation. This data can in turn be fed back to the S.L.P.M.'s to improve their understanding of their respective processes, and thus aid subsequent minimum cost predictions.

Furthermore, with this fed back and progressive learning process, it would be extremely foolish to loose the data held within the S.L.P.M.'s once the hole had been completed. By saving the two S.L.P.M.'s to the computers disc system each time a hole is completed, then reloading them at the start of the next hole, the optimisation system's "experience and knowledge" can be passed on from hole to hole, in a similar fashion to a human drilling engineer.

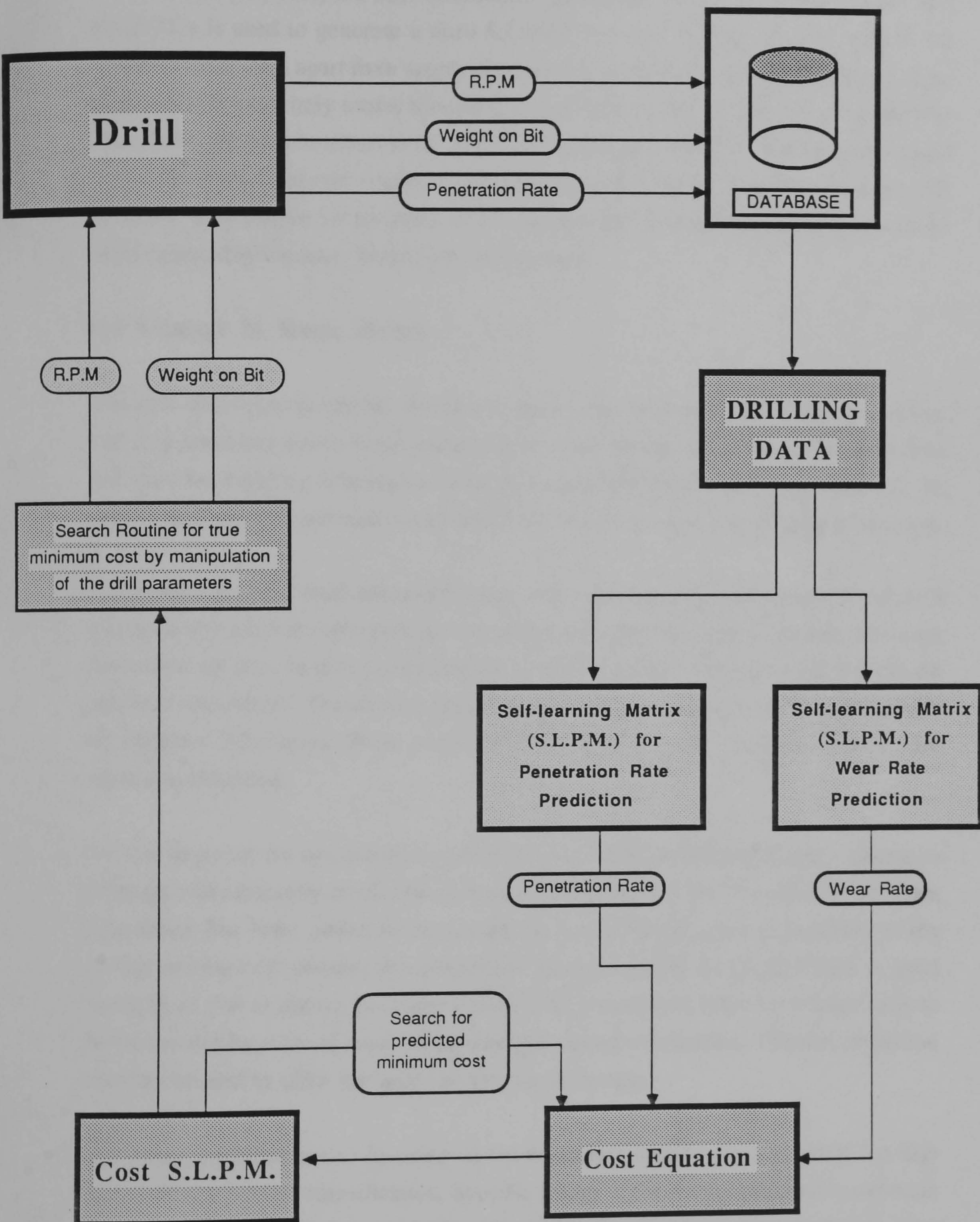


Figure 6.9 A Schematic Representation of the Cost Optimisation Control System

For research purposes, the cost information generated by cost equation and the two S.L.P.M.'s is used to generate a third S.L.P.M. for cost. It plays no real part in the optimisation system apart from supplying readily available cost data. For initial research purposes it is extremely useful however, as it allows access to what the computer has interpreted the cost function to be. When using the optimisation system in simulated mode, the interpreted cost function can be compared directly with the simulated cost function. This allows an accuracy of the interpretation to be determined, as well as ways to possibly improve the optimisation system.

6.4 Change in Rock Strata

The cost optimisation scheme discussed so far, has been made with the assumption that it is operating under homogeneous rock strata conditions. This is obviously rare and thus for differing lithologies, changes in penetration rate and wear rate will be seen. Therefore, any optimisation system must be able to cope with changing lithology.

The present system could adequately cope with rock strata changes, as the S.L.P.M.'s would slowly learn the new process associated with the new rock formation. However this would not only be time consuming but also destroy the information learnt about the previous rock strata. Therefore it would be advantageous to have a set of S.L.P.M.'s for different lithologies. These could be interchanged by the computer when a rock strata was indicated.

For this to occur, the optimisation system has to be able to initially detect a change in lithology and ultimately predict the new rock type being entered. The detection of strata boundaries has been under investigation for a number of years particularly in the surface mining environment to aid optimum blast design *(32,33,51,52,53,66)*. A good example of this is shown in Figure 6.10 where penetration rates have been used to determine the location of weak strata amongst strong overburden. This determination can then be used to allow the optimum placing of charges.

Increasing attention is also focusing on the parameter specific energy, which has also been used to aid strata identification. Specific energy is the energy required to excavate a unit volume of rock. It was originally proposed by Teale *(62)*, and is calculated by the equation 6.12.

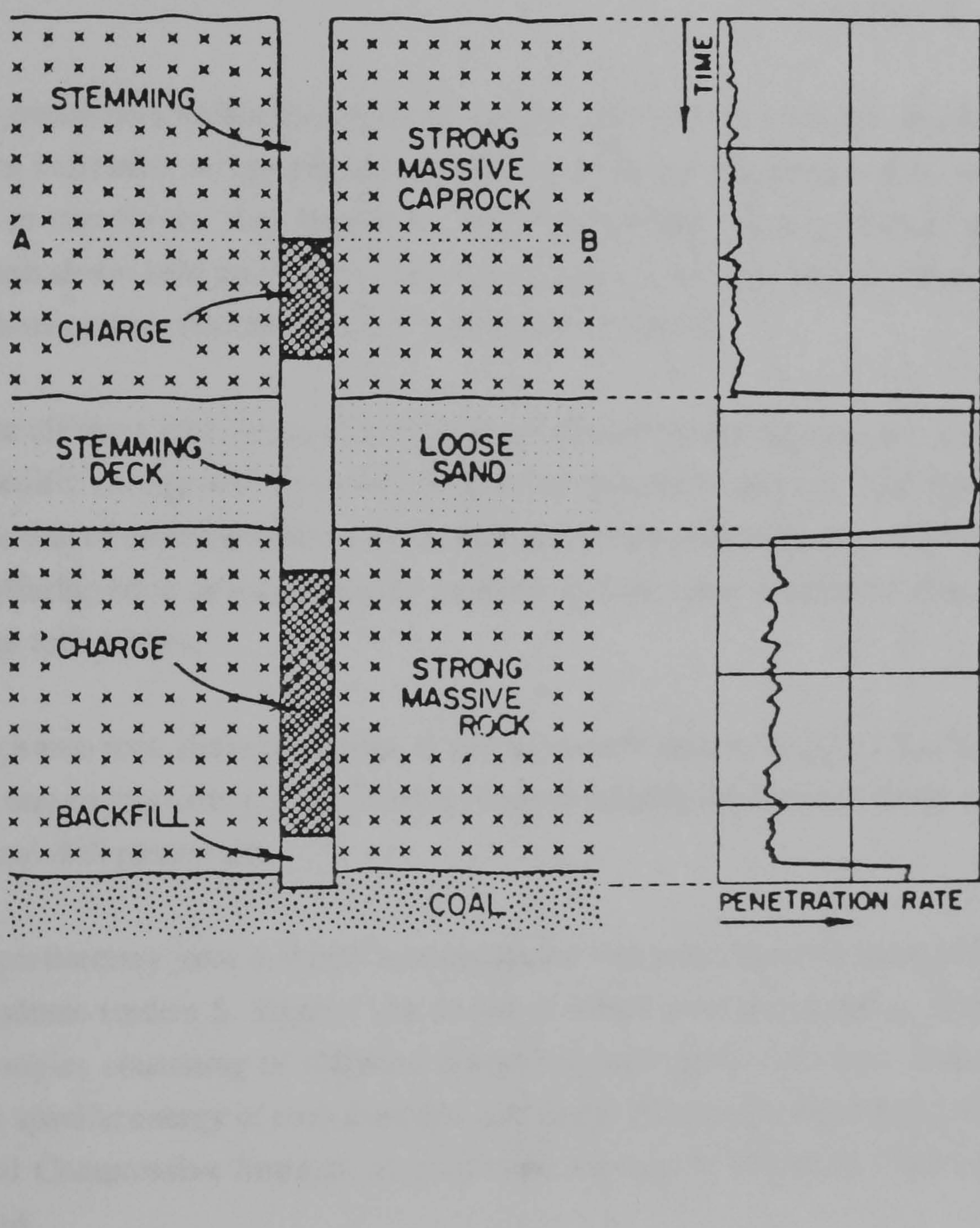


Figure 6.10 An Example of Strata Boundary Indication Through the Monitoring of the Drill Parameters

$$\text{Specific Energy (e)} = \frac{F}{A} + \frac{2\pi}{A} \cdot \frac{N \cdot T}{U} \quad \text{--- (6.12)}$$

where F = Force on the bit
A = Area of bit
N = Rotational speed
T = Torque
U = Penetration rate

All the parameters within this equation are generally easy to measure, and therefore a constant indication of specific energy can be obtained. However it was mentioned earlier in this thesis, that results are only worthwhile if the monitored data truly represents down hole conditions. In oil well drilling, the data may not be so, but it is the authors opinion that this problem will soon be resolved.

Thus for differing rock strata, differing ranges of specific energy are seen. It is unlikely that specific energy will be solely be able to be used to predict rock type. With a combination of other parameters such as torque, penetration rates etc, which all change with differing rock strata, it may be possible to find some method of characterising different rock stratas.

Research into rock strata prediction is still in is early stages *(21,32,51,52,71)*, but it is known that an increasing effort is being made to reliably predict rock strata types from monitored drill parameters.

Some preliminary joint research was conducted into strata identification with another post graduate student S. Rogers, the results of which were encouraging. A number of rock samples consisting of different limestones and sandstones were cored and the average specific energy of each core was calculated. Along with other such data such as Uniaxial Compressive Strength of each core, the graph shown in Figure 6.11 was produced.

It can be seen that there is a distinct zoning of the two rock types. At present, no further work has been undertaken to explore the possibility of whether other rock types fit into zones as well. If this is the case, this may allow an initial strata type predictor to be established.

Another important parameter which is also currently undergoing investigation is vibration analysis of the drill string. This is being used in an attempt to determine a

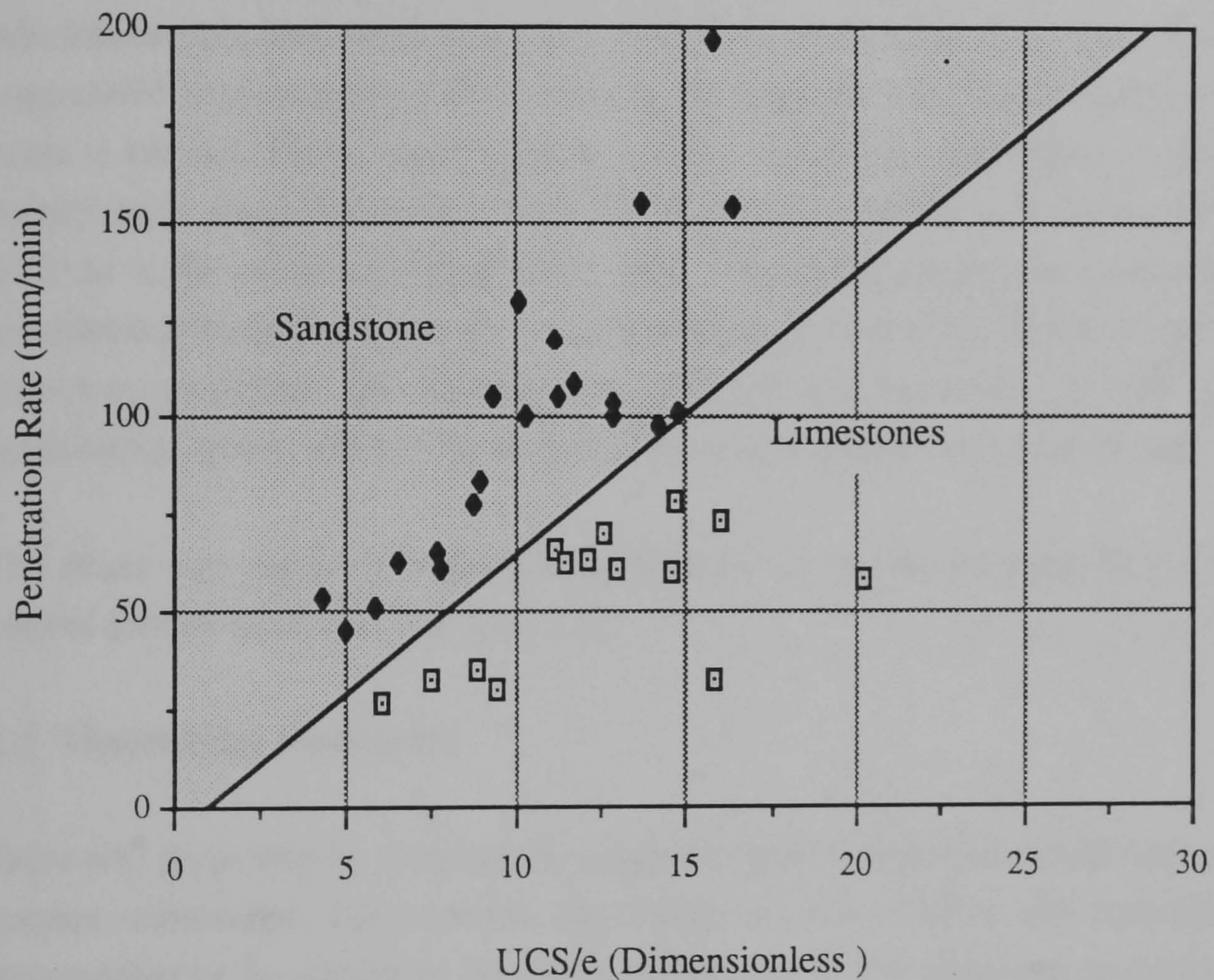


Figure 6.11 Relationship between Penetration Rate and the Dimensionless Index U.C.S /e (Ultimate Compressive Strength/ Specific Energy)

variety of information, ranging from bit wear to rock strata type, differing rocks having different vibration signatures *(51)*.

With a combination of such techniques, it is felt that a system capable of reliable rock strata prediction from monitored drill data, will be available in the foreseeable future.

Returning to the optimisation system, strata identification will thus allow the correct penetration rate and wear rate S.L.P.M.'s to be selected and used. Therefore progressive improvements will be made to the respective S.L.P.M.'s each time a rock strata is entered. Furthermore a check system can also be established to ensure the correct rock strata has been selected. On initial selection of a particular set of S.L.P.M.'s, the values contained within them can be compared to those actually being monitored. If large discrepancies are seen and persist, it is probable that a wrong strata type was predicted, and therefore re-selection can be made. In this way, the optimisation system will be able to cope with changing lithological conditions.

The strata type predictor and S.L.P.M. selector can be incorporated in the over all control scheme as shown in Figure 6.12.

6.5 Operating constants

There will frequently be situations in which the optimisation system will not be able to operate unbounded. For example directional controlled wells will necessitate the maintenance of the weight on bit within defined limits. The optimisation system could be developed to operate within certain operating constraints, in this example maintaining 'constant' weight on bit yet still optimising cost by controlling the other drilling parameters.

6.6 Conclusion

In conclusion, this chapter has developed a control strategy based on the cost equation 6.1, which was introduced in Chapter 4. A number of methods for determining the minimum cost operating point have been discussed. Initial attempts were focused on maxima and minima theory. A system was developed using this theory which worked successfully and gave a good insight to later work. However, in designing this system, the assumption that $W = f(P)$ was made, which in reality is not true. Therefore this method was abandoned. This method may be of great use however in improving the

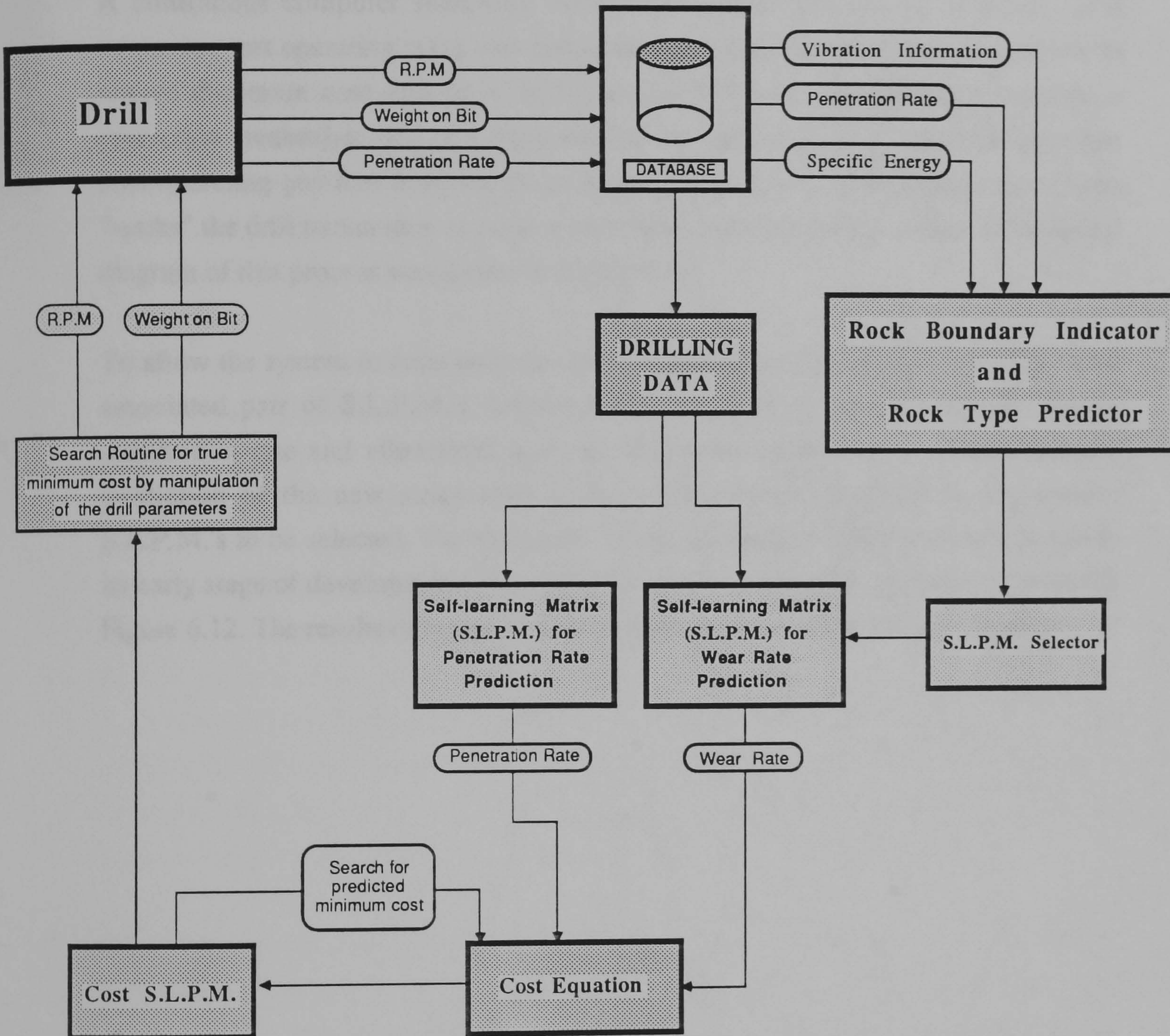


Figure 6.12 The Complete Cost Optimisation Scheme with Lithology Predictor

interpolation method of the predictors and locating multi-peak surfaces.Partial differentiation was also attempted but no solutions were found.

A continuous computer searching method was developed, which searches for a minimum cost operating point and continually manipulates the drilling parameters to ensure minimum cost drilling is being achieved. To aid this searching process, a prediction mechanism (the cost equation and the two S.L.P.M.'s) locates a minimum cost operating position from information previously learnt. The search routine then "walks" the drill parameters to the true minimum cost operating position. A simplified diagram of this process was shown in Figure 6.6.

To allow the system to cope with changes in lithology, each strata type will have an associated pair of S.L.P.M.'s. Using parameters such as specific energy, torque, penetration rate and vibrational analysis, rock boundaries will be detected and a prediction of the new strata type made, consequently allowing the appropriate S.L.P.M.'s to be selected. The prediction of multi-lithology holes however, is still in its early stage of development. The complete cost minimisation system was shown in Figure 6.12. The results of tests using this system are covered in the next chapter.

Chapter 7 - The Results of the Optimisation System

7.1 Introduction

The previous chapters have been concerned with the design of the cost optimisation scheme. This chapter discusses the development of the cost optimisation programme, and the results of the test work undertaken to validate the optimisation scheme. With the development of such a computer system, it is difficult to indicate to the reader in writing why certain methods are better than others and the success in performance of the optimisation scheme. However with the use of a 3-D plotting routine, it is hoped to convey this information, which would otherwise be easily shown visually by a demonstration of the optimisation system.

7.2 The Cost Optimisation Computer Programme

It has been previously been mentioned that the drill rig used in this research project, had been instrumented to allow monitoring and control of its parameters through a BBC Micro-computer. Due to the limited memory and processing power of this machine, the main optimisation system was developed on an I.B.M. type computer. To avoid the rebuilding of the drill electronics to suit the I.B.M., the BBC would be utilised in a front end processor role, with monitored data and control information being passed between the two machines via an RS232 data link.

The IBM supports many different languages, and therefore a decision on which one to base this optimisation system around had to be made. Several languages were considered 'C' and Pascal being the favoured two. Pascal is an extremely versatile language with both good user and graphics capabilities, as well as an easy structure. 'C' is a language which allows as standard many unorthodox practices enabling more innovative programming. However, this makes the code more difficult to understand. As this was an initial development system in which ready understanding of the various routines was necessary, Pascal was chosen.

The optimisation scheme in its entirety has been shown previously in Figure 6.12. It is a large and complex system. The development of the programme was therefore split into tasks which were developed, encoded and tested separately e.g. data transfer mechanism between the BBC and IBM, the data storage and interpolation method described in Chapter 5, the control scheme and search methods as discussed in Chapter

6. Many other minor tasks and utility programmes were also developed, such as a 3-D screen plotter, methods of developing customized simulation data, and X-Y plotter routines for hard copies.

If all these routines were contained in one programme, the size would be enormous hindering, editing and debugging. Therefore many of the tasks were split into Units (sub programmes which are compiled separately). These can be referenced (linked) to the main programme, and their contents used as normal.

7.3 The Testing of the Optimisation System

The majority of the test work focused on two main parts of the optimisation system, the data storage and interpolation method (S.L.P.M.'s) and the search routines for 'walking' the drill to the minimum cost operating point. The testing of the S.L.P.M.'s was covered in Chapter 5, and the results given. With this process developed, the testing of the search routines could be undertaken. The remainder of this chapter will focus on the results of the various search methods developed in Chapter 6 and the results of the overall cost minimisation system.

The testing of the optimisation system using the complete system i.e. the IBM, BBC and laboratory drill rig would have been extremely complex and tedious. Therefore it was decided to split the testing into several parts. An initial creditation phase would be conducted using the IBM alone, with set imaginary processes for penetration rates and wear rates. Once accomplished, the system could be tested by using the drill simulator incorporating the data transfer mechanisms between the IBM and the BBC, and finally the laboratory machine itself.

It was also felt that using the criteria of optimising by minimum cost would also add an extra degree of complexity due to the requirement of two simulators i.e for penetration rates and wear rates, to generate the cost data. The optimisation surface seen therefore, would bear no resemblance to either of these two processes. Consequently, this would hinder debugging and possible improvements to the search methods.

Therefore it was decided to test the various systems through maximisation of penetration rates. While this at first seem contrary to the design of the optimisation system, the criteria of both systems is to establish either a maximum or minimum point, by finding progressive improvements to the current operating point until such time that no improvements are made. Therefore by declaring whether an improvement is a lower value (i.e for minimising cost) or a higher value (for maximising penetration rates), the optimisation system can be used for both scenarios.

In this way, by using maximum penetration rates, only one simulation process is required. This gives a much simpler optimisation system, in which its search performance can be readily seen and interpreted. This would also aid later test work when using both the drill simulator and the laboratory drilling rig, as visual determination of maximum penetration rates is much easier than minimum cost.

7.3.1 Test Work Using the I.B.M Alone

Much of the development and test work was completed using the I.B.M on its own. This not only simplified the testing of the optimisation system as no data transfer mechanism etc was necessary, but also and more importantly reduced the time taken for each test, which was essential for debugging and further development work.

The series of tests conducted initially sought to establish the best search method for "walking" the optimisation system to the maximum penetration rate position. This search method would then be tested under more severe conditions. With this complete and the test results satisfactory, the optimisation system would be changed to minimum cost and the system tested under progressively adverse but realistic conditions.

7.3.1.1 Maximisation of Penetration Rates

As penetration rates are generally available on line, their ready availability negated the need for a prediction and interpolation mechanism, as this only serves to improve the overall understanding of the penetration rate process, and does not help optimisation. Therefore, when the optimisation scheme was tested using the maximisation of penetration rate mode, the ripple method was switched off, increasing the speed with which optimisation was achieved. For the description of the results however, it has been used to show how the ripple system aids overall understanding of the simulated penetration rate process.

Figure 7.1 shows the simulated penetration rate process used for all these tests. Each test was also started at the same point to allow some comparison to be made.

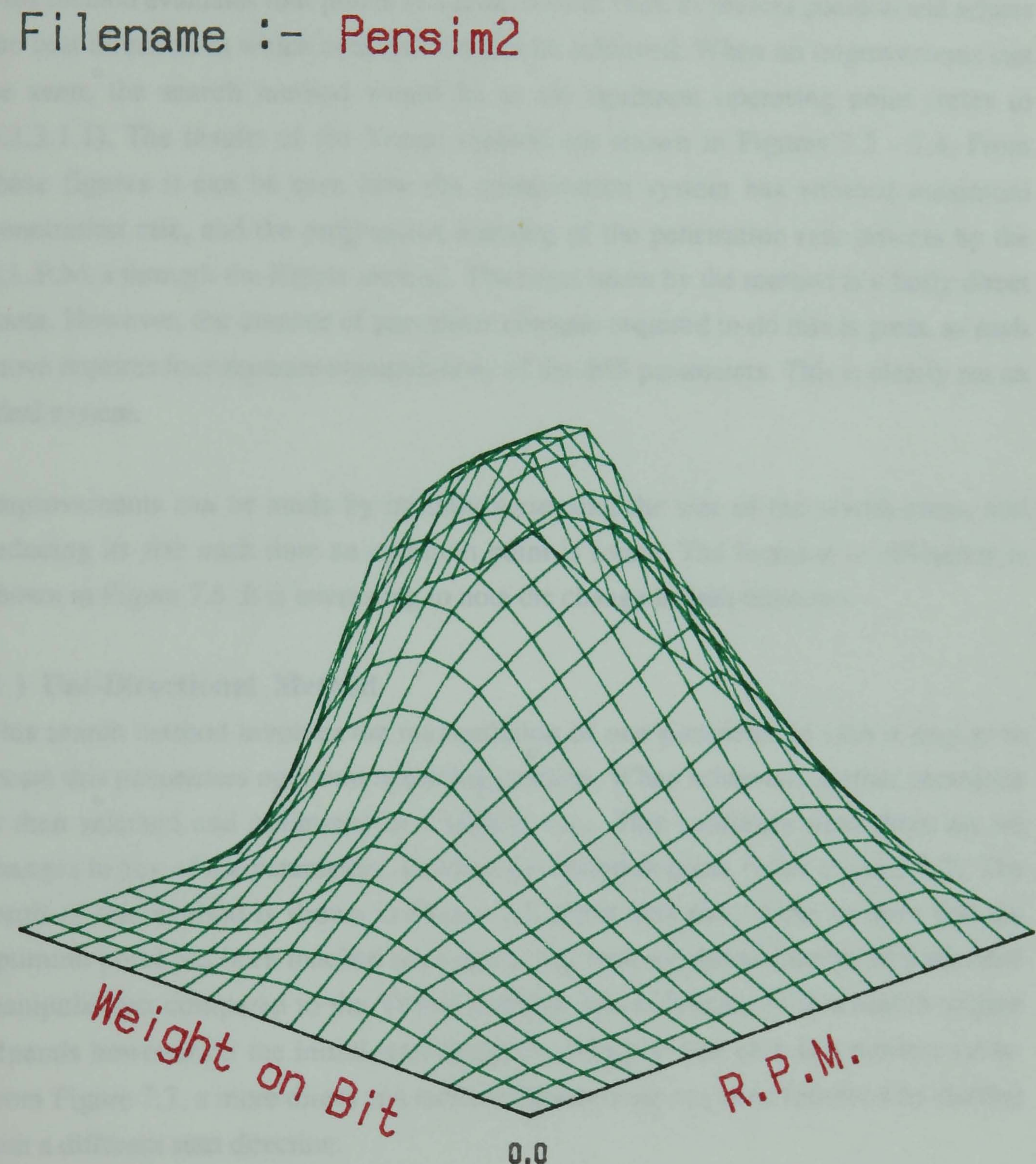


Figure 7.1 A 3-Dimensional Plot of the Simulated Penetration Rates Used in the IBM Alone Tests

7.3.1.1.1 Establishment of the Search Routine

i) Vector Method

This method evaluates four points in a cross format from its present position and selects the best direction in which optimisation can be achieved. When no improvements can be seen, the search method would be at the optimum operating point (refer to 6.2.3.1.1). The results of the Vector method are shown in Figures 7.2 - 7.4. From these figures it can be seen how the optimisation system has attained maximum penetration rate, and the progressive learning of the penetration rate process by the S.L.P.M.'s through the Ripple method. The route taken by the method is a fairly direct route. However, the number of parameter changes required to do this is great, as each move requires four separate manipulations of the drill parameters. This is clearly not an ideal system.

Improvements can be made by initially increasing the size of the search cross, and reducing its size each time an optimum point is found. The increase in efficiency is shown in Figure 7.5. It is interesting to note the change in path direction.

ii) Uni-Directional Method

This search method involves the manipulation of one parameter in such a way as to locate this parameters optimum operating position. When achieved, another parameter is then selected and optimised in a similar way. This continues until there are no changes in any of the parameters, yielding the optimum point. (refer to 6.2.3.1.2). The result of this method is shown in Figure 7.6. From this plot, it can be seen that the optimum point has been reached once again, but with a reduced number of parameter manipulations compared to the Vector method. The efficiency of this search routine depends however on the initial start direction, which in this case is a random value. From Figure 7.7, a more direct and hence efficient route has been followed by starting with a different start direction.

iii) Combined Vector and Uni-Directional Method

To eliminate the faults of the last two systems i.e, the large number of holes required by the Vector method and the varying efficiency of the Uni-Directional method, a combined system was developed.

In this search method, the initial start direction would be determined by the Vector method. The Uni- Directional method would then continue to optimise in this direction until an optimum was found. The Vector method would be used once again to select

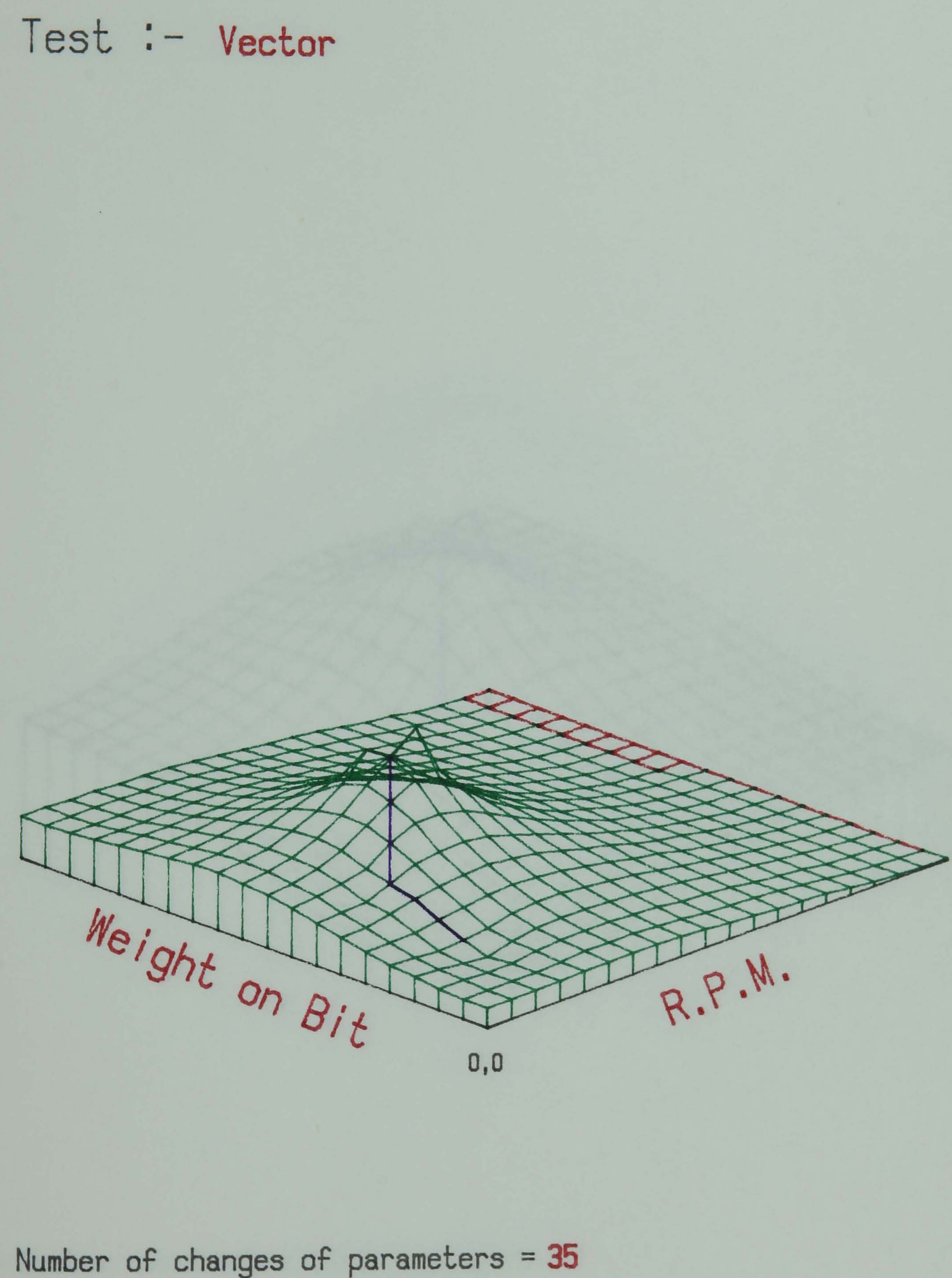


Figure 7.2 An Early Stage of the Vector Method Locating Maximum Penetration Rate Process

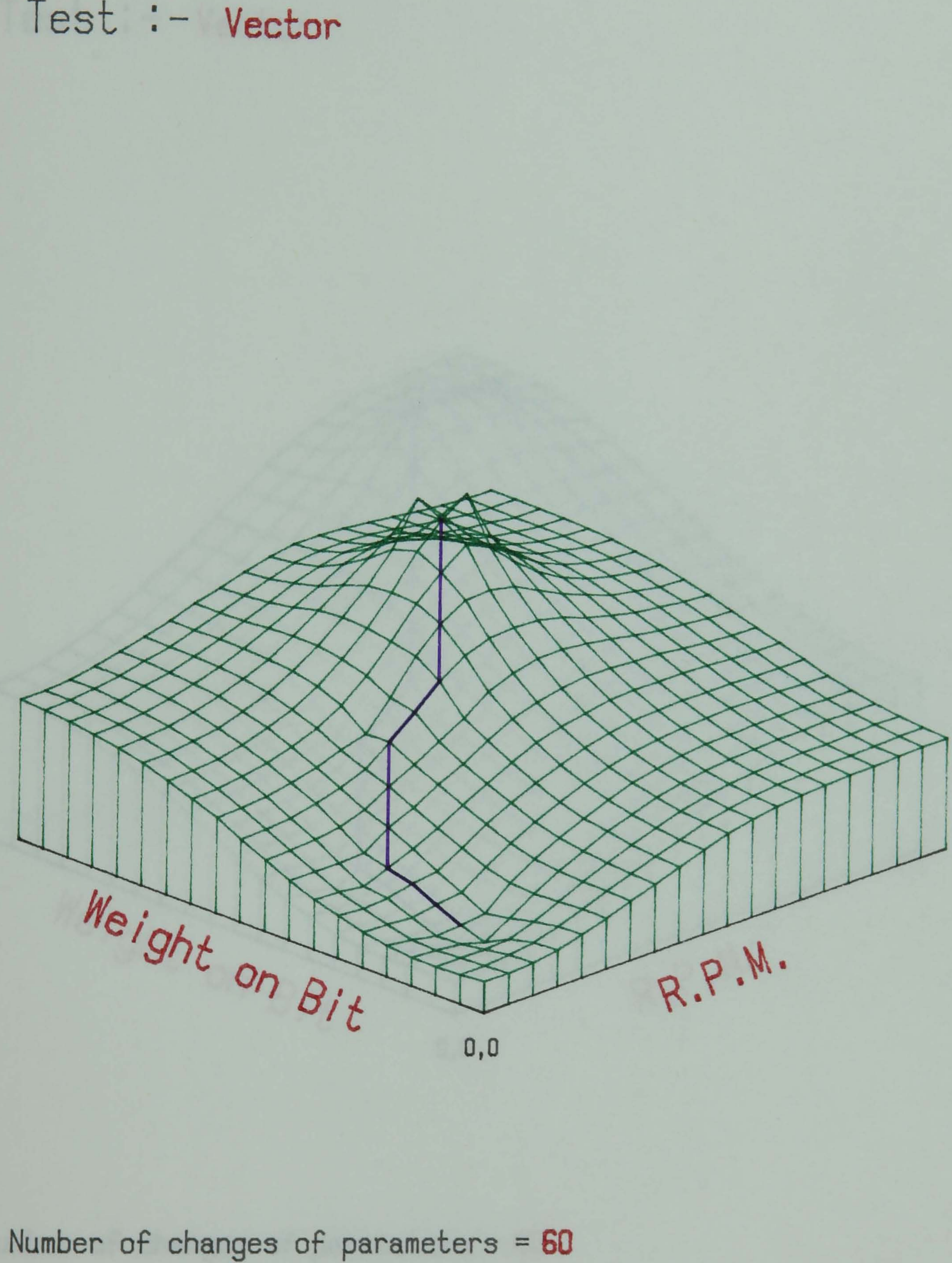


Figure 7.3 An Intermediate Plot of the Vector Method Test Showing the Progressive Learning by the S.L.P.M.of the Penetration Rate Process

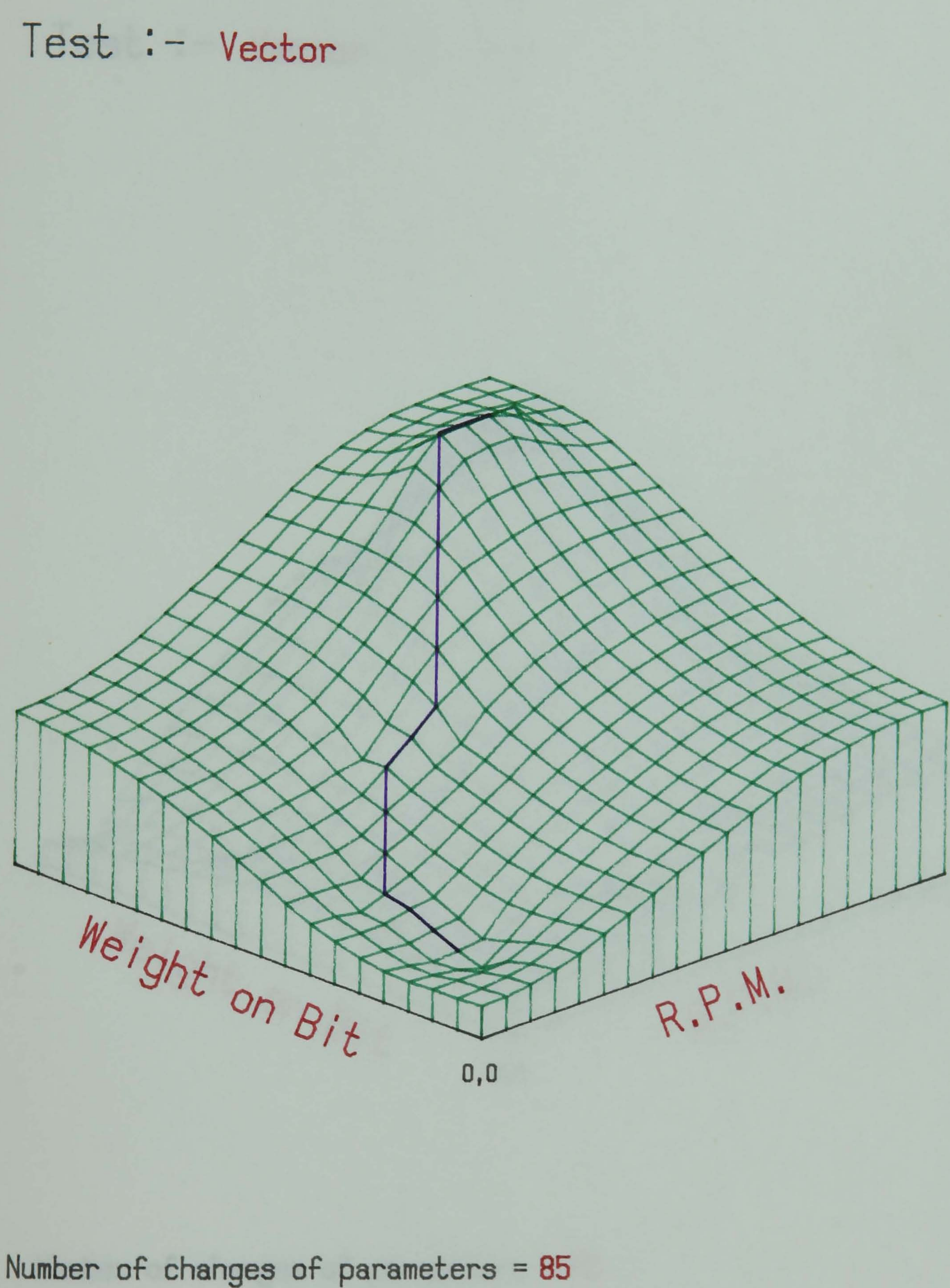


Figure 7.4 The Final Path Taken by the Vector Method to Locate Maximum Penetration Rate

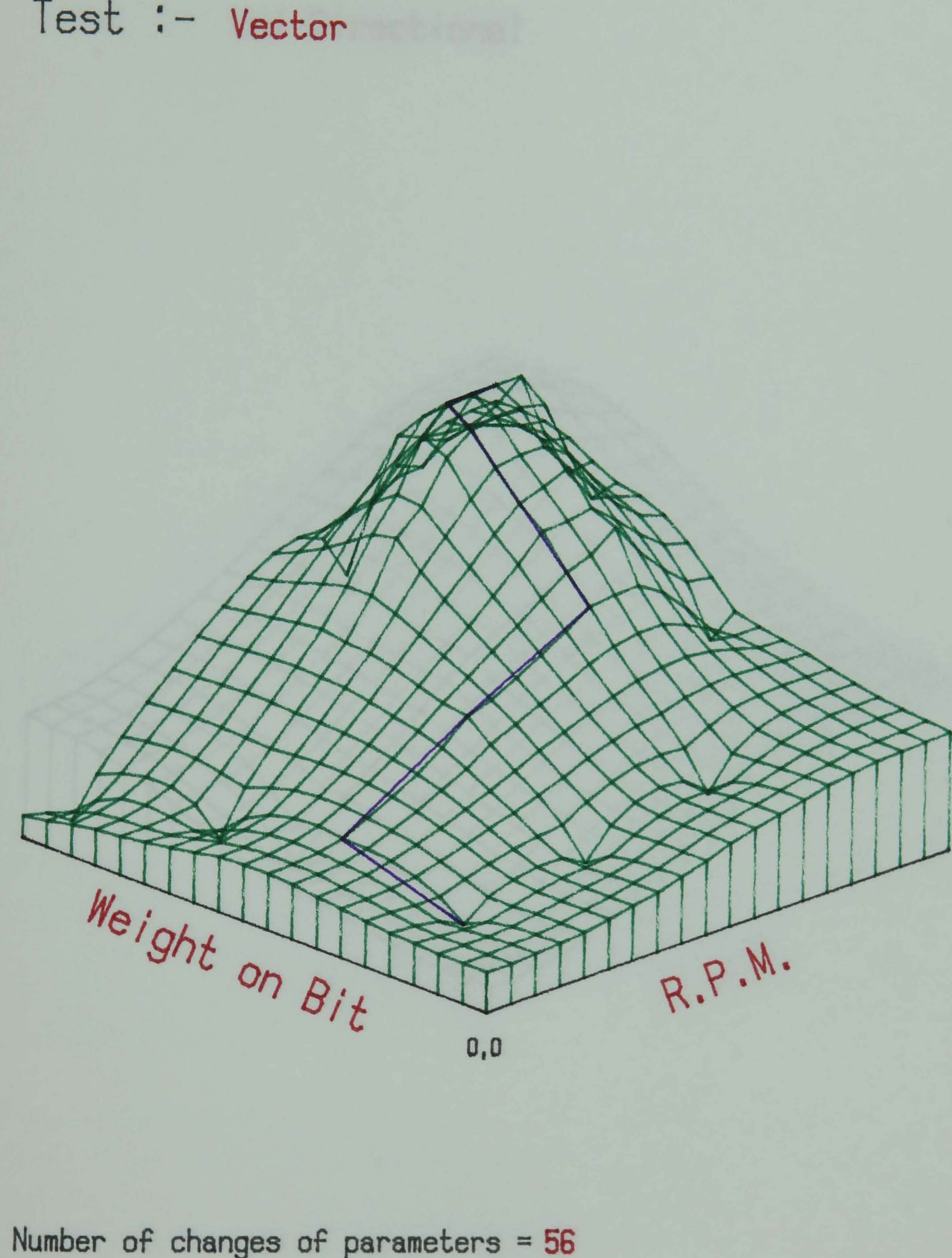


Figure 7.5 An Illustration of the Improvement in Efficiency of the Search by Increasing the Size of the Search Cross

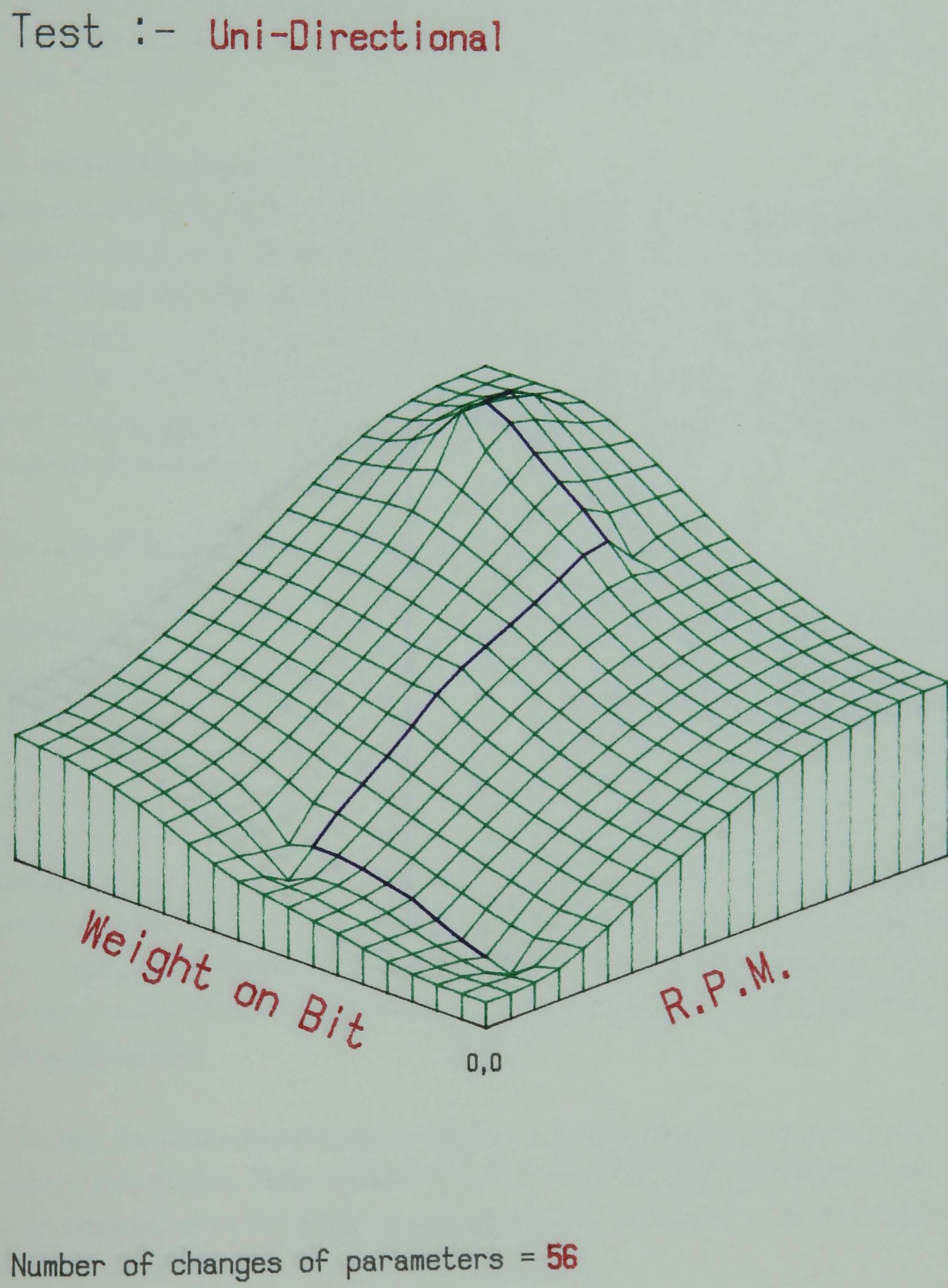


Figure 7.6 A Plot of the Final Path Taken by the Uni-Directional Method to Locate Maximum Penetration Rate

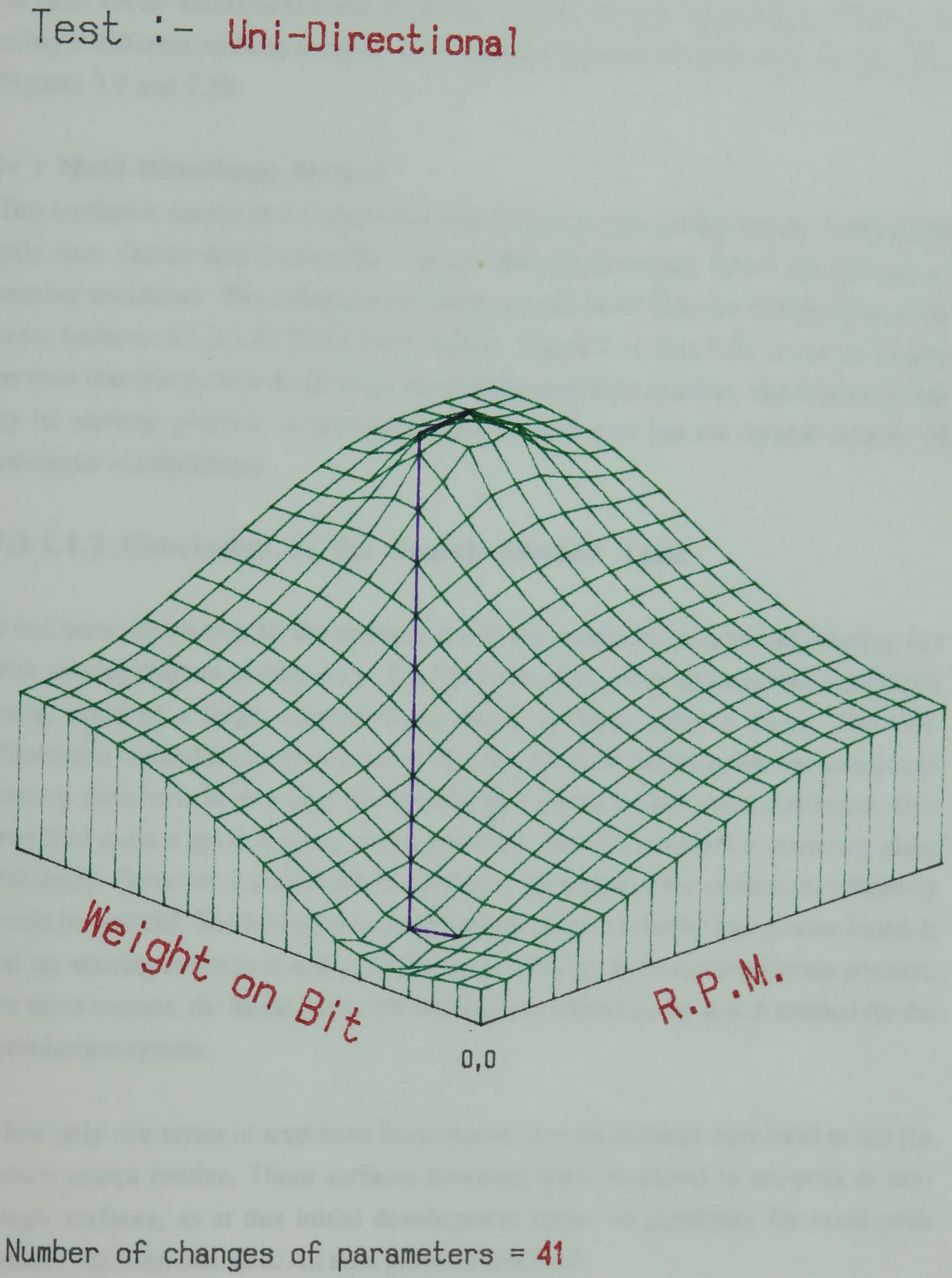


Figure 7.7 The Change in the Efficiency of the Uni-Directional Method Caused by a Different Starting Direction

another direction for optimisation by the Uni-Directional method. This would continue until no further changes were seen. Figure 7.8 shows the result of this method. Ironically, in this case it has followed the same path as the Uni -Directional method, as on each vector assessment these directions proved the most promising. However by using a different starting location the benefit of the combined system can be seen - Figures 7.9 and 7.10.

iv) Multi-Directional Method

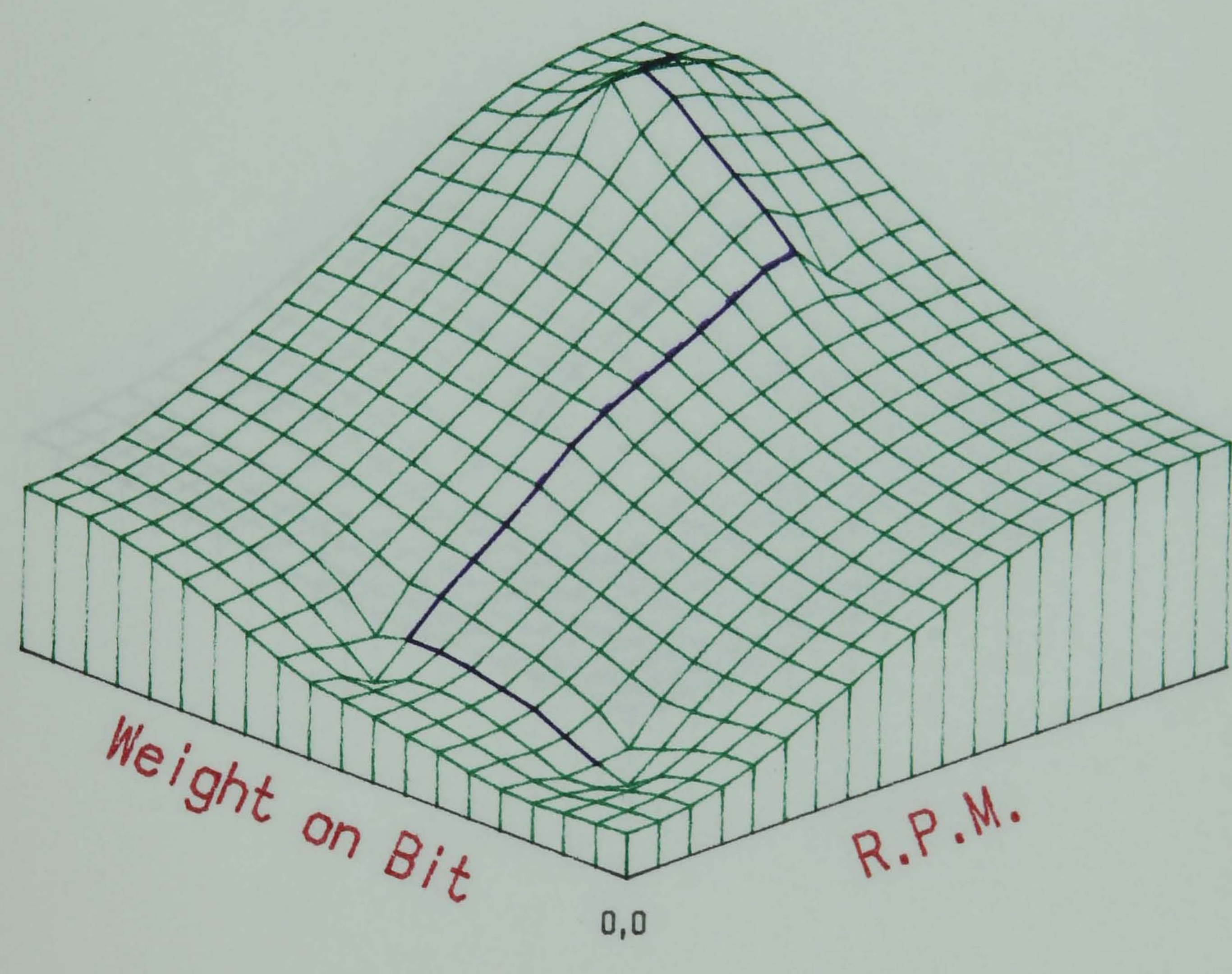
This method is similar to the uni directional method but the parameters are manipulated only once (rather than continually until an optimum is found), before the selection of another parameter. The rotational selection repeats itself until no further change are seen, (refer to 6.2.3.1.3). From these results, Figure 7.11 and 7.12, it can be clearly be seen that this picks a direct route locating the optimum position, and is not effected by its starting position or direction. This method also has the lowest number of parameter manipulations.

7.3.1.1.2 Conclusion of the Search Method Tests

It has been shown that all the methods found the maximum penetration position, but with varying degrees of efficiency. The Vector method while choosing the most direct route, required a large number of parameter manipulations to do so. The Uni-Directional method could also be one of the most efficient methods, but was sensitive to starting direction. In an effort to enhance both systems, they were combined. This produced quite a good system, which generally found the optimum operating point efficiently. However in certain situations due to the nature of the surface, its efficiency would be reduced. The Multi-Directional method proved to be the best routine tested. It had no starting constraints and established a near direct route to the optimum position. For these reasons, the Multi-Direction method was chosen as the search method for the optimisation system.

While only one series of tests have been shown, several surfaces were used to test the chosen search routine. These surfaces however, were restricted to uni-peak or uni-trough surfaces, as at this initial development stage, no capability for multi-peak surfaces has been included. All tests proved successful.

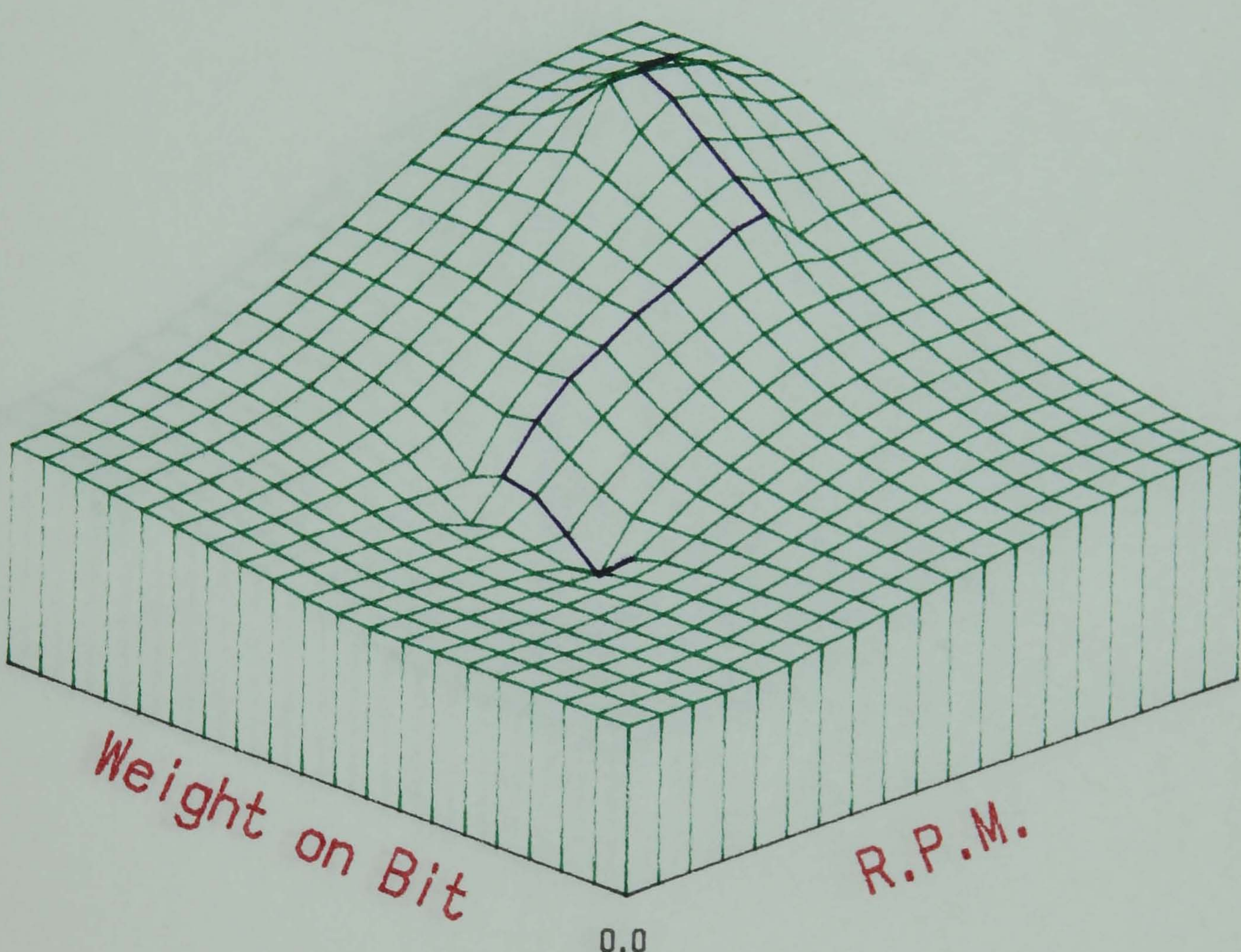
Test :- Combined Vector and Uni-Directional



Number of changes of parameters = 71

Figure 7.8 The Final Path Taken by the Combined Vector and Uni-Directional Method to Locate Maximum Penetration Rate

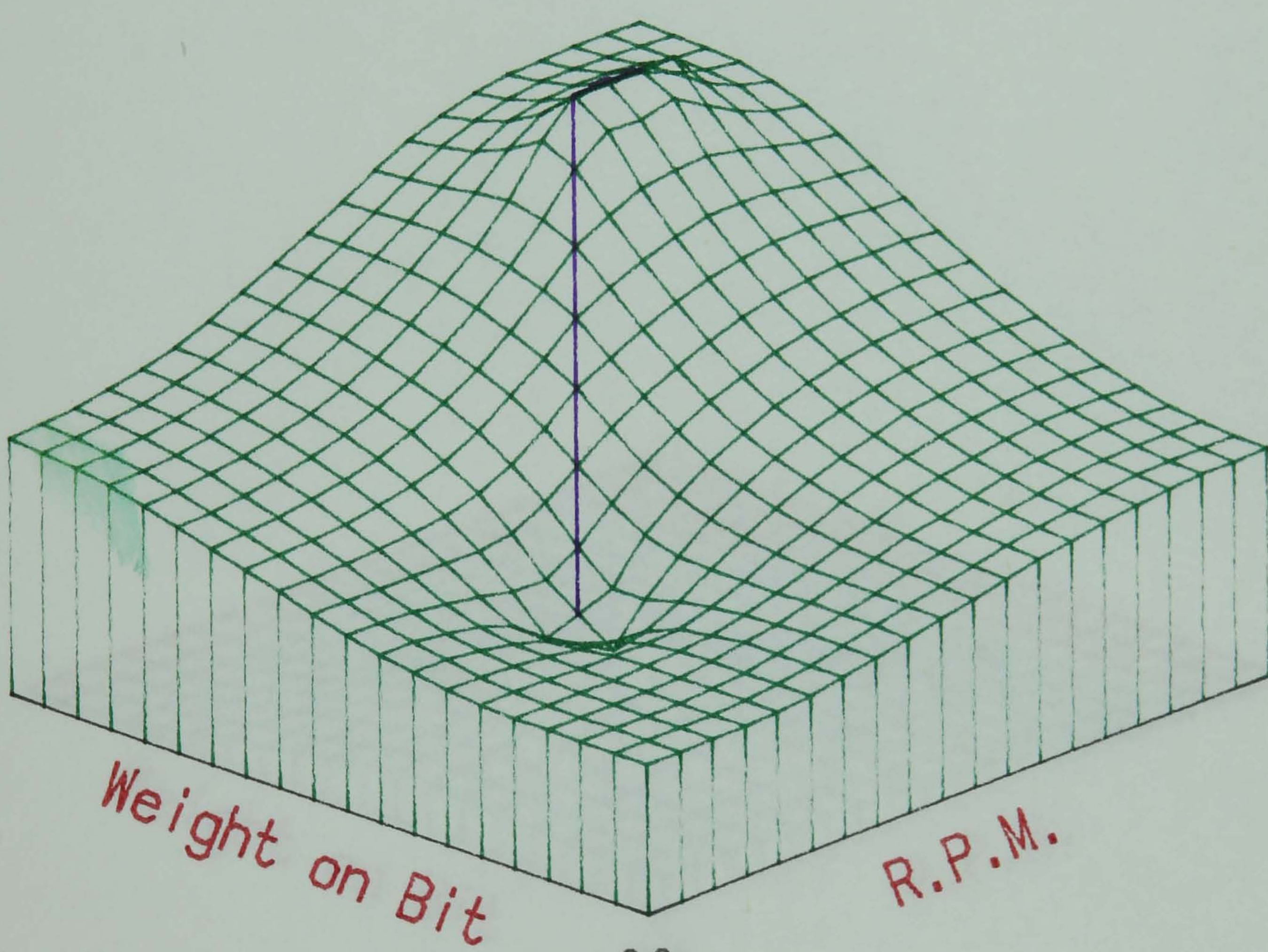
Test :- Uni-Directional



Number of changes of parameters = 43

Figure 7.9 The Path Taken to Locate Maximum Penetration Rate by the Uni-Directional Method from a Different Starting Position

Test :- Combined Vector and Uni-Directional



Number of changes of parameters = 77

Figure 7.10 The Benefit of the Combined Method Over the Uni-Directional Method Starting from the Same Location

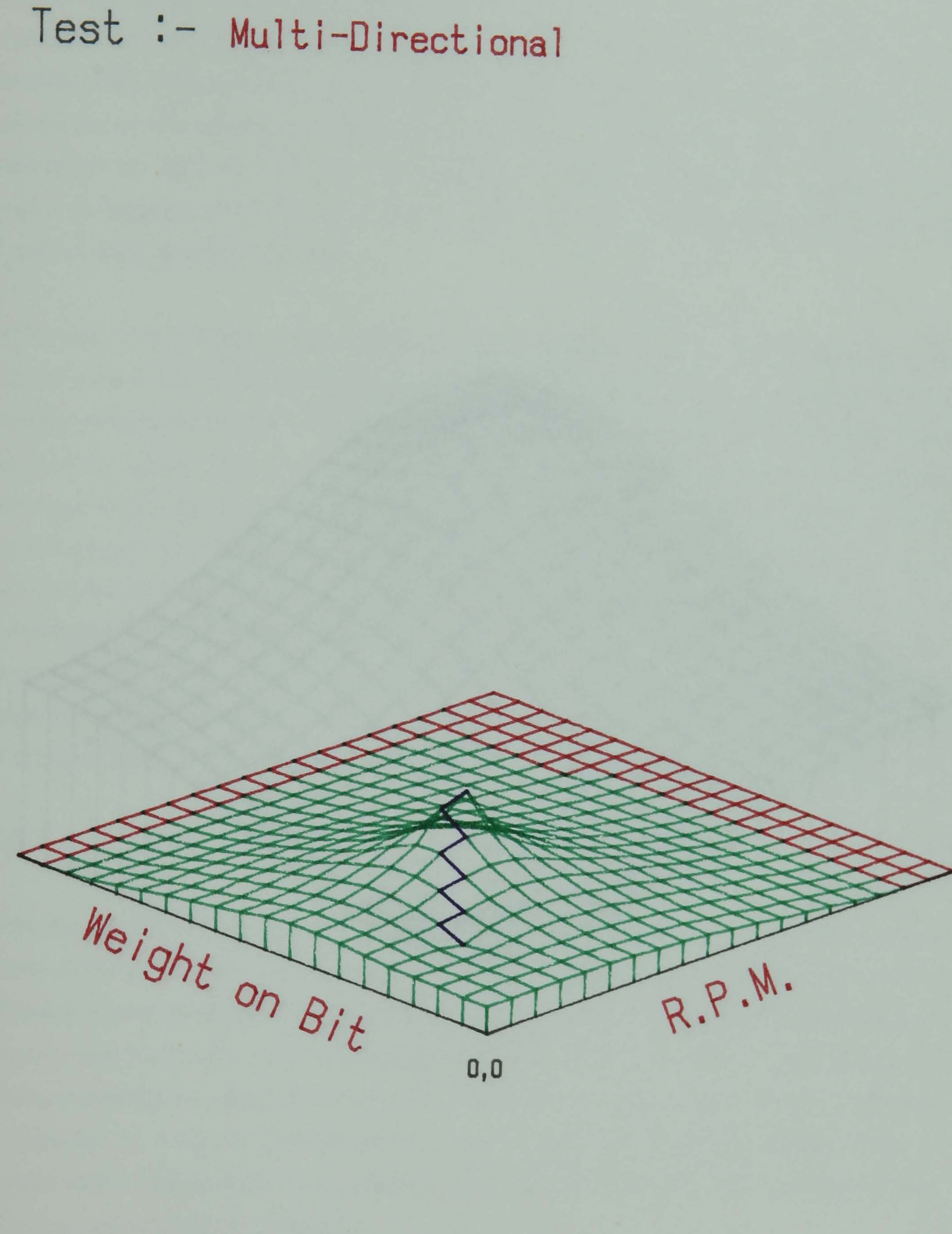


Figure 7.11 An Intermediate Plot of the Multi-Directional Method Showing the Progressive Learning of the Penetration Rate Process by the S.L.P.M.

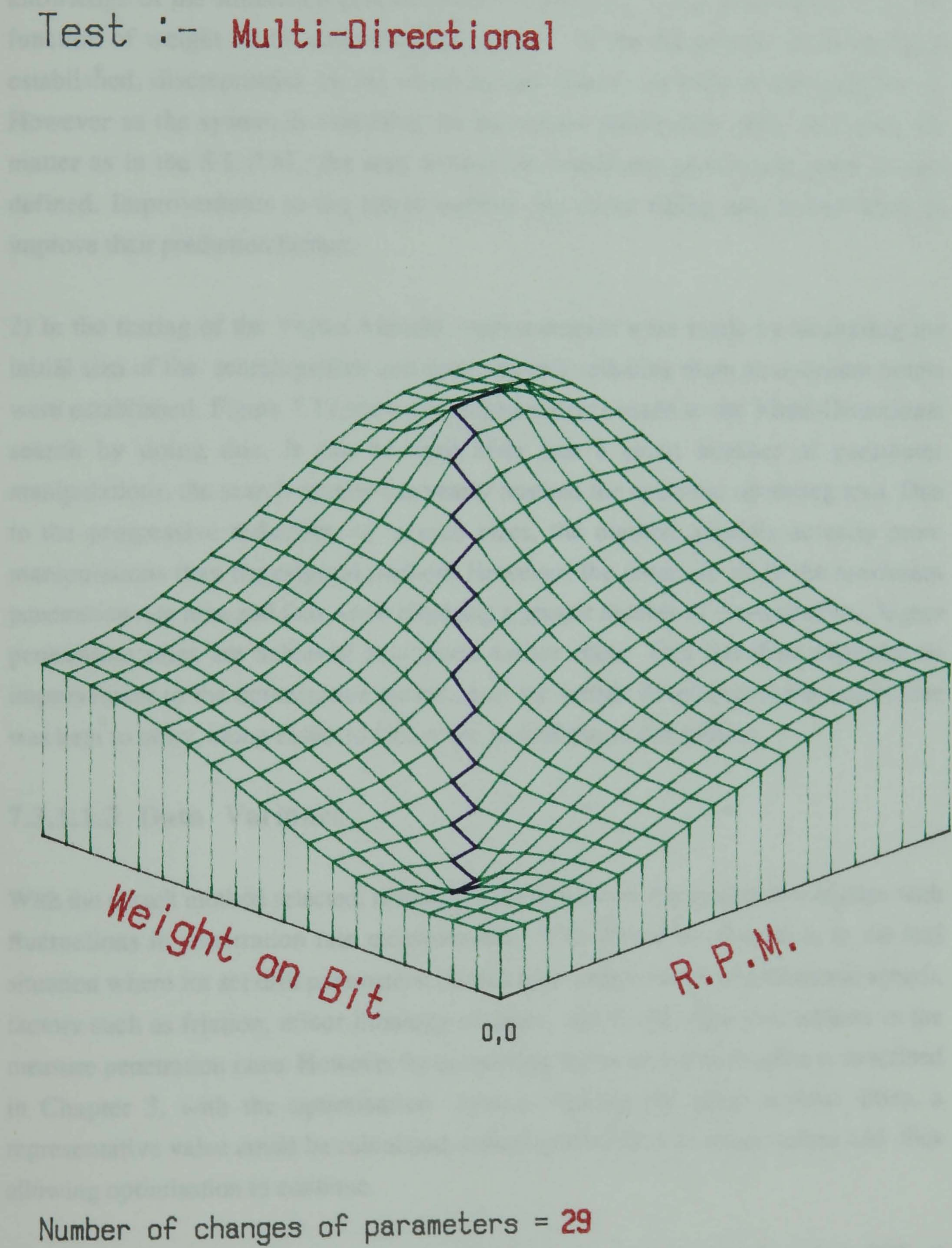


Figure 7.12 The Final Path Taken by the Multi-Directional Method to Locate Maximum Penetration Rate

Several other points are also worth noting at this stage:-

1) It can be seen that the Ripple method in all cases has enhanced the S.L.P.M.'s knowledge of the simulation process shown in Figure 7.1, (i.e. penetration rate as a function of weight on bit and rotational speed). While the general trend has been established, discrepancies by the interpolation system do exist at the peripheries. However as the system is searching for maximum penetration rates, this does not matter as in the S.L.P.M., the area around the maximum penetration point is well defined. Improvements to the ripple method (by curve fitting etc) would serve to improve their prediction further.

2) In the testing of the Vector Method, improvements were made by increasing the initial size of the search pattern and progressively reducing them as optimum points were established. Figure 7.13 show the improvements made to the Multi-Directional search by doing this. It can be seen after just a small number of parameter manipulations, the search routine has nearly reached the optimum operating area. Due to the progressive reduction of search sizes, the method requires actually more manipulations than the original method. However, the latter are all in the maximum penetration rate area and thus while requiring a greater number of manipulations, higher penetration rates are achieved at a much earlier stage. This therefore provides an improvement to the optimisation system, but for further development the search size was kept to unity, being easier to follow the path of the search routine.

7.3.1.1.3 Data Variance

With the search method selected, it was decided to see how the system would cope with fluctuations in penetration rate measurements. This would be more akin to the real situation where for set drill parameters, (in this case weight on bit and rotational speed), factors such as friction, minor lithology changes, etc would cause fluctuations in the measure penetration rates. However by calculating the mean for each point as described in Chapter 5, with the optimisation system visiting the point several times, a representative value could be calculated, reducing the effect of rouge values and thus allowing optimisation to continue.

Using the simulated process as shown in Figure 7.1, a random variation of $\pm$ 20% of the simulation value was introduced. The results of the optimisation test were quite surprising, with the search method attaining the maximum penetration rate area in quite a short time, Figure 7.14. The word area is used because, unlike in the non variance

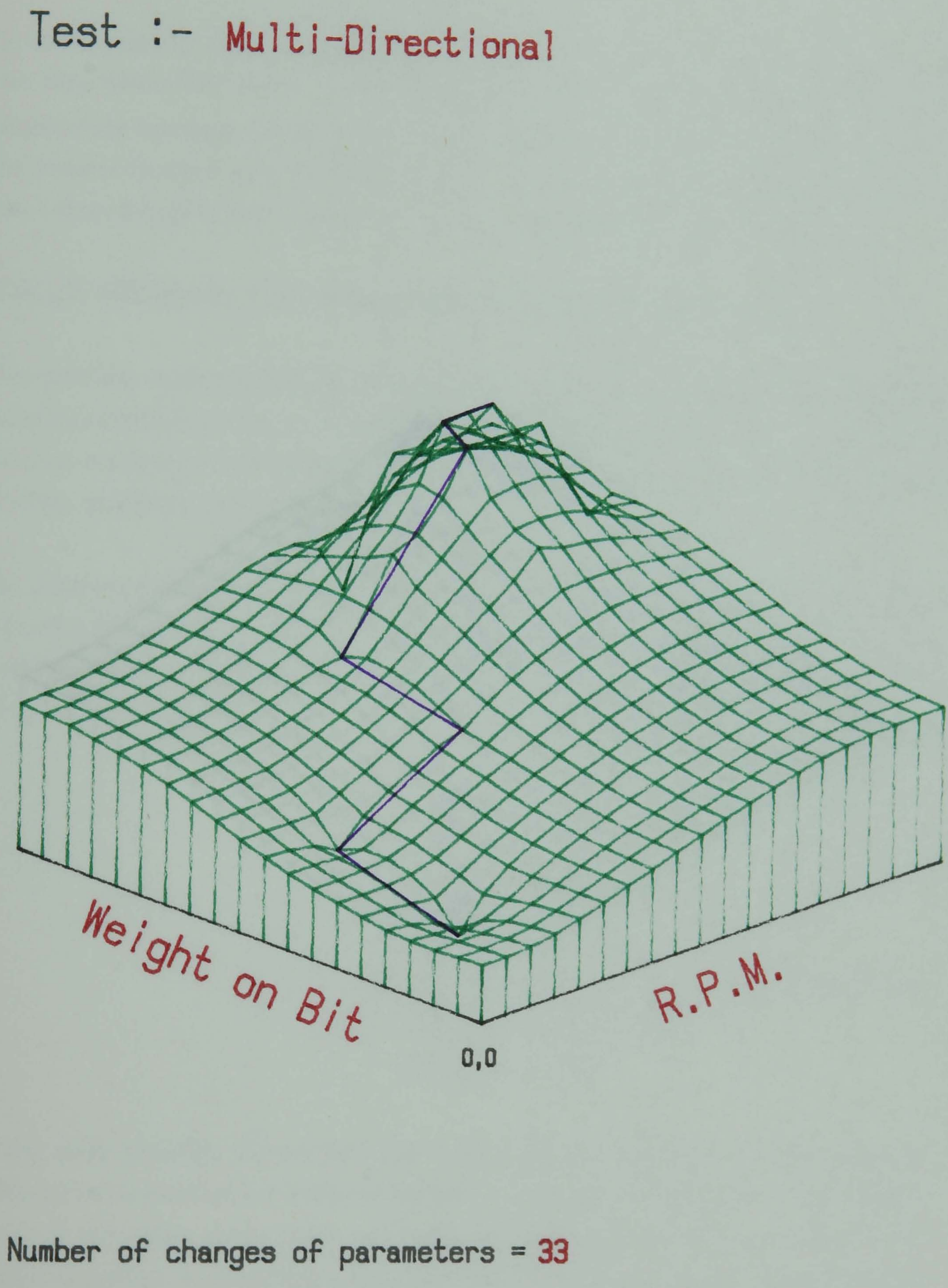


Figure 7.13 The Improvement in Efficiency to the Multi-DirectionalMethod by Increasing the Size of the Search.

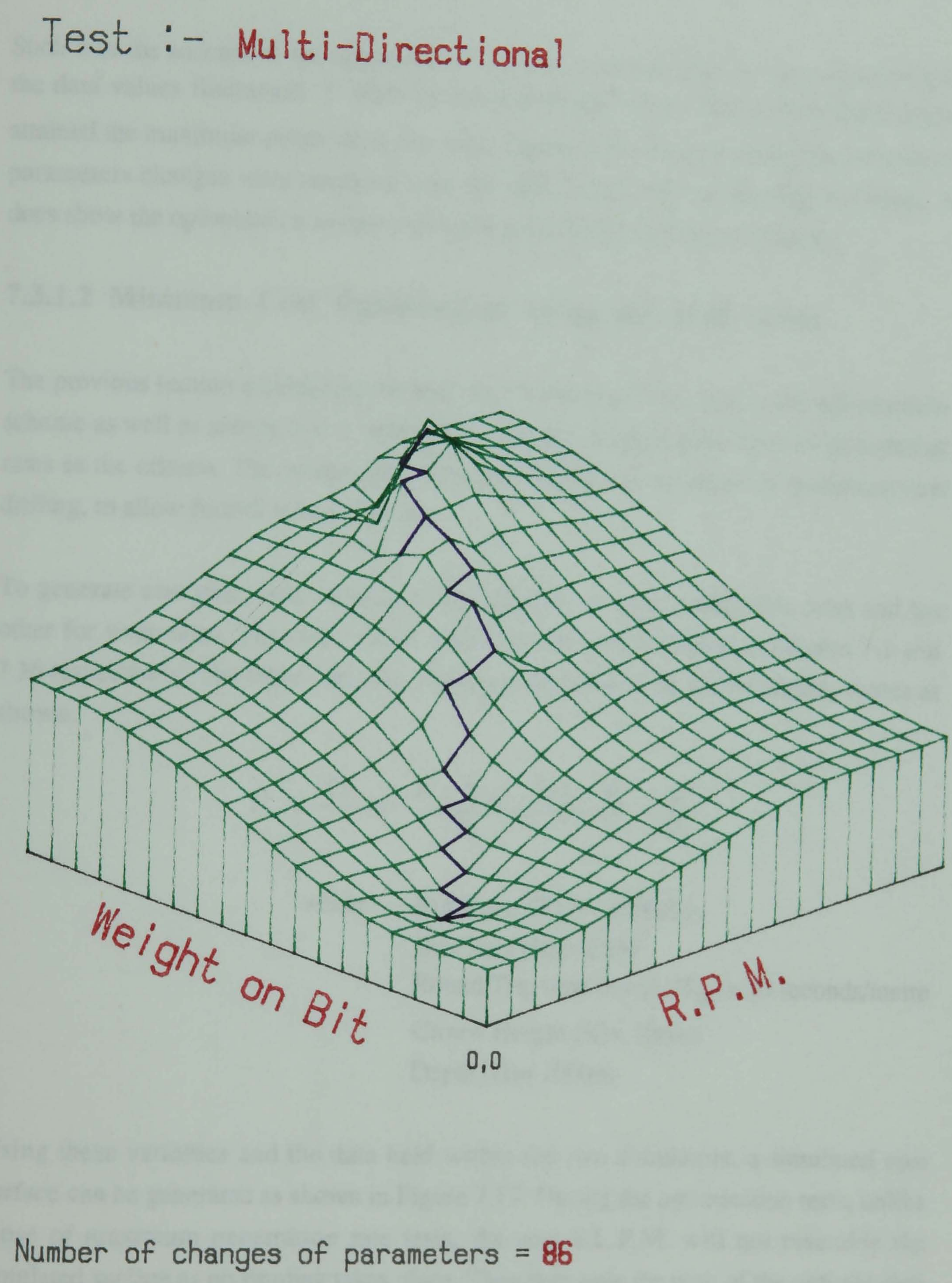


Figure 7.14 A Plot of the Optimisation System Attaining Maximum Penetration Rates with a ±20% Variation in Penetration Rate Values

system where values are constant, the fluctuation in data has the effect of varying the mean values, slightly causing the search method to "wander" around this maximum value area.

Such was the success of the optimisation system, a second test was developed where the data values fluctuated $\pm$ 60% of the simulated value. The system once again attained the maximum penetration rate area, Figure 7.15, but a considerable number of parameters changes were required, with the path being fairly contorted. However, it does show the optimisation system can work under fairly extreme conditions.

7.3.1.2 Minimum Cost Optimisation Using the IBM Alone

The previous section established the best search method to be used in the optimisation scheme as well as testing it to a satisfactory degree, using maximisation of penetration rates as the criteria. The system was therefore changed to optimise by minimum cost drilling, to allow further test to continue.

To generate cost data, two simulators are required, one for penetration rates and the other for wear rates. The two used in this series of tests is shown in Figures 7.1 and 7.16 respectively. The other variables in the cost equation were set to constant values as shown.

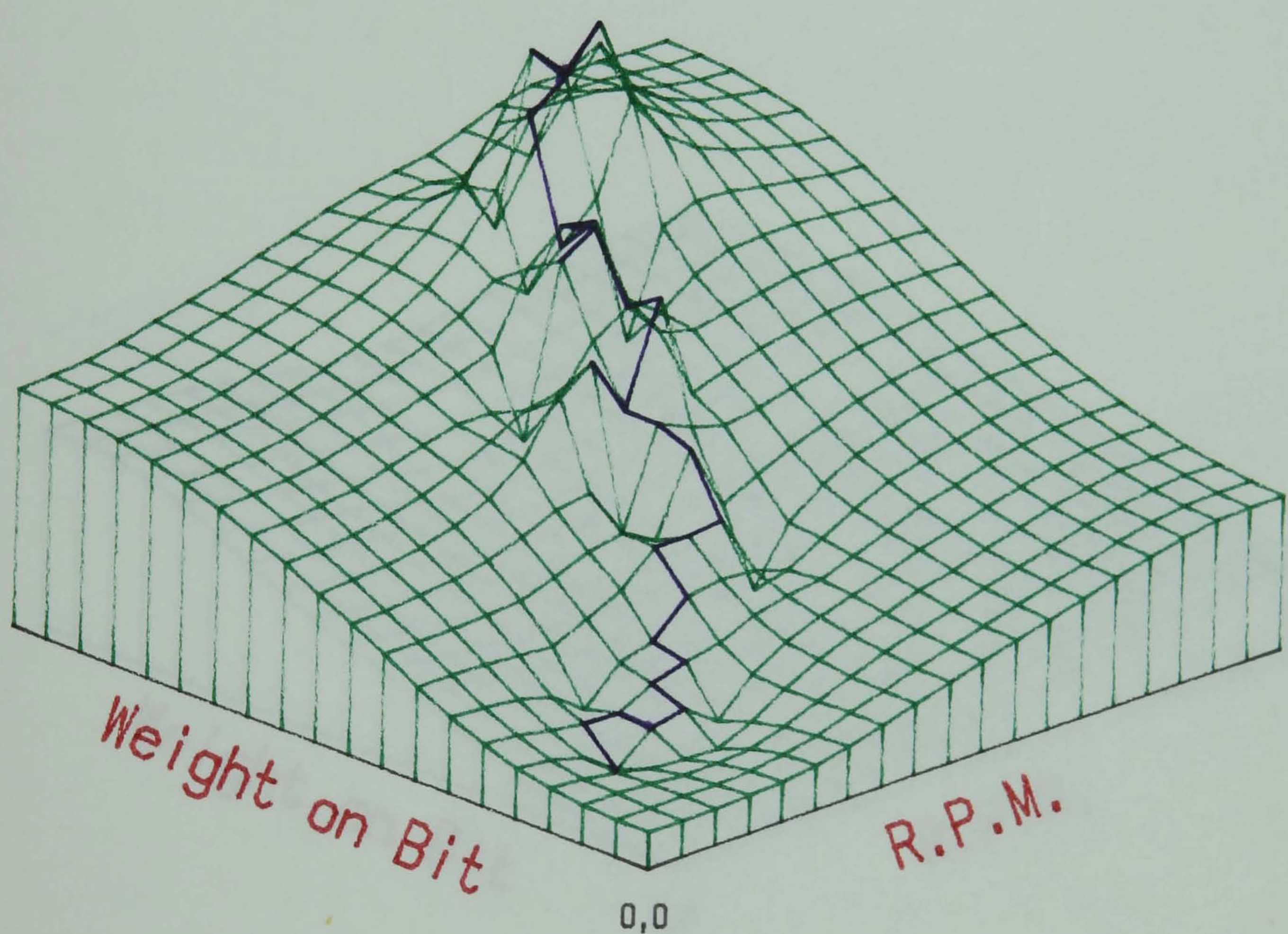
$$C = \frac{(B + R \cdot T_m \cdot D) \cdot W}{K} + \frac{R}{P}$$

where Rig Costs (R) = £1000/day
Bit Costs (B) = £500
Round Trip time /metre (T_m)= 20 seconds/metre
Crown Height (K)= 10mm
Depth (D)= 1000m

Using these variables and the data held within the two simulators, a simulated cost surface can be generated as shown in Figure 7.17. During the optimisation tests, unlike those of maximum penetration rate tests, the cost S.L.P.M. will not resemble the simulated surface as no rippling takes place. Therefore only the path of the optimisation system will be shown along with the cost calculated values.

To test the optimisation system under the minimum cost drilling criteria, four scenarios were used with increasing severity, but increasing realism. In each test, the search

Test :- Multi-Directional



Number of changes of parameters = 419

Figure 7.15 The Optimisation System Attaining Maximum Penetration Rates with a $\pm 60\%$ Variation in Penetration Rate Values

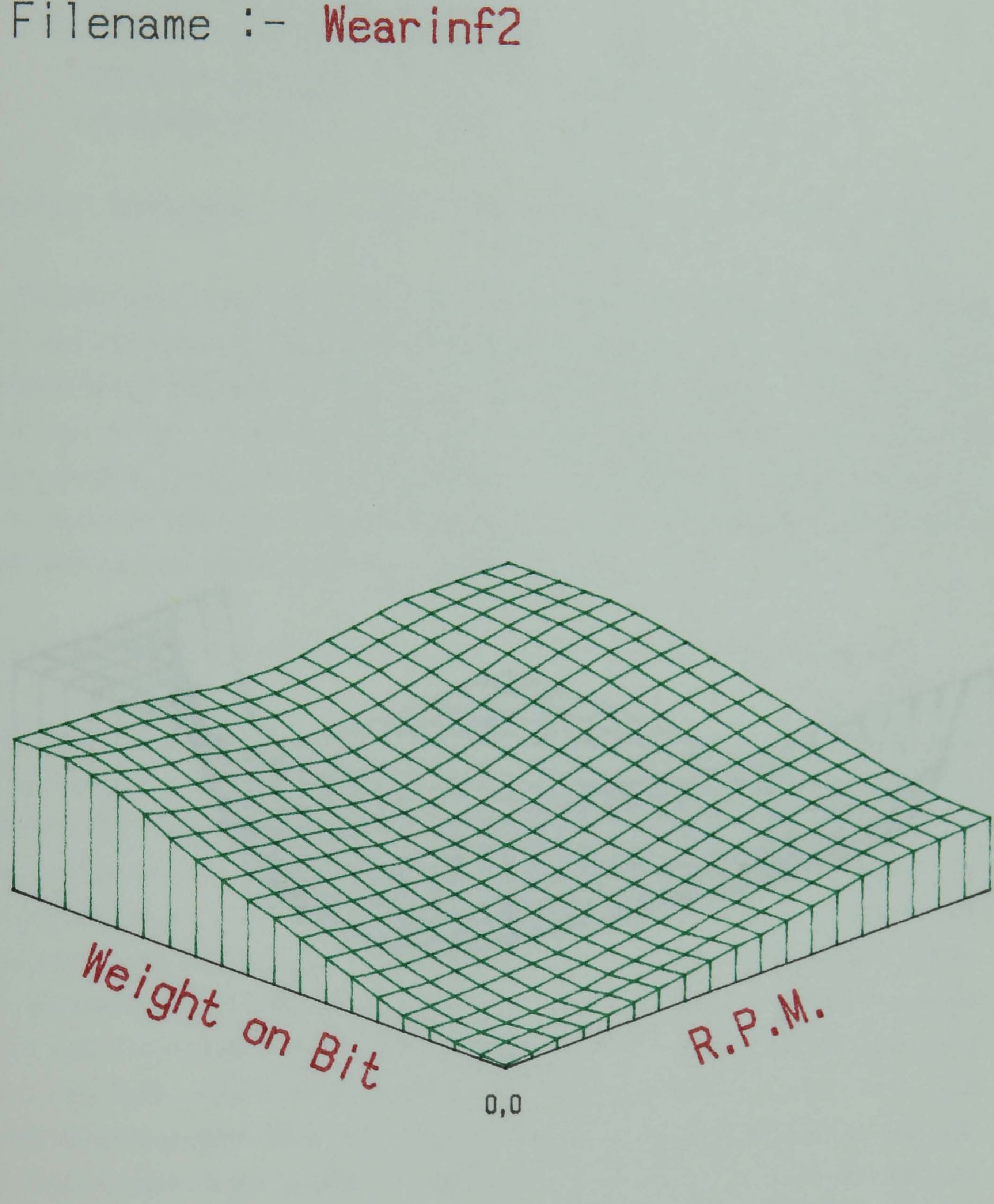


Figure 7.16 The Simulated Wear Rate Process

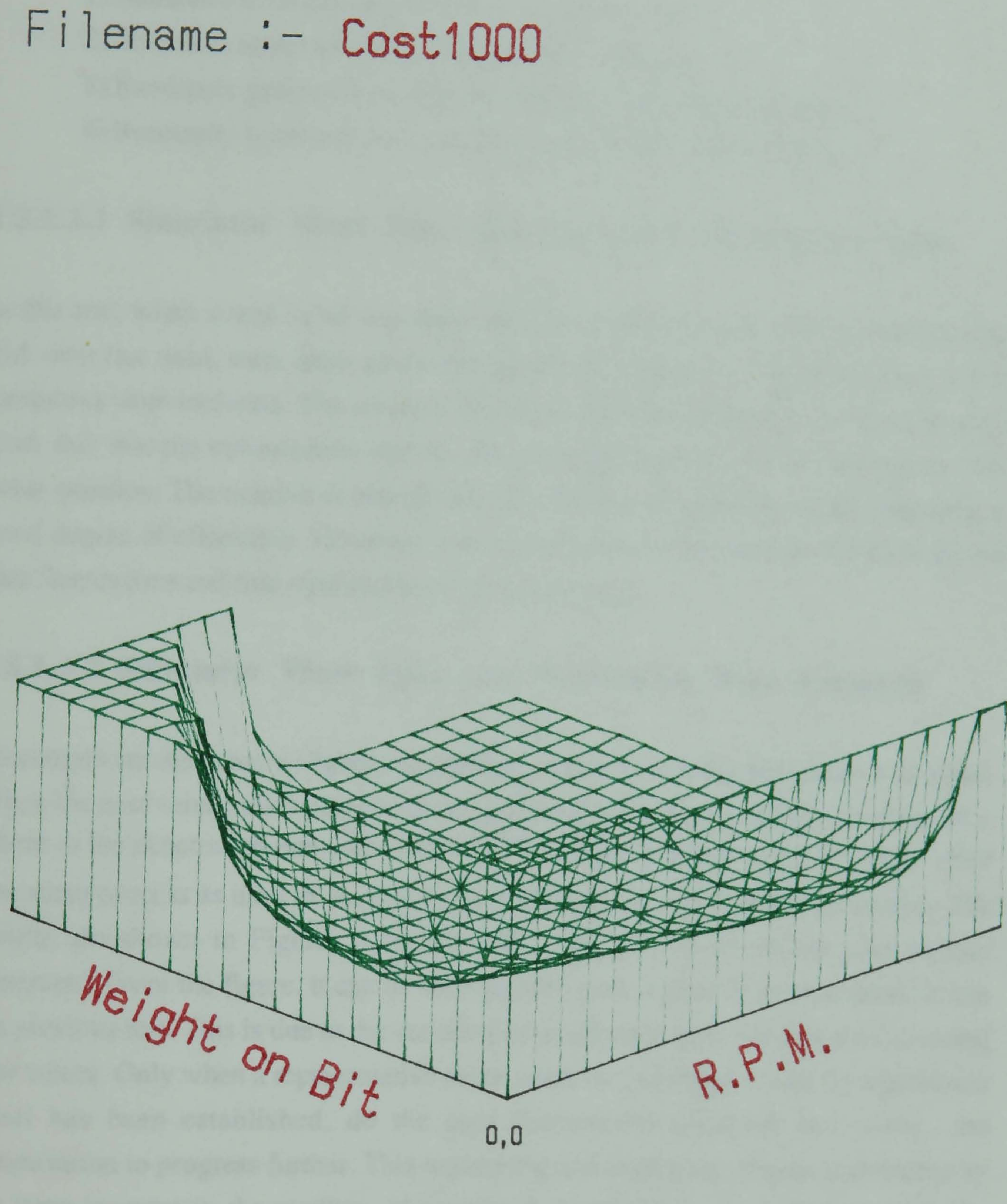


Figure 7.17 The Cost Surface Generated by the Cost Equation, Using the Two Simulators and the Defined Cost Variables

method would remain the same, but the data from both simulators would be changed according to the test. The tests are listed below.

1) Simulator wear rate and simulator penetration rate
2) Simulator wear rate and penetration rate variance
3) Randomly generated wear values and simulator penetration rate
4) Randomly generated wear values and penetration rates variance

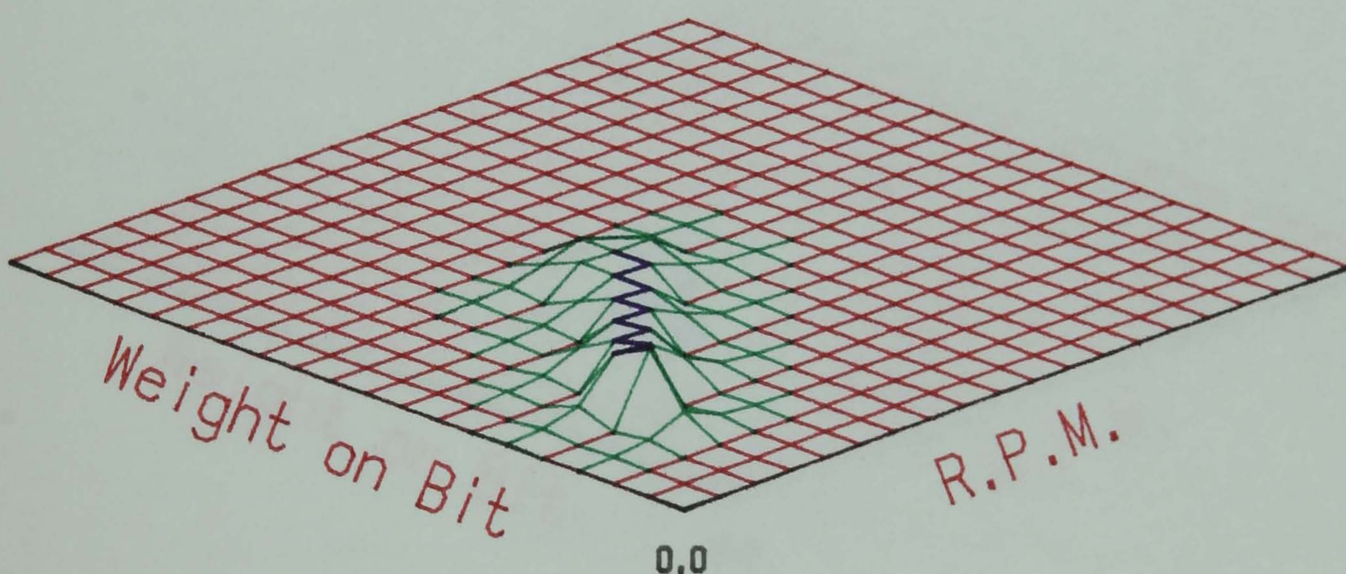
7.3.1.2.1 Simulator Wear Rate and Simulator Penetration Rate

In this test, when a cost value was required for a point, the values of penetration rate and wear rate used, were those given directly by the respective simulators, i.e. no data variations were included. The result of this test is shown in Figure 7.18. It can be seen from this that the optimisation system, has directly "homed" into the minimum cost value position. The number of manipulations to do this is relatively small, indicating a good degree of efficiency. However, it does have to be remembered that there are no data fluctuations and thus optimisation is relatively easy.

7.3.1.2.2 Simulator Wear Rate and Penetration Rate Variance

To complicate the process slightly, a degree of variation in penetration rates was added. When the cost values were calculated, the wear rate was that returned by the simulator, where as the penetration rate value had a $\pm 20\%$ variance added to the simulator value (the same process as used in the latter tests of maximisation of penetration rates). The results are shown in Figures 7.19 and 7.20. Figure 7.19 shows the cost surface generated. From the figure, it can be seen that the path is slightly more contorted than the previous test. This is due to the variation of penetration rates altering the calculated cost values. Only when a representative mean value for penetration rates for a particular point has been established, do the cost fluctuations diminish and allow the optimisation to progress further. This wandering and averaging process is reflected by the large increase in the number of parameter manipulations required to attain the minimum cost position. Figure 7.20 shows the penetration rate S.L.P.M., and it can be seen that the penetration rate process has only been partially learnt. However as the minimum cost position has been located, the knowledge that greater penetration rates can be achieved is irrelevant as a movement in this direction would only cause an increase in cost from the present situation. Therefore this shortcoming does not matter.

Test :- Multi-Directional



Number of changes of parameters = 42

Figure 7.18 A Plot of the Optimisation System Locating the Minimum Cost Position with No Data Fluctuations

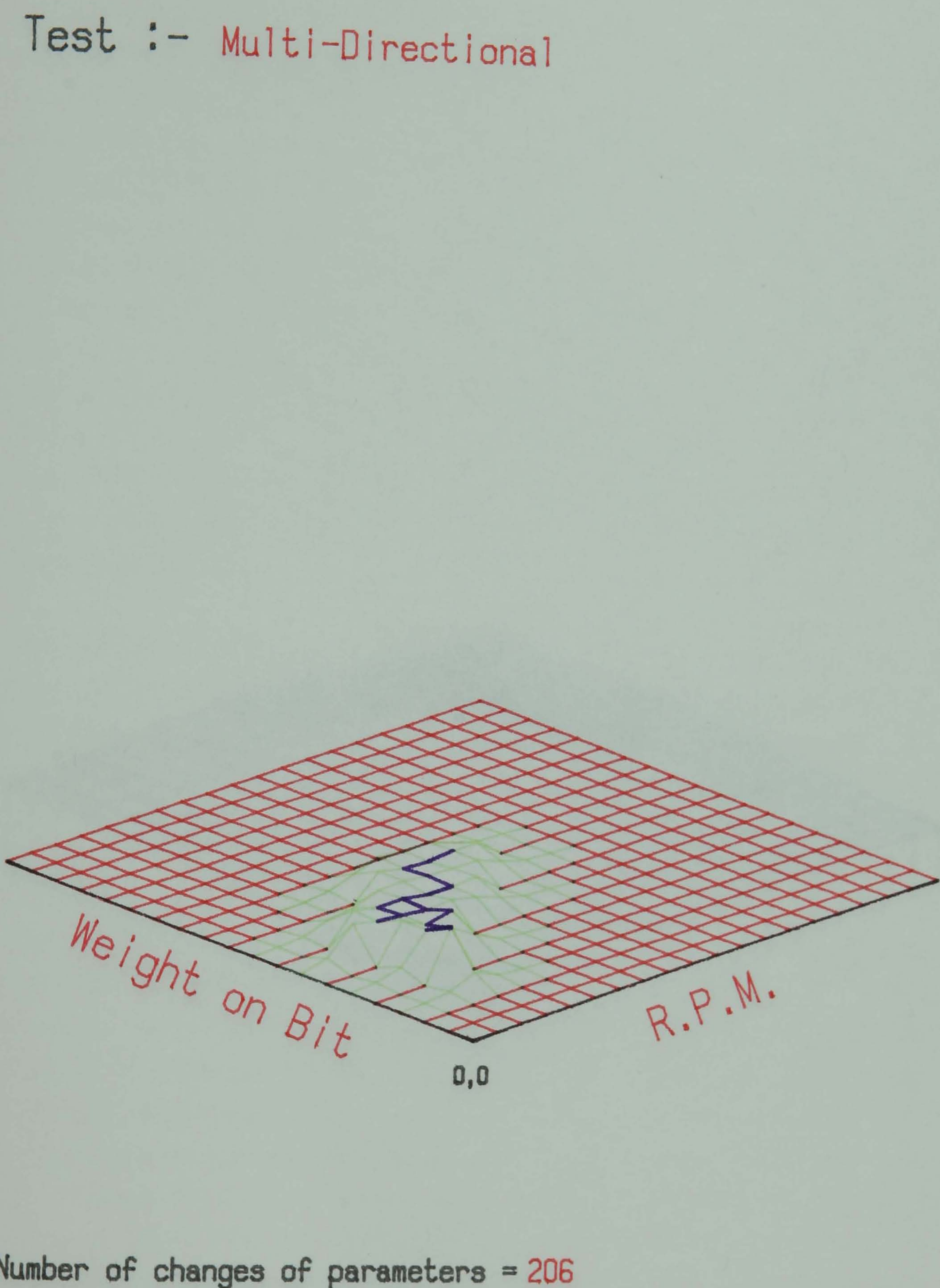


Figure 7.19 The Cost Surface Generated During Testing with Simulator Wear Values and Penetration Rate Variance

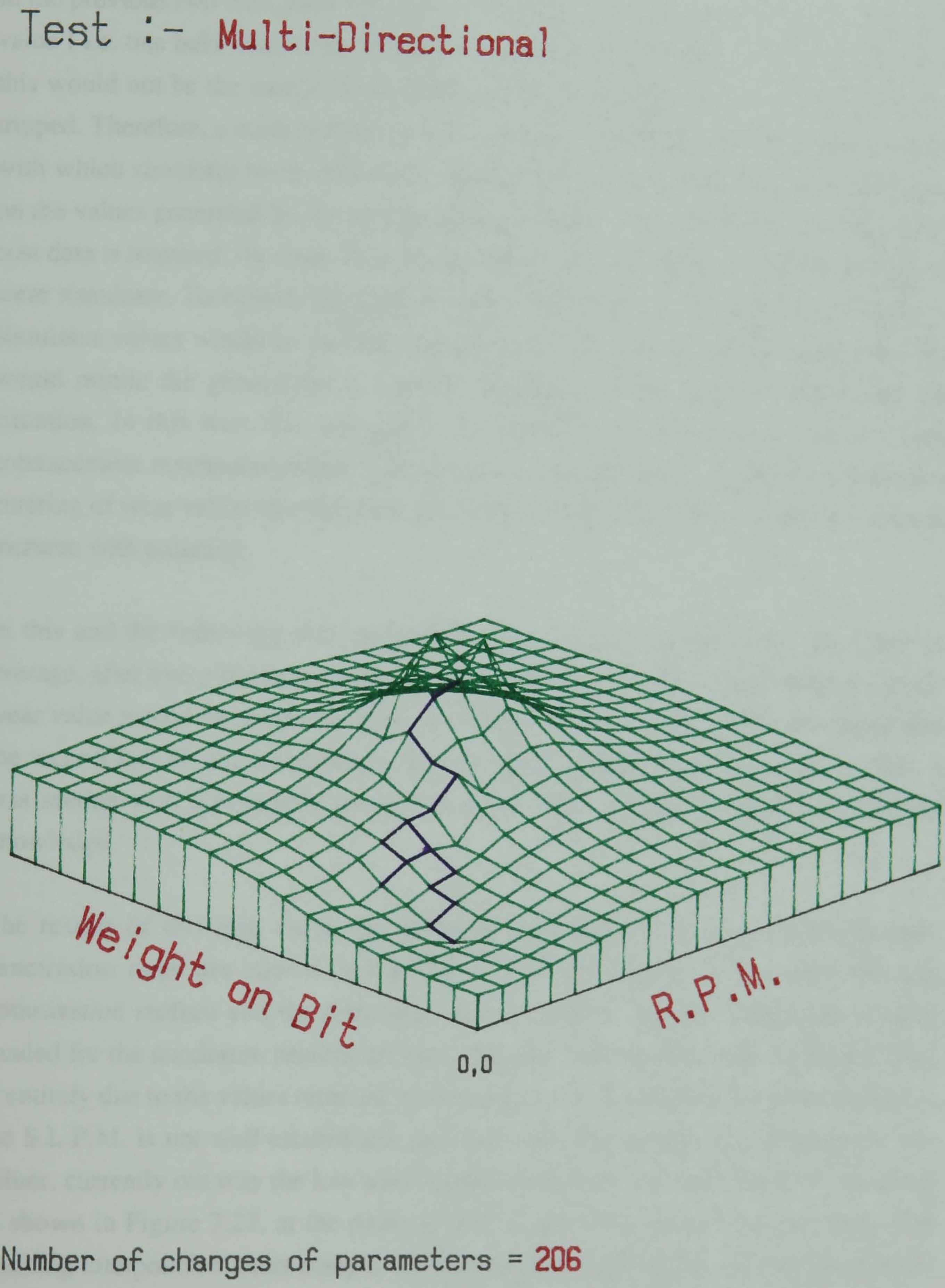


Figure 7.20 The Associated Penetration Rate S.L.P.M. Surface Generated During Testing with Simulator Wear Values and Penetration Rate Variance

7.3.1.2.3 Randomly Generated Wear Values and Simulator Penetration Rate

In the previous two tests, each time a cost calculation was required, a known wear rate value (i.e. one held within the simulator) was returned. However in the real situation, this would not be the case as wear values would be generated only when the bit was tripped. Therefore, a more realistic scheme must be developed, to reduce the regularity with which simulator wear values are entered into the wear S.L.P.M., and rely more on the values generated by the interpolation system i.e. the ripple method. Thus when cost data is required, the wear value is returned from the wear S.L.P.M. rather than the wear simulator. To ensure that some known values are passed to the wear S.L.P.M., simulator values would be entered into the wear S.L.P.M. at random intervals. This would mimic the generation of a newly measured wear values as with a real life situation. In this way, the wear S.L.P.M. would be performing its role as a data enhancement mechanism rather than a straight storage system. With the progressive entering of wear values into the wear S.L.P.M., the predicted wear values returned will increase with accuracy.

In this and the following test, the random variance was set at twenty, such that on average, after every twenty parameter manipulations and thus cost calculations, a new wear value would be generated from the wear simulator. This would be entered into the wear S.L.P.M. and interpolated. To aid initial prediction of the wear S.L.P.M., it was seeded with 5 randomly positioned wear values, to imitate some limited prior knowledge.

The results of this test, using the randomly generated wear values and simulator penetration rates are shown in Figures 7.21 -7.22. Figure 7.21. shows the cost optimisation surface and the path taken. It can be seen that the system has initially headed for the maximum penetration rate area, and then unexpectedly 'U' turned. This is entirely due to the values returned by the wear S.L.P.M. Initially the wear process in the S.L.P.M. is not well established, and therefore, the increases in penetration rate values, currently out way the low wear values returned by the wear S.L.P.M. However as shown in Figure 7.22, at the point of turn, a new wear value was generated. The resulting interpolation alters many of the surrounding wear values, to ones closer to the simulator wear values. In this case, much higher. Consequently, subsequent cost calculations using the new wear S.L.P.M. values reveal this area to be unattractive with high cost values. The optimisation system thus walks back to a region of lower wear

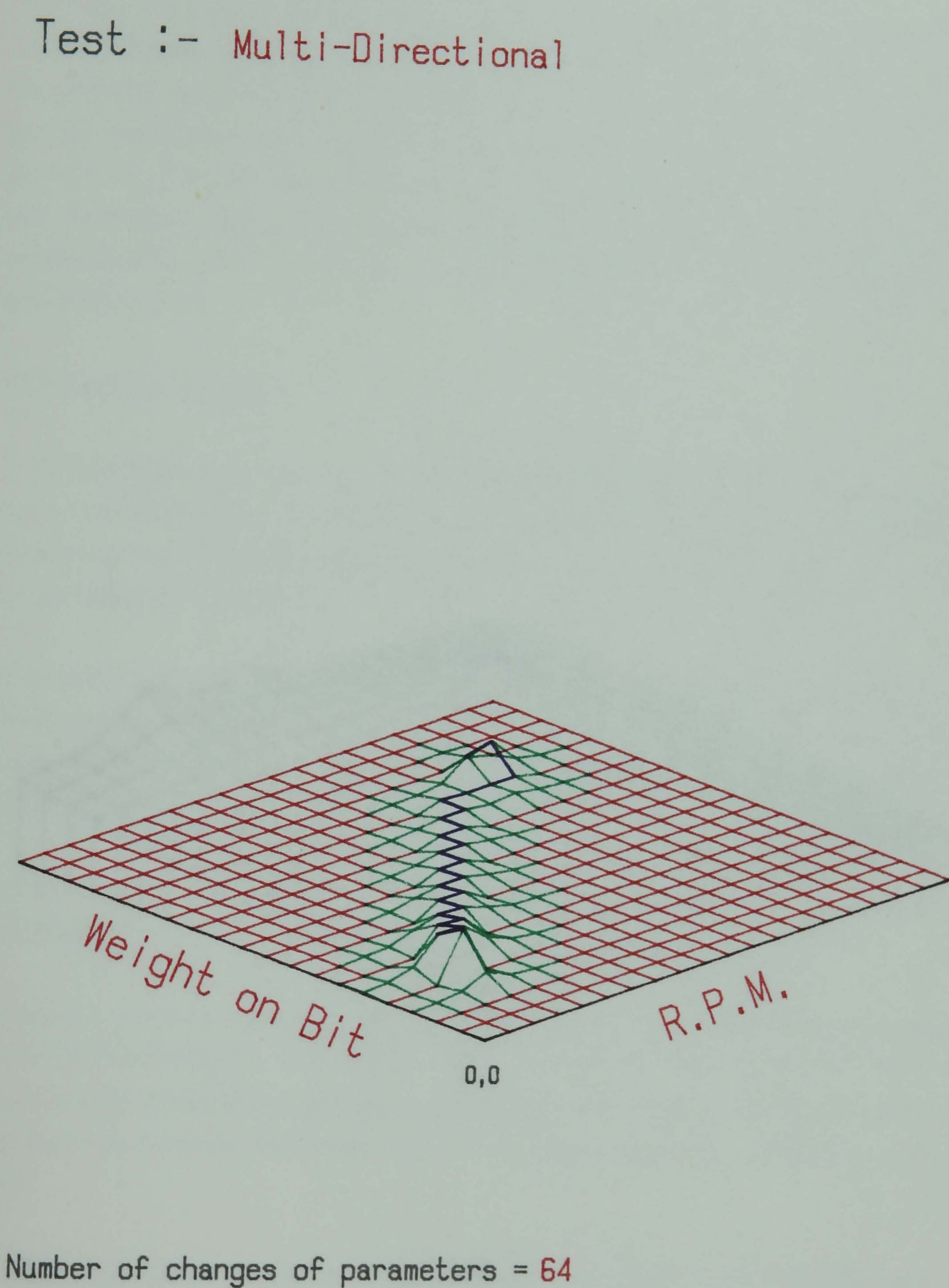


Figure 7.21 An Intermediate Plot of the Cost Surface During Minimum Cost Optimisation Using Randomly Generated Wear Values and Simulator Penetration Rates

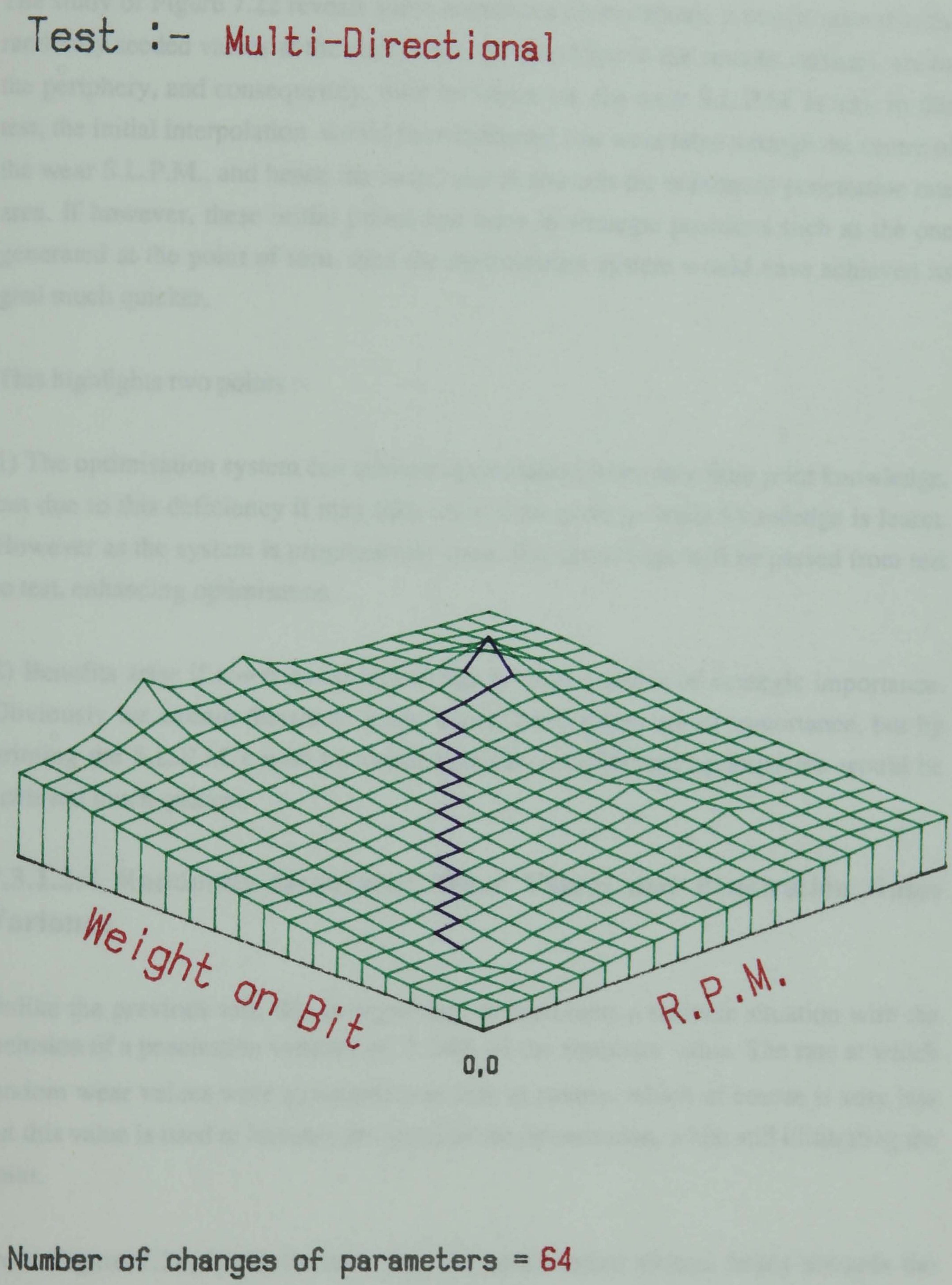


Figure 7.22 An Intermediate Plot of the Penetration Rate S.L.P.M. During Minimum Cost Optimisation Using Randomly Generated Wear Values and Simulator Penetration Rates

values, eventually 'homing' in on the true minimum cost area. Figure 7.23 shows this later stage.

The study of Figure 7.22 reveals some interesting observations. It can be seen that the randomly seeded values at the start of the test (the blips in the smooth surface), are on the periphery, and consequently, their influence on the wear S.L.P.M. is less. In this test, the initial interpolation would have indicated low wear rates through the centre of the wear S.L.P.M., and hence the initial search towards the maximum penetration rate area. If however, these initial points had been in strategic positions such as the one generated at the point of turn, then the optimisation system would have achieved its goal much quicker.

This highlights two points :-

1) The optimisation system can achieve optimisation from very little prior knowledge, but due to this deficiency it may take some time to do so while knowledge is learnt. However as the system is progressively used, this knowledge will be passed from test to test, enhancing optimisation.

2) Benefits arise if some initial knowledge is known and is of strategic importance. Obviously we cannot dictate or know which wear values are of importance, but by priming the S.L.P.M.'s with historical data etc, it is felt that optimisation would be achieved much quicker.

7.3.1.2.4 Randomly Generated Wear Values and Penetration Rates Variance

Unlike the previous test, this is beginning to represents a realistic situation with the inclusion of a penetration variance of $\pm$ 20% of the simulator value. The rate at which random wear values were generated was kept at twenty, which of course is very low but this value is used to increase the speed of the optimisation, while still illustrating the point.

From Figure 7.24, it can be seen that the optimisation system heads towards the minimum cost area but in a contorted fashion due to the variation in penetration rates. Once again however, the generation of low cost values from the initially deficient wear S.L.P.M., cause the search method to establish a minimum cost position in the maximum penetration rate region. As randomly generated wear values entered into the

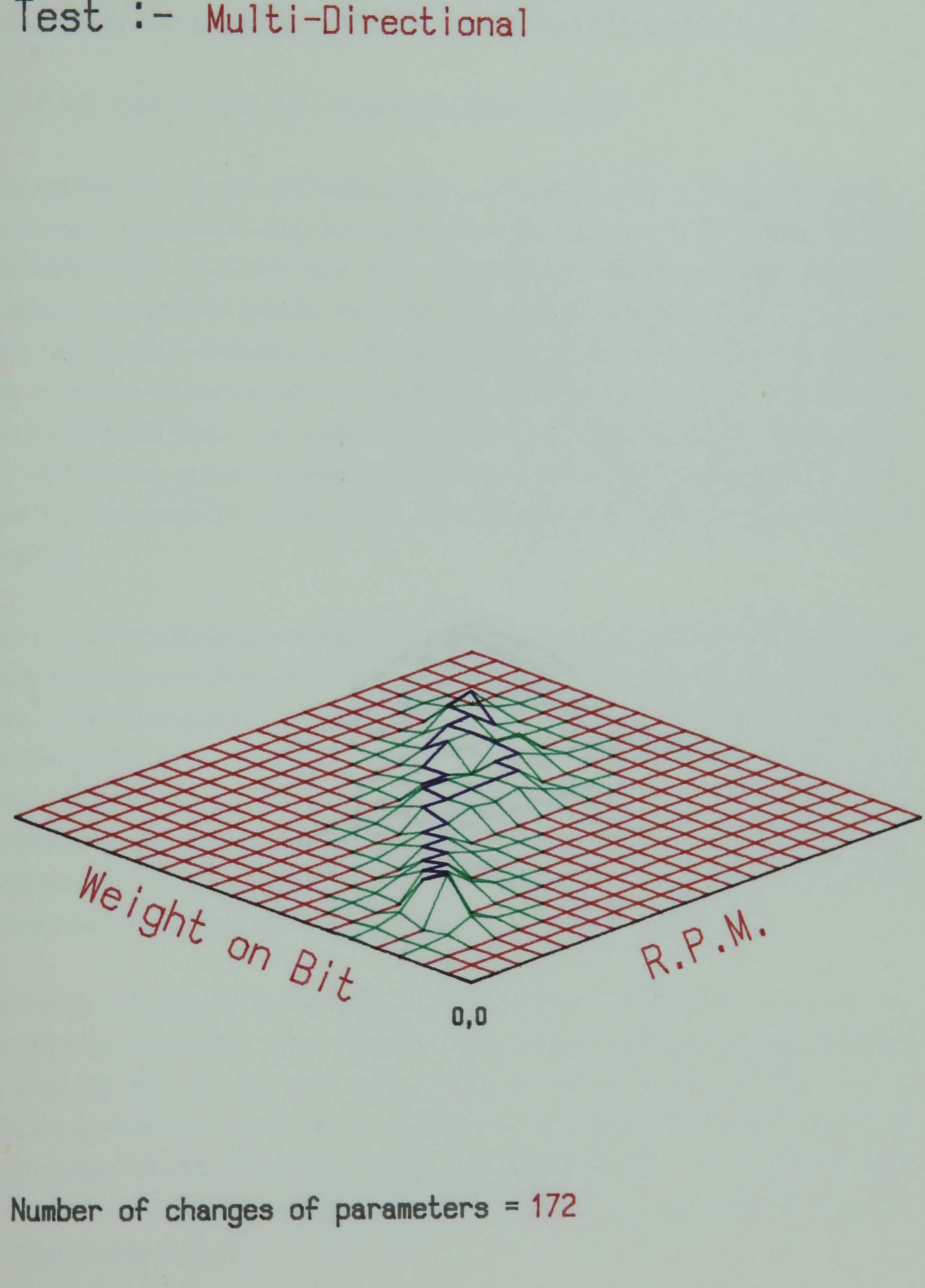


Figure 7.23 A Later Plot of the Cost Surface with the Minimum Cost Position Obtained

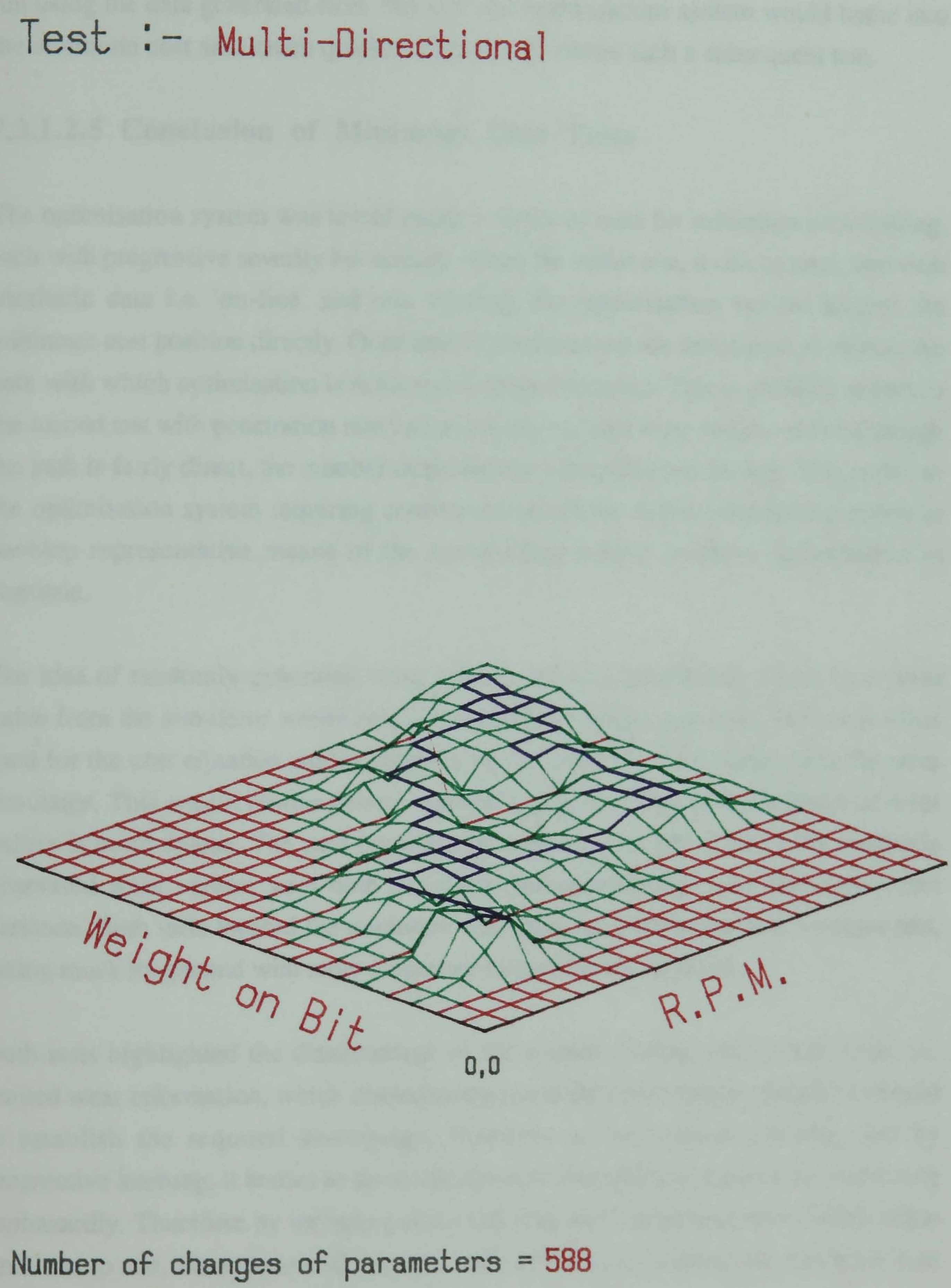


Figure 7.24 The Cost Surface Generated by the Test Using Randomly Generated Wear Values and Penetration Rate Variance

wear S.L.P.M., the system back tracks to the minimum cost area. In so doing, a large number of parameter manipulations are required. Despite this, it can be seen that the system has achieved the minimum cost drilling area. Furthermore if another test was run using the data generated from this test, the optimisations system would home into the minimum cost area much quicker. Figure 7.25 shows such a subsequent test.

7.3.1.2.5 Conclusion of Minimum Cost Tests

The optimisation system was tested under a series of tests for minimum cost drilling, each with progressive severity but realism. From the initial test, it can be seen, that with idealistic data i.e. 'on-line' and non varying, the optimisation system locates the minimum cost position directly. Once data fluctuations etc are introduced as shown, the path with which optimisation is achieved is more contorted. This is partially shown in the second test with penetration rate variance but simulator wear values, where although the path is fairly direct, the number of parameter manipulations is high. This is due to the optimisation system requiring continuous searching of the surrounding points to develop representative means of the surrounding points, to allow optimisation to continue.

The idea of randomly generated wear values was also introduced, where by a wear value from the simulator would only be entered at random intervals. The wear value used for the cost equation would be given by the wear S.L.P.M. rather than the wear simulator. This would mimic a more realistic situation where the generation of wear values is more sparse. The cost optimisation scheme was tested using the randomly generated wear values, with both simulator penetration rates and penetration rate variance. Both tests located the minimum cost area, the penetration rate variance test, taking much longer and with more parameter manipulations required.

Both tests highlighted the disadvantage of the system starting from a null state, i.e. limited wear information, which consequently cause the optimisation system to wander to establish the required knowledge. However as the system showed, that by progressive learning, it homes to the minimum cost area quickly, rather than wandering haphazardly. Therefore by including historical data and the passing on of information from test to test, the system will become more efficient at locating the minimum cost position readily as shown by Figure 7.25.

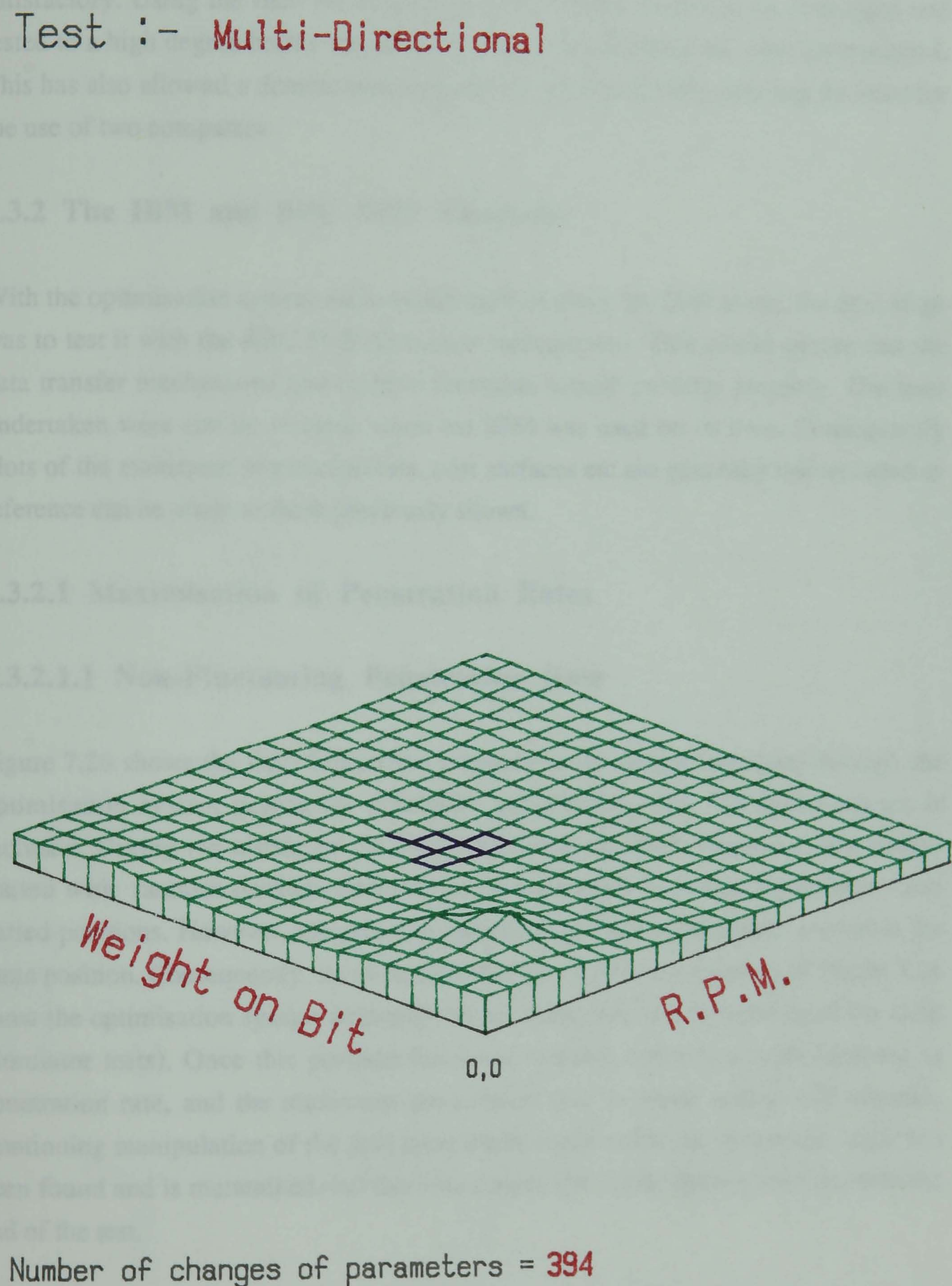


Figure 7.25 The Effect of Passing On of Knowledge From Test to Test

7.3.1.3 Conclusion of IBM Alone

The system was tested under both optimisation criteria, and all the results proved satisfactory. Using the IBM on its own has allowed the system to be developed and tested to a high degree before the complexities of data transfer etc were incorporated. This has also allowed a demonstration system to be established, negating the need for the use of two computers.

7.3.2 The IBM and BBC Drill Simulator

With the optimisation system successfully proven using the IBM alone, the next stage was to test it with the BBC Drill Simulator incorporated. This would ensure that the data transfer mechanisms and relative functions would perform properly. The tests undertaken were similar to those when the IBM was used on its own. Consequently plots of the maximum penetration rate, cost surfaces etc are generally not included as reference can be made to those previously shown.

7.3.2.1 Maximisation of Penetration Rates

7.3.2.1.1 Non-Fluctuating Penetration Rate

Figure 7.26 shows the Drill Simulators response to the control provided through the optimisation system geared for maximum penetration rates. No data variance is included. During the testing of the Drill Simulator, the Drill Simulator was always started with random starting conditions, to allow testing to start from unknown and varied positions. However, the previous optimisation tests were always started at the same position. Consequently, it can be seen that the first twenty seconds of Figure 7.26 show the optimisation system attaining this position (this will be seen in all the Drill Simulator tests). Once this position has been reached, there is a rapid increase in penetration rate, and the maximum penetration rate is found within 100 seconds. Continuing manipulation of the drill parameters ensures that the maximum value has been found and is maintained, but this also causes the cyclic pattern seen towards the end of the test.

The time taken to achieve optimisation is fairly short, but no data variance occurs, and the response if the simulator is immediate. If the laboratory drill rig was used, optimisation would take much longer as the drill would require several seconds to attain the requested parameters.

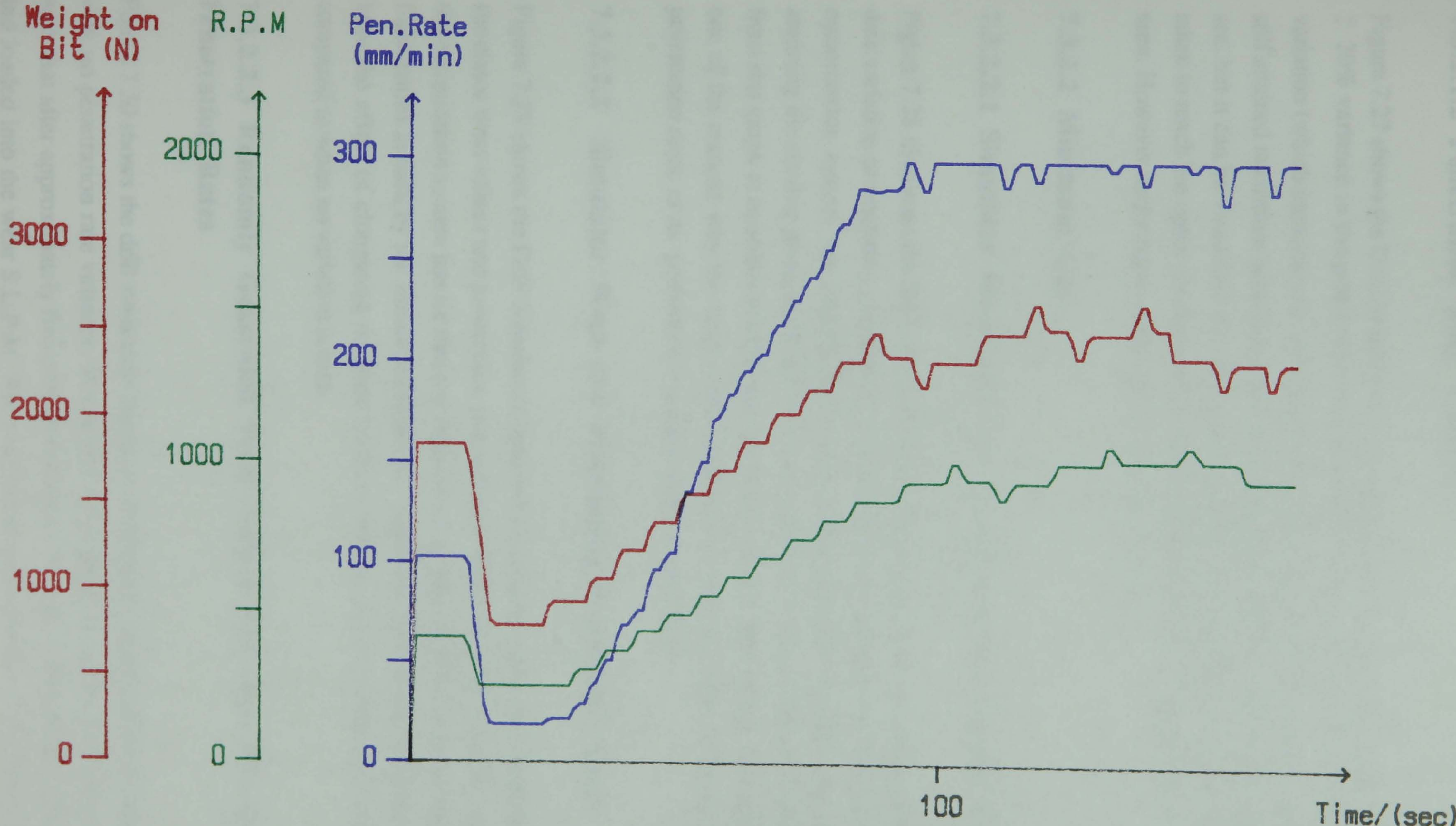


Figure 7.26 The Response of the Drill Simulator to the Control Provided by the Optimisation System Set for Maximisation of Penetration Rates

7.3.2.1.2 Penetration Rate Variance

Figure 7.27 shows the Drill Simulator under optimisation of penetration rates but with a $\pm$ 20% variance in the penetration rate readings. It can be seen that despite the data variation (which increase with increasing penetration rate), the optimisation system has still attained maximum penetration rate. However with data fluctuations it is difficult to see, but it can be visualised that the average would tend towards this value. The time taken to reach the optimum position is much greater than when no data fluctuations are seen. However under these conditions, it is not surprising.

7.3.2.2 Minimum Cost

7.3.2.2.1 Simulator Wear and Non Fluctuating Penetration Rates

Figure 7.28 illustrates the Drill Simulators response to minimum cost optimisation. No data variation or randomly generated wear rates have been used. It can be seen that the optimisation system has located the minimum cost position readily after initially attaining the starting position. However unless calculations are performed it is difficult from this graph to establish whether true minimum cost has been found. This highlights one of the reasons why the optimisation system was initially tested using maximum penetration rates, as its performance is much easier to determine.

7.3.2.2.2 Simulator Wear and Fluctuating Penetration Rates

Figure 7.29 shows the Drill Simulators response to minimum cost optimisation using simulator wear values and penetration rate variance. From the plot, it can be seen that the optimisation system has located the minimum cost area, despite the penetration rate fluctuations as seen by the simulators response. Again the penetration rate fluctuations have the effect of elongating the time taken to achieve the minimum cost position, compared to when no variation is seen.

7.3.2.2.3 Randomly Generated Wear Values and Non Fluctuating Penetration Rates

Figure 7.30 shows the drill simulators response to randomly generated wear values but with no penetration rate variance. In this test the random value has been set to five, such that after approximately five cost calculations a new wear rate value is generated and loaded into the wear S.L.P.M. The cost optimisation surface is shown in Figure

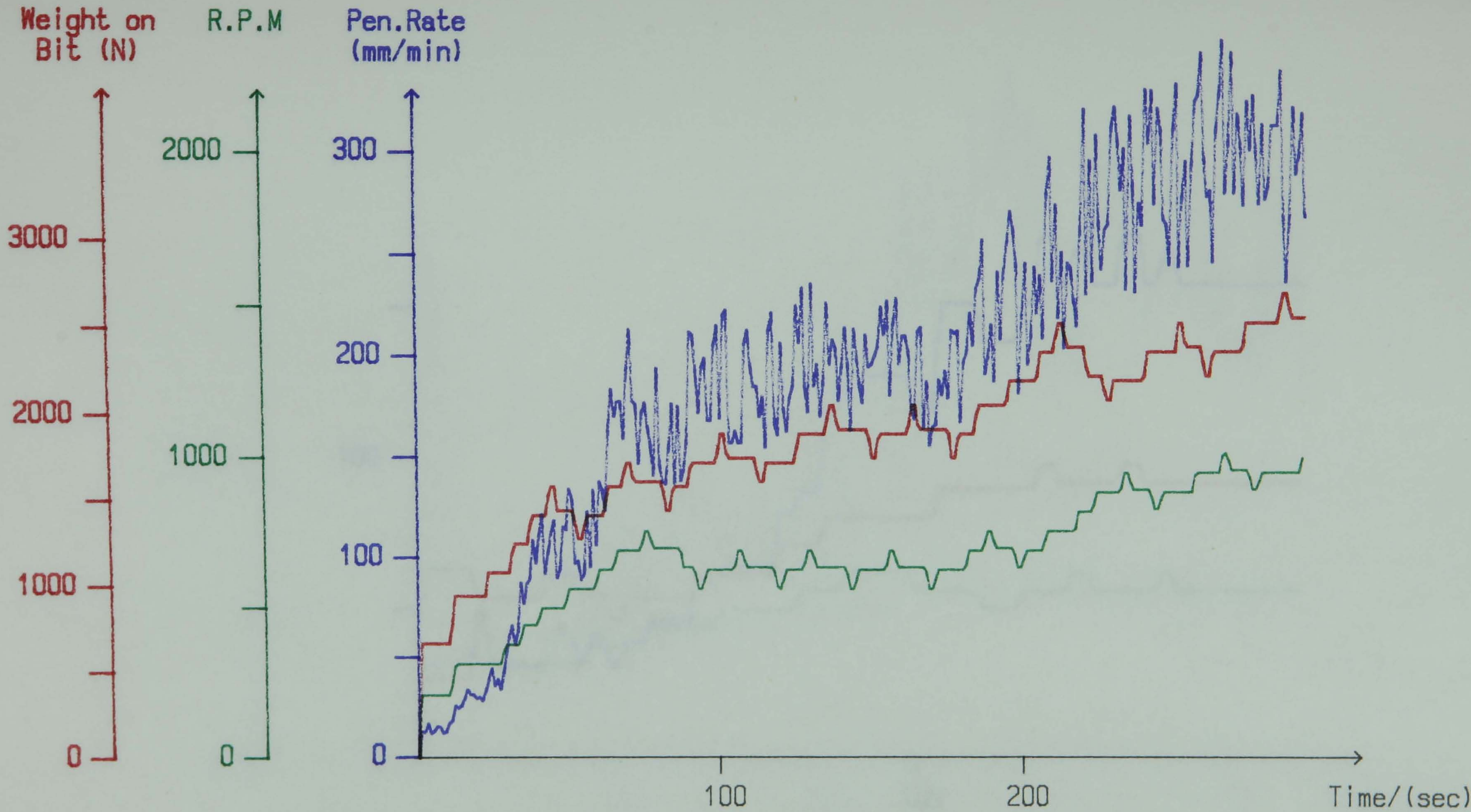


Figure 7.27 The Drill's Simulator's Response to the Control Provided by the Optimisation System Set for Maximisation of Penetration Rates but with Penetration Rate Variance

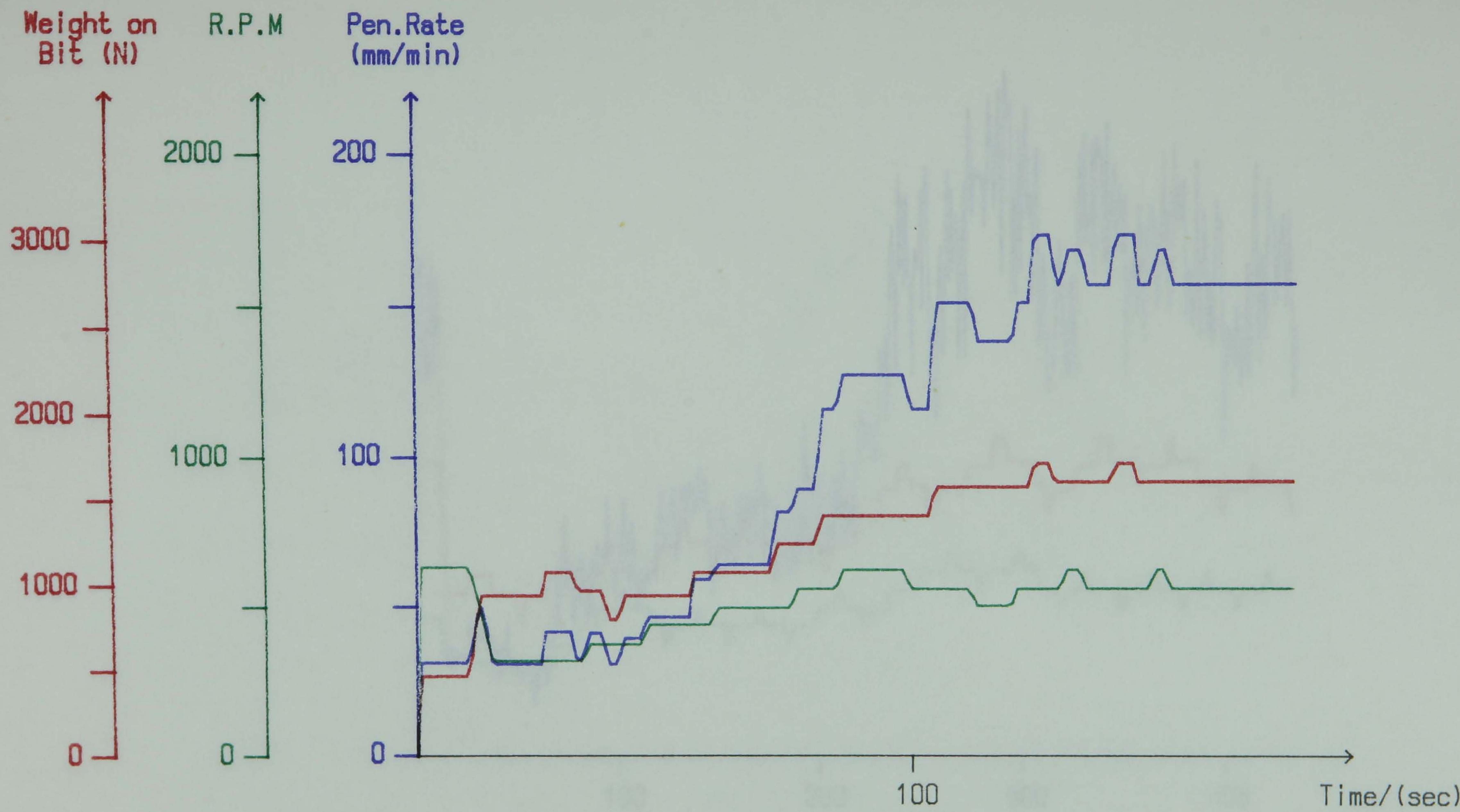


Figure 7.28 The Drill Simulator's Response to Optimisation by Minimum Cost, No Data Fluctuations Present

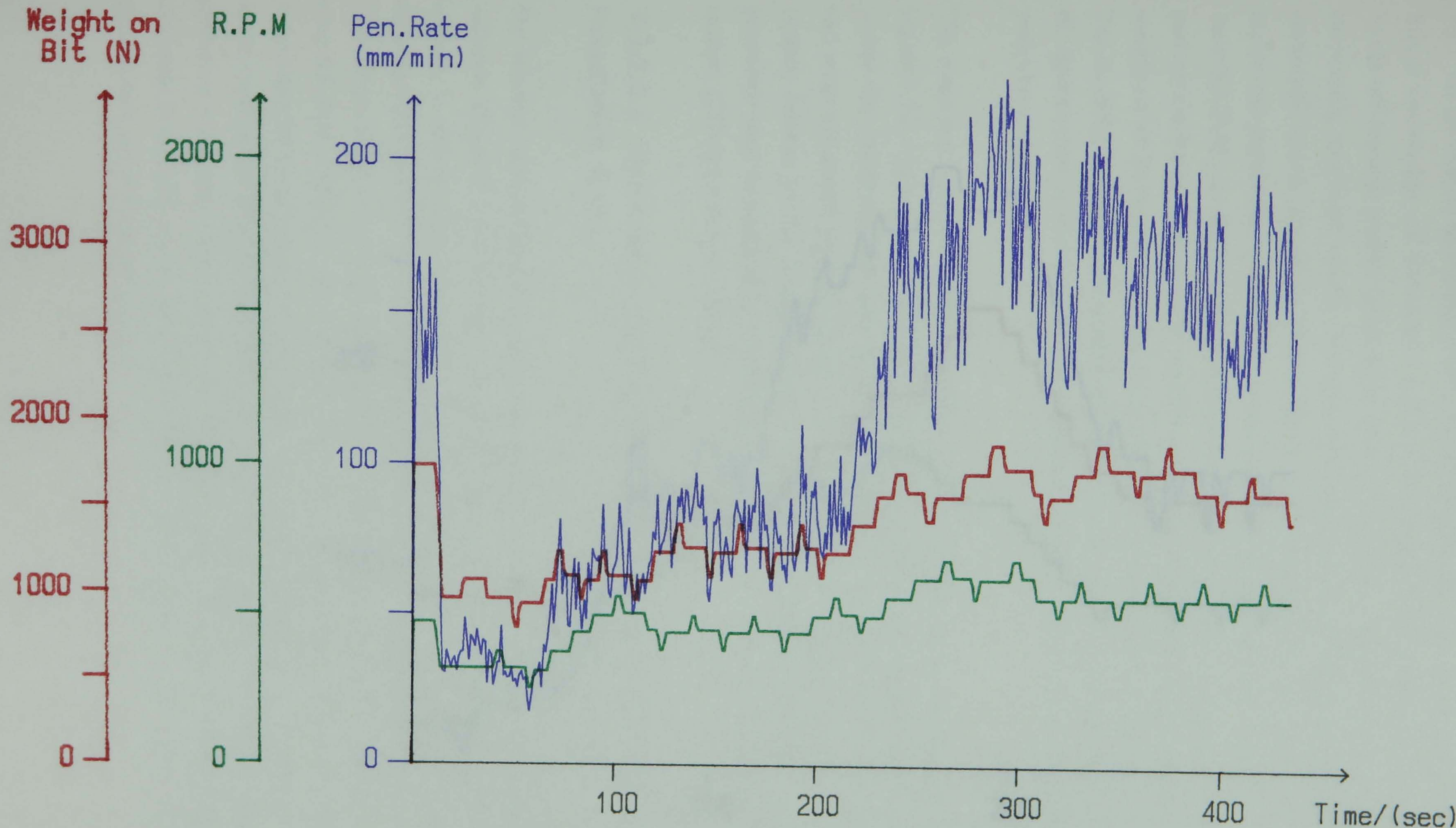


Figure 7.29 The Drill Simulator's Response to Optimisation by Minimum Cost, with Penetration Rate Variance

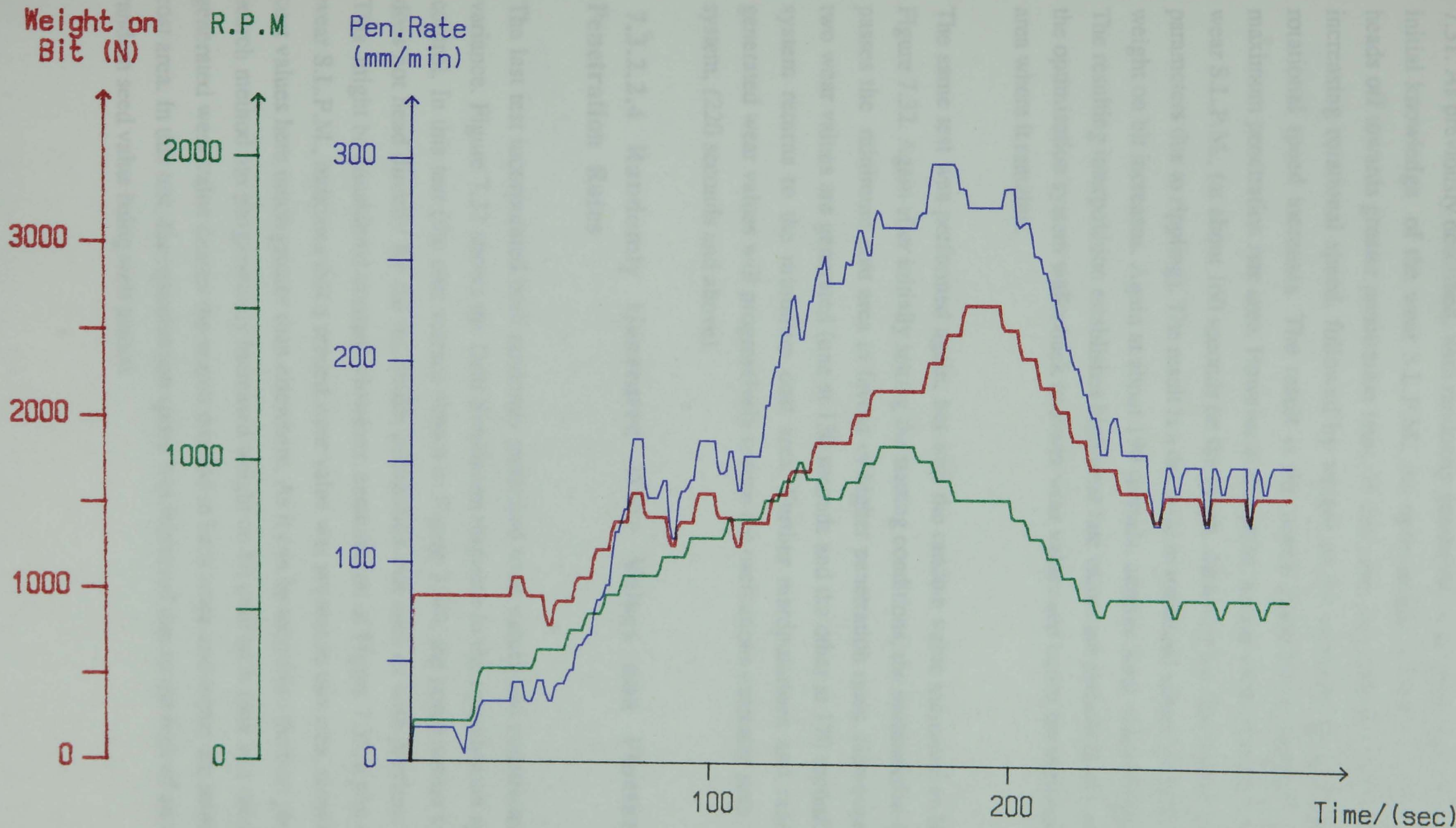


Figure 7.30 The Response of the Drill Simulator to Optimisation by Minimum Cost, with Randomly Generated Wear Values, the Randon Value Set at 5

7.31. As previously described, with randomly generated wear values due to the lack of initial knowledge of the wear S.L.P.M., the optimisation system at the beginning heads off towards greater penetration rates. In this case, improvements are gained by increasing rotational speed, followed by weight on bit increases with intermittent rotational speed increases. The result is the search point being located near the maximum penetration rate area. However at this point, a wear value is entered into the wear S.L.P.M., (at about 160 seconds on the graph, shown by the flat lines of all three parameters due to rippling). The result is a decrease in rotational speed but with further weight on bit increases. Again at about 190 seconds, another wear value is generated. The resulting interpolation establishes high wear rate values are present in this area and the optimisation system walks back to lower wear values and hence the minimum cost area where it remains.

The same test was performed again, but with the random value increased to twenty, Figure 7.32. Again after initially setting the starting conditions, the optimisation system passes the minimum cost area in favour of higher penetration rates. However, after two wear values are generated (one at 130 seconds and the other at 170 seconds), the system returns to the minimum cost area. Further manipulations and randomly generated wear values will progressively reduce the oscillations currently seen in the system, (220 seconds and above).

7.3.2.2.4 Randomly Generated Wear Values and Fluctuating Penetration Rates

The last test incorporated both randomly generated wear values and penetration rate variance. Figure 7.33 shows the Drill Simulators response to the optimisation system control. In this test (the cost surface shown in Figure 3.34), the optimisation system does not head directly for the maximum penetration rate area as with previous tests. This might be considered unusual. However, examination of Figure 7.35, a plot of the wear S.L.P.M., indicates that a seeded wear value was present in this area, resulting in cost values here much greater than elsewhere. As it can be seen from the cost plot, the search method has progressively increased weight on bit until such time as a randomly generated wear value causes the search method to back track and locate the minimum cost area. In this test, the optimisation speed was increased due to the luck of an initial random seed value being well placed.

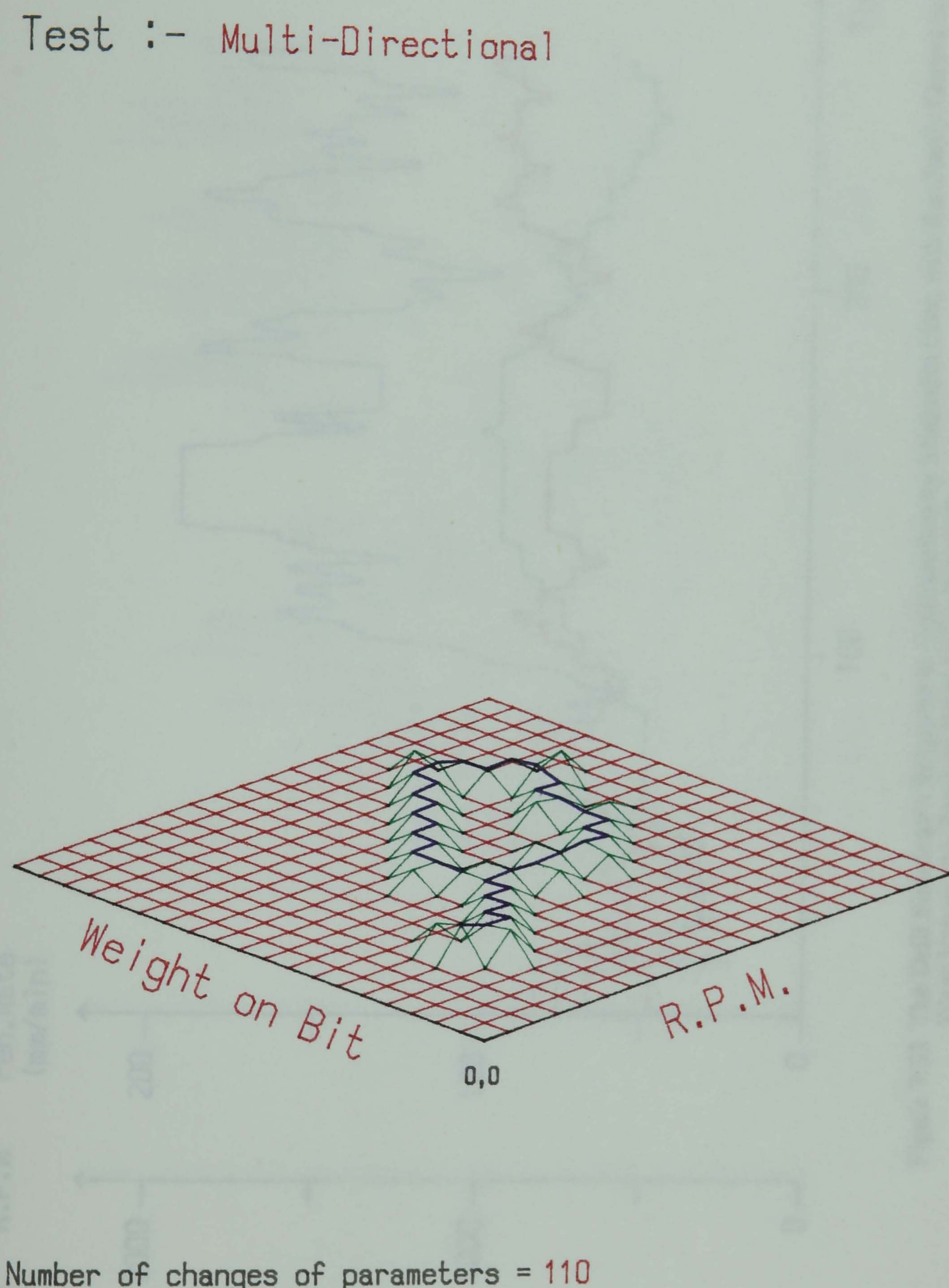


Figure 7.31 A Plot of the Cost Surface Generated by Optimisation Through Minimum Cost with Randomly Generated Wear Values, the Random Value Set at 5

Figure 7.32 The Drill Simulator's Response to Optimisation by Minimum Cost, with Randomly Generated Wear Values, the Random Wear Value Set at 20

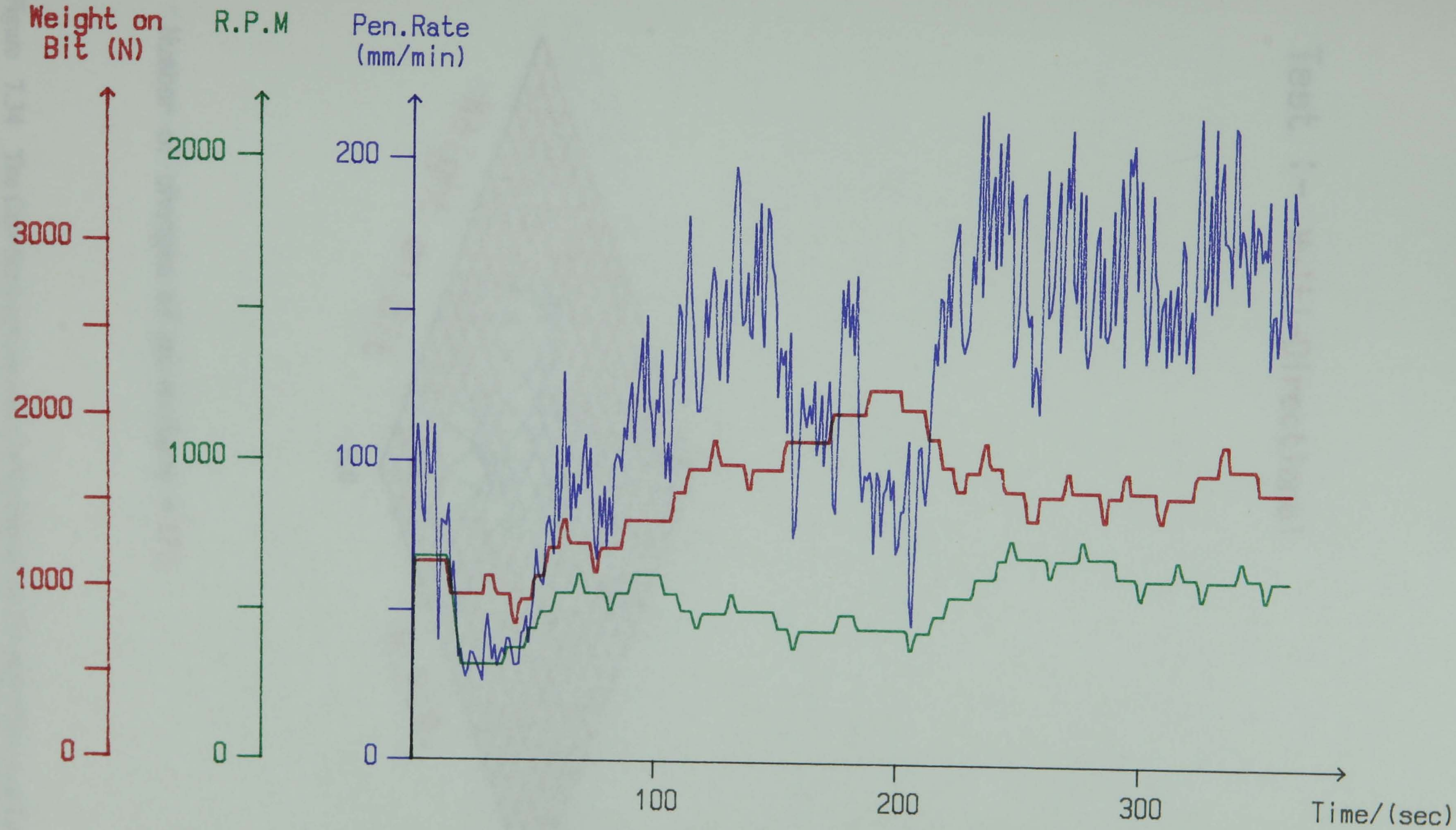
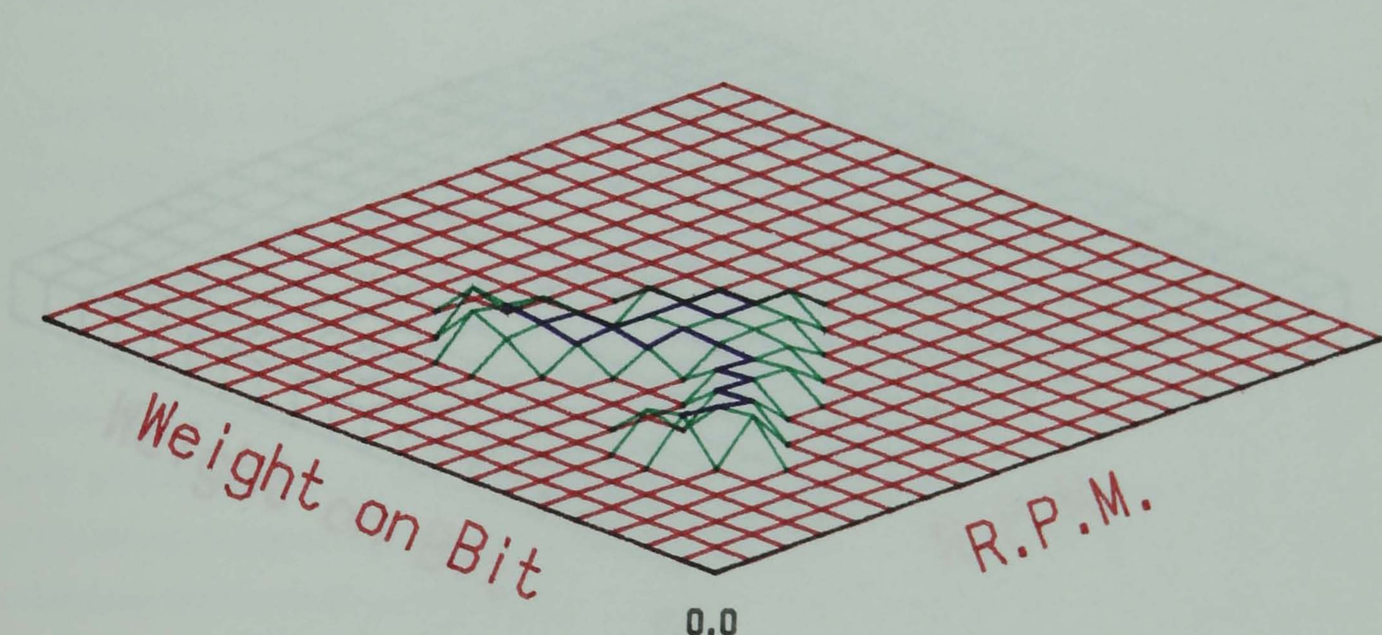


Figure 7.33 The Response of Drill Simulator to Optimisation by Minimum Cost, with Randomly Generated Wear Values and Penetration Rate Variance

Test :- Multi-Directional



Number of changes of parameters = 172

Figure 7.34 The Cost Surface Generated by Optimisation Through Minimum Cost Using the Drill Simulator, with Randomly Generated Wear Values and Penetration Rate Variance

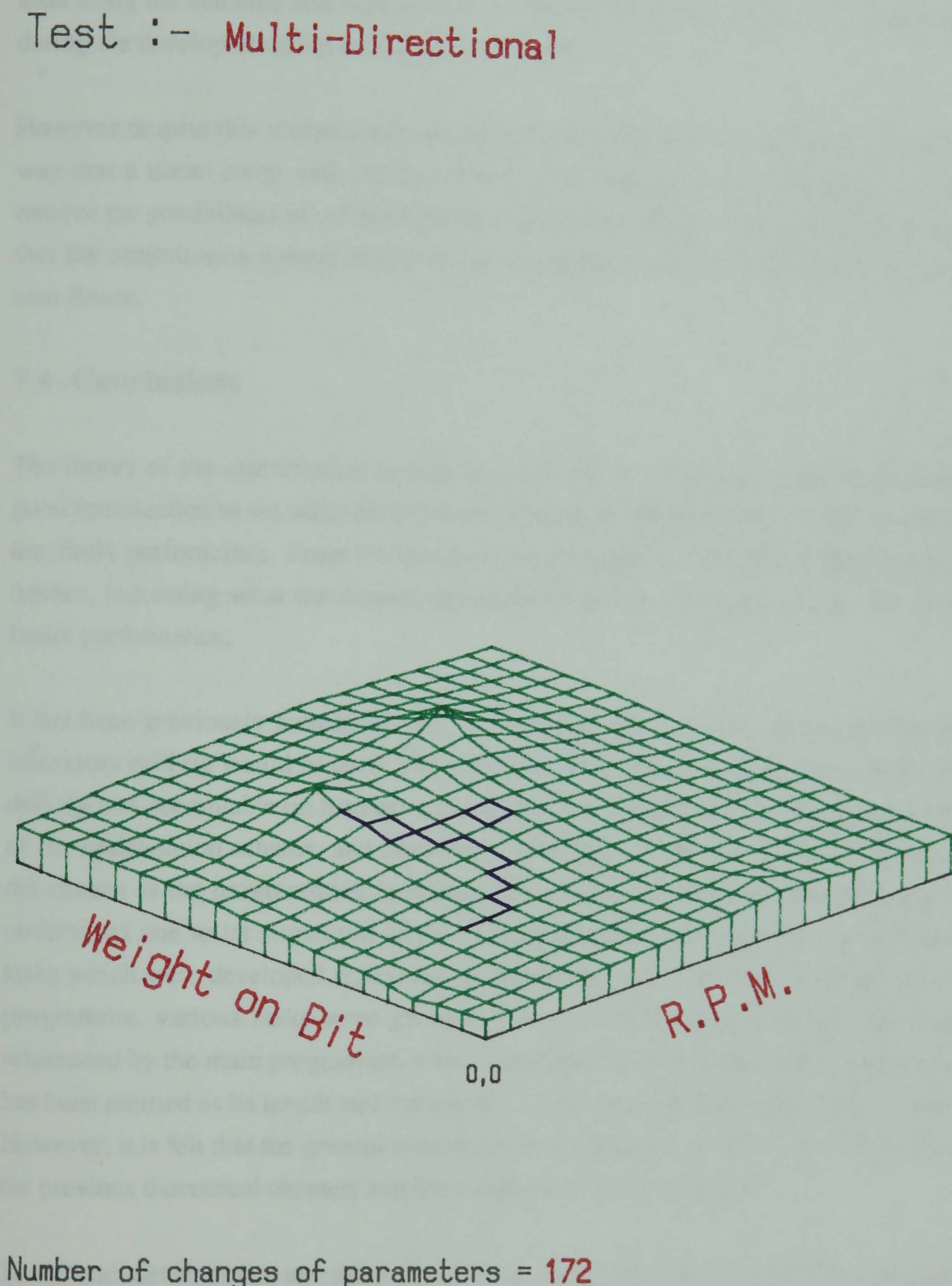


Figure 7.35 The Wear Rate S.L.P.M. Generated by Minimum Cost Optimisation Using the Drill Simulator, with RandomlyGenerated Wear Values and Penetration Rate Variance

7.3.3 The IBM and the Laboratory Drill

Unfortunately due to the lack of time, machine testing was not accomplished. Several tests using the machine and various parts of the optimisation system were undertaken during the development, but no results were saved.

However despite this shortcoming, the BBC Drill Simulator was developed in such a way that a direct swop with the Laboratory drill software can take place. This will remove the possibilities of software problems in the near future. The author is confident that the optimisation system will perform as planned during real drilling trials in the near future.

7.4 Conclusions

The theory of the optimisation system was covered in previous chapters and gave a good introduction to the ideas behind the optimisation scheme, how it works as well as the likely performance. From the results of this chapter, this has been taken one step further, indicating what the current optimisation system is capable of and its likely future performance.

It has been previously mentioned that for the development of the initial system, the laboratory drill rig would be used. The computer system used to monitor an control the drill rig was not suitable (in memory capacity and processor speed) for the development of the optimisation scheme, and therefore a IBM type machine was used. Pascal was the chosen as the programming language, being both versatile and relatively easy to understand due to its structured nature. The optimisation programme was split into tasks which were developed separately, to aid debugging. With the long length of the programme, various tasks were grouped into Units (Sub-programmes) which are referenced by the main programme, when required. Documentation on the programme has been omitted as its length and complexity would take a separate volume to explain. However, it is felt that the general working of the programme can be understood, from the previous theoretical chapters and the results shown in this chapter.

To aid both development and prove the system, the optimisation scheme has undergone a large testing programme. It has been accomplished in several stages, involving different levels of complexity, utilizing the IBM alone, the IBM and BBC drill simulator and the laboratory drill rig.

Initial development test work, used the IBM alone to establish the most effective and efficient search method with which to locate the optimum position. When using the IBM alone, simulators have to be used to generate both the wear rates and penetration rates required. To reduce the complexities further, initial test used maximisation of penetration rates rather than minimisation of cost as the optimisation criteria, being both easier to develop (only one simulator required) and more readily visualised. Of the four search methods tested, Figures 7.2 to 7.12, the combination of the Vector and the Uni-Directional method proved satisfactory, but the Multi-Directional method proved by far to be the best. It found near direct paths to the optimum point, and its efficiency was not dependent upon starting position or direction.

With the search method selected, the testing of the optimisation system was taken a stage further, and a variance was added to the penetration rates. In the first test, the variance was set to $\pm 20\%$, and the optimisation system attained maximum penetration rates readily, Figure 7.14. Such was the success of the system, the variance was increased to $\pm 60\%$ of the simulated value. The path taken in this case, is much more contorted and required many more parameter manipulations, but the system once again has attained the maximum penetration rate area, Figure 7.15.

The success of these initial tests allowed the optimisation system to be switched to search for minimum cost. This required the use of the two simulators, i.e. the penetration rate simulator and the wear rate simulator. The other variables in the cost equation were assigned values, which remained the same for all subsequent tests.

The first test under the minimum cost criteria used straight simulator values i.e. no data fluctuations were incorporated. This was accomplished with relative ease, Figure 7.18. Penetration rate variance was added, and again the optimisation system attained the minimum cost position, but required substantially more parameter manipulations. This increase was due to the fluctuations in the penetration rates, altering the calculated cost values. Only when a representative mean was develop, did the fluctuations in the penetration rates and hence cost reduce.

In the real situation, wear rate values would only be generated at random intervals, unlike in the previous tests which relied on a simulator value for every cost calculation. Therefore, a randomly generated wear value system was developed. Wear values for the cost calculations were obtained from the wear S.L.P.M. , rather than from the wear simulator. New wear values were only entered into the wear S.L.P.M. and rippled, at defined random intervals. Consequently the wear S.L.P.M. would perform its true role as a data enhancement system, rather than just a straight data storage mechanism.

Two tests were performed using randomly generated wear data, one with simulator penetration rates, Figure 7.23, and the other with penetration rate variance of $\pm$ 20%, Figure 7.24. Both tests achieved the minimum cost drilling area, the penetration rate variance taking much longer. In both tests, the optimisation system headed towards the maximum penetration rate area, as the wear values returned by the wear S.L.P.M. were much lower than corresponding ones in the wear simulator, due to the wear S.L.P.M.'s initial limited knowledge. However as wear data was generated in this area, the ripple system revealed the extent of the high wear rates in this region, and therefore the high costs. As a consequence, the optimisation system returned to areas of lower wear rates and thus attained the minimum cost position.

These two tests highlight that the system can work from very little prior knowledge, but the time taken to do so may be great. However the speed of optimisation could be increased if some knowledge was present before hand, e.g. the priming of the wear S.L.P.M. with historical data. Furthermore, with the passing of of knowledge from test to test, wear predictions will progressively improve, increasing optimisation speed, Figure 7.25.

A set of similar tests were performed using the IBM and The BBC Drill Simulator, to incorporate the data transfer mechanisms etc. The results (Figure 7.26 - 7.35), show both plots of the optimisation surfaces, as well as graphs of the drill simulators response. The true effect of the penetration rate variance can be seen on some of these tests. All the tests achieved their optimum position, their efficiency depending on the severity of the test. The success of these tests has paved the way for Laboratory drill test trials, as the drill simulator was designed to directly interchange with the laboratory drill monitor and control programme.

At the time of writing, laboratory test trials had not conducted. The author though is confident that the optimisation system will perform successfully on the laboratory rig, with the results being presented at the forth coming SPE/IADC Drilling Conference in Amsterdam, March 91

Chapter 8 - Conclusions

In the exploitation of mineral reserves, drilling is an essential part of the location and extraction processes, so much so that drilling expertise is essential for the success of such operations. The increases in present technology, has enable the capability limits to be pushed further each year, and new ways are continually developed to improve or optimise drill performance. However, the development of an automatic drill, capable of self-optimisation is a long way into the future. Some initial attempts have been made to produce such a system, the earliest being in 1968, where the Humble Oil and Refining Company conducted full scale trials on a oil type drill rig. Other more recent developments have mainly been associated with mining type drill rigs such as those manufactured by Tamrock. However the success of these projects has been varied but to the author's knowledge, none have been commercially successful. Therefore, scope exists for the development of a drilling optimisation system.

A brief introduction was made into optimisation and more specifically into drill optimisation in Chapter 1. The Chapter also described that from work conducted by Ambrose, a trade off between penetration rates and wear rates was apparent, which could possibly be used as the control rationale for a drill optimisation system. This formed the basis for this research project, i.e. to develop a drill optimisation system using the trade off between penetration rates and wear rates.

A Laboratory drill rig was already in existence, which used diamond impregnated drill bits. It was used for both Laboratory work as well as research purposes. It was decided to develop the optimisation system around this machine, while not being ideal, it would serve to prove the point. Chapter 2 described, that as the optimisation system would require control as well as monitoring capabilities, due to the constraints in the old drill electronics, the electronic system was rebuilt to allow many additional features to be added, such as rotational speed control, weight on bit control and stop / start control of the drill rig. The modifications to the wear measurement jig were also described as inaccuracies were established, as the jig was progressively used.

At an early stage, it became apparent that the capabilities of the drill monitoring computer / control computer would be insufficient to host the optimisation scheme. Therefore, it was decided to use the BBC as a front end processor, i.e. solely dedicated to monitoring and control of the drill rig, and have the optimisation system running on a separate computer. This was chosen to be an IBM type machine. Data would be passed from machine to machine via an RS232 link. Originally this was thought to be an easy process, but it proved to the contrary, and only by some unorthodox practices was a link eventually established. While this is obviously not an ideal situation, as the system was to be an initial development phase, with future development using a different computer and possibly drill rig, it was though not worthwhile rebuilding the drill electronic to be geared towards the IBM.

In Chapter 3, some initial tests were conducted to generate ideas on drill optimisation techniques as well as highlight any problems that may occur while using the laboratory rig. The initial test took the form of a simple optimisation scheme designed to attain maximum penetration rates. The system worked well as shown by the results. However, some problems did occur with both the optimisation algorithm and drill control. As the optimisation algorithm was only for tests purposes, no modifications to it were made. The drill control problems were of importance however, and corrective measures were taken to alleviate them. The discovery of these problems proved invaluable in later tests and with the lessons learnt about the laboratory rig as well as for a future optimisation system, made these initial tests worthwhile.

These tests, also highlighted the inefficiency of initial testing of the computer software with the laboratory rig, due to the necessity for collaring etc for each test run. This made debugging time consuming and extremely frustrating. Therefore a Drill Simulator was developed in which the simulator programme would exactly mimic the drill rigs monitoring and control processes. Penetration rates were provided by a matrix type system, such that for differing drill parameter values (in this case Weight on bit and rotational speed) different penetration rate values would be returned. By changing the simulation matrices, different responses could be attained, such as would be seen in different rock strata. This would allow testing to be accomplished away for the laboratory rig with increased efficiency. Once the programmes had been proven on the drill simulator, testing could return to the laboratory drill. Many other additions and complications were added to the simulator as the research project developed to assist development, by trying to establish more realistic scenarios. This allows quite comprehensive testing before laboratory trials are required.

With the initial test trials of the laboratory controls etc complete and a drill simulator established with which to aid development, attention turned to developing the main optimisation system. Using the criteria of the trade off between penetration rates and wear rates, ways in which this could be achieved through various drill parameters were examined as described in Chapter 4. Several ways were looked at, such as time for each bit run, total time to completion as well as maximising penetration rates. However all these proved not suitable for various reasons, either not fitting the trade off criteria or being to complex and inflexible to provide a good optimisation scheme. The cost of the operation was also looked at, and a brief cost analysis was conducted, to establish the main cost centres of the drilling operation. While optimising by minimising total cost to completion was rejected as being to inflexible, minimising cost per metre was developed and established as the control mechanism by which this optimisation scheme would work. It had a number of advantages, it was a flexible system, capable of coping with unforeseen problems, good economic benefits as well as the fact that most drilling parameters could be related to it.

A well establish equation existed with which to calculate cost per metre and it was adopted to be used for the main control equation (equation 4.18). However, it did not contain any controllable parameters associated with the drilling operation, and therefore some mathematical manipulation was required, to derive equation 4.27. This relates cost per metre to both penetration rate and wear rate. This equation would be used as the main decision process in the optimisation system. It was also noted in this chapter that this was a fairly simple equation, but the optimisation system would designed to allow a more complicated one covering more of the cost centres to be used, once the initial system had been developed and tested to a satisfactory degree.

A sensitivity analysis was performed on this equation to understand the trends etc associated with the various parameters involved to aid the development of the optimisation scheme.

With the optimisation equation derived, the problem of attaining reliable drilling data for use in the equation, and hence for optimisation was covered in Chapter 5. While penetration rates are generally easy to measure and are often available on line, wear rates are much harder to obtain. Some equations etc, are available which may be used to predict wear, but these can never improve their prediction. Therefore, a data enhancement system was developed to initially store known wear values, and estimate unknowns. The method used a matrix based system in which wear rates could be referenced to various parameters by the dimensions of the matrix. Theses matrices became known as S.L.P.M.'s.

To enhance known data, an interpolation system was developed, known as the ripple method, which would radiate the influence of a known point outwards, until no effect was seen. An extensive testing programme was conducted, to establish the reliability of the ripple method, and the results were shown. Generally, the results proved satisfactory but with complex surfaces, the predictions began to deteriorate. However, when considering that a development system was required, they were adequate at this stage. Improvements could take place at a later date once the main cost optimisation scheme was developed.

The data enhancement mechanism allowed ready available and reliable data with which to use in the cost equation, and thus design and development of the optimisation scheme could take place. This was elaborated in Chapter 6. The chapter described several schemes which were tried, maxima and minima being the first. By establishing a relationship between penetration rates and wear rates, differentiation of the cost equation could occur and hence a solution could be found. A computer programme was developed to use this method, and while this method was abandoned for logistic reasons, it did generate some ideas, which were useful in the development of the current system.

With no solution being found by mathematical means, a computer based search system was developed which from known data, would locate the minimum cost position as shown in Figure 6.6. However as the data may only be partially known, the true optimisation position may yet be undetected, and therefore the search method must also be capable of 'walking' the drill to the true optimisation position by manipulation of the drill parameters. Several method were designed to do this, their theory being covered in Chapter 6. The design of the complete cost optimisation scheme was shown in Figure 6.9.

The current cost optimisation scheme design has not considered the effect of changes in rock strata. This was also dealt with in Chapter 6. The optimisation system would cope as it stands with a change in rock strata, the penetration rate and wear rate S.L.P.M.'s learning the new process corresponding to the new rock type. However this would be a time consuming process and irradicate all the information learnt about the previous rock strata. Therefore it was proposed that each rock strata would have its own set of S.L.P.M.'s. For this to be incorporated into the optimisation system though, detection of a change in rock strata must occur in addition to its prediction. Detection of strata boundaries is possible through the use of specific energy and other related parameters. Rock strata prediction from the measured drilling variables, however is much more difficult. Research in this area is relatively new, with many different ideas being followed. At present no reliable prediction system has been developed but it is thought that one will be developed in the foreseeable future.

With such a system incorporated into the scheme (Figure 6.12), once a rock boundary has been indicated and the prediction on the rock type made, the appropriated S.L.P.M.'s can be selected allowing the optimisation process to continue. The interchanging of the S.L.P.M's and the progressive use of the system, will allow the gradual build up of knowledge for each rock strata. At the time of writing the optimisation system does not include the capability for changes in rock strata.

The testing of the optimisation system was covered in Chapter 7, which described the various tests which were used to prove the drill optimisation system. Initial testing used the IBM alone to eliminate the requirement for data transfer between the two computers. It also used maximum penetration rates as its optimising criteria requiring only a penetration rate simulator, rather than the two required by the cost system.

The first series of tests involved the selection of the search routine to locate the true optimum position through manipulation of the drill parameters. Four methods were proposed in Chapter 6, and their results indicated that the Multi-Directional method was be the best, (Figures 7.2 - 7.13. This method found a near direct route to the optimum position, and its efficiency was not effected by starting position or direction. To test the durability of this method a variance in the penetration rates was added. Initially this was set at $\pm 20\%$ of the simulator value and then increased to $\pm 60\%$. Both these tests acquired the maximum penetration rate region, the $\pm 60\%$ variance taking much longer and requiring many more parameter manipulations, Figures 7.14 -7.15.

With these tests performed satisfactorily, the system was switched to optimise by minimum cost. With no data fluctuations incorporated the system located the minimum cost position directly, Figure 7.18. Penetration variance was added, and although the path to minimum cost was more contorted and required a larger number of manipulations, the minimum cost position was found once again, Figure 7.19.

The two previous tests had relied 'on line' wear measurements i.e. for every cost calculation, a wear value was returned from the wear simulator. In reality however, this is not possible as wear values are generated at intermittent intervals. Therefore a randomly generated wear value mechanism was developed. In this process, the wear values for the cost calculations were returned from the wear S.L.P.M., rather than the wear simulator. To enable the wear S.L.P.M.to learn the wear process as in real life, wear values were entered into the wear S.L.P.M. at a variable random interval. In this way, the wear S.L.P.M. perform the role of a data enhancement mechanism rather than a data storage system.

Two tests were performed, one using simulator penetration rate and the other with penetration rate variance, Figures 7.20 -7.24. The initial limited knowledge of the wear S.L.P.M. caused some initial wandering, but once the wear process had been learnt by additionally generated wear values, the minimum cost position was located. The effect of the passing on of information was also demonstrated by the running of the same test, but with the information of the previous test included, and showed the minimum cost position to be located much quicker, Figure 7.25.

With the testing of the system on the IBM alone complete, a similar series of tests were conducted using the IBM in conjuction with the BBC Drill Simulator to incorporate the data transfer mechanisms etc. All tests again proved satisfactory as shown by the results, Figures 26-35. The time taken however was much longer due to the response of the Drill Simulator. This test phase ensured that the system would work with the BBC and that the data transfer software was free form errors. As the simulator programme was designed to directly interchange with the laboratory drill monitor /control programme, and thus, these tests paved the way for laboratory drill test trials.

Unfortunately due to time constraints, full scale laboratory test trials did not take place. However various parts were tested with the laboratory rig and worked satisfactorily. However no results were retained at the time. The author is confident though that test trials in the near future will prove the validity of this drill optimisation system.

In concluding, a drill optimisation system has been developed which is capable of achieving drill optimisation either by maximising penetration rates or more importantly by minimum cost per metre drilling. The theory of the optimisation system has been covered and much of the development work conducted described. Results of the first phase of testing of the optimisation system have also been included and described. They indicate the success of this initial development minimum cost drilling optimisation system and highlight the potential it holds for revolutionising current drilling practices.

Chapter 9 - Recommendations for Future Work

In this thesis, a description of the first stages of the development of a drill optimisation system have been given. It has also shown the initial testing of the system, highlighting the potential for further development, with the ultimate aim of producing a commercially viable drill optimisation system. However before this system becomes commercially viable, there are many more research and development stages which must be accomplished. Some ideas and thoughts for future work are covered in this Chapter. It has been split into two parts, firstly initial improvements to the optimisation system itself and secondly, more general recommendations.

9.1 Improvements to the Optimisation System

9.1.1 Rock Boundary Indication and Strata Prediction

This subject was briefly covered in Chapter 6, where reference was made to the detection of strata boundaries, and the ultimately the prediction of strata type. However, research and conclusions in this area are still vague and thus a comprehensive literature survey and analysis would be beneficial to establish present states of the art and possible areas where additional strata prediction research could be undertaken. The research conducted by Rogers and Rowsell shown in Figure 6.11 should also be continued further as these results proved promising.

A strata boundary indicator and rock type prediction mechanism should be also incorporated into the optimisation scheme, however elementary for the following reasons:-

1) It would allow the development of the various S.L.P.M. switching routines which will be required, as well as some sort of testing routine to check whether the correct selection has been made, i.e if the drill parameters show large continual discrepancies from the S.L.P.M. values, a wrong selection may have been made.

In addition, the problem of data corruption within the S.L.P.M.'s can be addressed. When passing through strata boundaries bedding planes etc, are likely to corrupt the data values held within the previous rock strata S.L.P.M.'s. Furthermore, the wrong rock type prediction, and thus wrong S.L.P.M. selection would also cause undesired data corruption. Therefore some mechanism, such as a buffering procedure, to store and vet the data needs to be developed, to limit the possibility of corrupting the S.L.P.M.'s.

2) If the two processes i.e. boundary indication and strata prediction are unitised, when better recognition systems are developed, they may be directly switched with the old methods, thus not incorporating any programme alterations as would be the case if the prediction mechanisms were incorporated into the main optimisation programme. Furthermore, this would allow a very basic initial predictor to be used to enable point 1 to be accomplished.

3) A better understanding and possible use of the parameters measured and calculated, may be developed when concerned with strata identification.

9.1.2 Rolling Depth

All the minimum cost test, presently formed are with the depth being held constant. This should be changed to allow the depth to be increased at the rate of penetration as the test progresses. As the depth increases a continual change in the cost profile will be seen, thus requiring constant re-establishment of the minimum cost position. However, particularly in the simulated tests, the depth increase may be required to be accelerated say by a factor of ten, since by using real time penetration rates, the time taken to reach depths of 1000 metres will be great.

9.1.3 Multi-Peak Surface Prediction and Improvements to the Ripple Method

In Chapter 6, a method of locating the minimum cost position using Maxima and Minima theory was described. To enable differentiation of the cost equation, a substitution had to be made. This was achieved by fitting a polynomial equation to the data in question, to eliminate one of the unknown parameters. While this method was rejected, it does have several important processes which could be used to improve the performance of the optimisation system.

i) Multi-Peak Surface Predictor.
The simulation processes etc used so far have only had one maximum or minimum point, for simplicity reasons. Some research has suggested that drilling costs will have only one such value *(31)*. However, it would be advantageous if the optimisation system could cope with multi-peak surfaces in case they arose. Such a system could be

developed, by using the polynomial curve fitting routine used for the maxima and mimima system. A series of curves could be fitted to the data held within the S.L.P.M.'s for each set of parameters. The general trends of these equations could be established to see if a second hump or trough was present. Depending on the optimisation required, the search algorithm could be switched to investigate this region. If improvements were seen, then the optimisation system would remain at this new position, otherwise it would return to the previously located optimum point.

Furthermore the use of these curves could also be used to establish trends in the data to aid the Multi-Directional search method locate the optimum point with increased speed.

ii) S.L.P.M. Prediction Accuracy

From the results of the ripple method it was apparent that on non linear surfaces, the prediction accuracy was reduced, being more pronounced on complex surfaces. This is due to the linear averaging process employed, being unable to cope with a non-linear process.

The process could be again enhanced by using the curve fitting routine for interpolation purposes, instead of or in conjunction with the Ripple Method. By fitting curves to the data contained within the S.L.P.M.'s, depending on the accuracy of the fit, the unknown data points could be adjusted to the values attained from the resulting polynomial equation. This would enable a much better interpolation system for non-linear surfaces.

Only outline sketches of these two recommendations have been made but it is in the authors opinion that it would be a valuable contribution (particularly the improvements to the prediction accuracy) if developed and incorporated into the optimisation system.

9.1.4 Wear Rate Variance

The generation of the randomly generated wear rate mechanism went along way to improving the realism of the optimisation tests. However, the values entered into the wear S.L.P.M. were those of the simulator, and thus contain no variance, i.e. if the same point was entered twice, the same value would be returned from the simulator. Therefore it is proposed to include a variance mechanism in the wear rates values such as those seen for the penetration rates, as it is very unlikely that in the field that variation in wear rates will not occur.

9.1.5 Examination of the Optimisation Programme

During the research project, every effort was made to keep the optimisation programme as tidy and as structured as possible. However, with progressive developments etc, this is always difficult to maintain. Furthermore, when initially developing routines, solutions are required and generally the first found becomes the only one due to time constraints. As a consequence, many of the routines written may be inefficient. It is felt that at this stage, it would be beneficial to initially tidy up the optimisation and support programmes, and examine the various routines to see if improvements in efficiency can be obtained.

9.2 General Improvements and Recommendations

9.2.1 Machine Test Trials

Of all the recommendations for further work this must be the most important and which due to time constraints was not performed. While simulation tests etc are worthwhile and serve to reduce awkward laboratory testing, especially when developing and debugging software, they are no substitute for the real situation. Therefore it is recommended that the series of initial tests performed on the IBM alone, and the IBM and drill simulator are performed to the laboratory drill rig in the near future. This will give creditation to the optimisation system indicating it can work in a real environment as well as a simulated case.

9.2.2 Wear Data

Most of the minimum cost test work was conducted using totally hypothetical wear scenarios based on the work conducted by Ambrose on diamond impregnated bits. Despite this work, there is insufficient wear data to establish a comprehensive wear scenario. Although the optimisation system can (and is designed to) run with limited wear knowledge and enhance its knowledge through the generation of new wear rate values as drilling proceeds, in the laboratory situation, such a testing programme is impracticable as it would take an exceedingly long time to accomplish just one test.

This lack of real knowledge, thus prevents the system from being tested with real data, and hence being able to determine whether realistic solutions are being achieved. Information such as this could be obtained from some of the wear predictor equations such as Galle and Woods and it is recommended that this is undertaken to see the simulators response.

However, historical data from industry would also be beneficial in two ways. Initially the data could be used to prime the wear S.L.P.M. and the results of this analysed. Secondly, with more information such as penetration rates, weight on bit, torque, stratagraphic columns etc, the optimisation system could be run to see the correlation between those reported by the historical data, and that by the optimisation system. If the results were widely different, examination could determine whether further improvements to the optimisation system were necessary or whether it could predict lower cost holes.

9.2.3 Field Test Trials

While this is some way into the future, it is worth mentioning as some steps could be taken to aid this process. The installation of the optimisation system on a industrial drill rig poses many problems with both safety and reliability, compared to that of a laboratory rig. Therefore it is proposed that a survey is conducted to establish what electronic monitoring and control systems i.e. transducers etc, is available and permissible for use on such a drill rig. This would enable early selection to be made, allowing the required electronics and software to be developed.

Once the hardware side has been developed, it is envisaged that field trials would take a two phase approach, the first using the optimisation system solely in a monitoring role, with the optimisation system results being displayed as a suggestive action. In this way, creditation of the optimisation system could be achieved with regards to transducer reliability, optimisation predictions etc, without directly interfering with the drilling operation. Secondly once the initial stage was successfully proven, the control side could be incorporated and the optimisation system run in its entirety.

With these recommendations and further research work, it is hoped that this drill cost optimisation system may in the future be a indispensable requirement of the rig floor.

References

1) **Allen, J. H.**,1977: 'Determining parameters that affect rate of penetration'. Oil and Gas Journal, 3 October, P.94-139.

2) **Ambrose, D.**,1987: 'Diamond Core Bit Performance Analysis'. Unpublished PhD Thesis, University of Nottingham.

3) **Arehart, R. A.**,1989: 'Drill bit Diagnosis Using Neural Networks'. SPE 19558. 64th Annual Technical Conference and Exhibition, San Antonio.

4) **Barrett, W. L.**,1984: 'Costing a Drilling Programme'. Geodrilling, February, P.18-22.

5) **Blick, E. F. and Chukwu, G. A.**,1990: 'How to predict when to pull the bit'. Petroleum Engineer International, January, P.39-41.

6) **Bode, D. J., Noffke, R. B. and Nickens, H. V.**,1989: 'Well Control Methods and Practices in Small-Diameter Wellbores'. SPE 19526. 64th Annual Technical Conference and Exhibition, San Antonio.

7) **Bourdon, J. C. and McCann, D.**,1989: 'Comparison of Field and Laboratory-Simulated Drill-off Tests'. SPE 16162. SPE Drilling Engineering, December, P.329-334.

8) **Brett, J. F. and Summers, M. A.**,1984: 'Planning and Practical Problem Solving Using an Engineering Simulator for Drilling'. SPE 13206. 59th Annual Technical Conference and Exhibition, Houston.

9) **Brett, J. F., Warren, T. M. and Behr, S. M.**,1989: 'Bit Whirl: A New Theory of PDC Bit Failure'. SPE 19571. 64th Annual Technical Conference and Exhibition, San Antonio.

10) **Brown, E. T., Carter, P. and Robertson,** W.,1984: 'Experience with a prototype instrumented drilling rig'. Geodrilling, February, P.10-15.

11) **Bullen, G. J.**,'The challenge of synthetic versus natural diamond in the field of hard rock drilling'. Industrial Diamond Review.

12) **Bullen, G. J.**, 'Continuing investigations into the behaviour of impregnated mining bits in hard rock drilling'.

13) **Burgess, T. M. and Lesso, W. G.**,1985: 'Measuring the Wear of Milled Tooth Bits Using MWD Torque and Weight-on-Bit'. SPE 13475. SPE/IADC 1985 Drilling Conference, New Orleans.

14) **Cassapi, V. B., Ambrose, D. and Waller, M. D.**,1987: 'Performance and wear characteristics in diamond core drilling'. Drillex 87, P.5 -20.

15) **Chen, W. and Tian, J.**,1988: 'Multiple Objective Programming in Drilling Optimisation Technique'. Chinese Journal of Petroleum Drilling and Production, No.2, P.1-5.

16) **Collin, W. D.**,'Achieving Optimum Drill Bit Performance - A Practical Method with Particular Relevance to Deep Hole Drilling'.

17) **Cooper, G. A.**,1986: 'Advanced Techniques for Laboratory Full-Scale Drilling Tests'. SPE 14783. IADC/SPE 1986 Drilling Conference, Dallas.

18) **Crain, I. K.**,1969: 'Computer Interpolation and Contouring of Two-Dimensional Data: A Review'. Geoexploration, Vol. 8, P.71 - 86.

19) **Cunningham, R. A.**,1960: 'How high rotary speed shortens bit life, increases drilling costs'. Oil and Gas Journal, Vol. 58, No 28, 11 July, P.91-96.

20) **Cunningham, R. A.**,1978: 'An Empirical Approach for Relating Drilling Parameters'. SPE 6715. Journal of Petroleum Technology, Vol. 30,No 7, July, P.987-991.

21) **Danell, R. E.**,1990: 'Drill Monitoring for the Estimation of In-Situ Material Strength'. Advances in Mining Equipment Performance Monitoring, McGill University,Montreal,Canada.

22) **Dareing, D. W.**,1984: 'Vibrations increase available power at the bit'. Oil & Gas Journal, Vol 82, No 10, March 5, P.91-98.

23) **Eckel, J. R.**,1968: 'How mud and hydraulics affect drill rate'. Oil and Gas Journal, 17 June, P.69-73.

24) **Elliot, L. R., Barolak, J. G. and Coope, D. F.**,1983: 'Recording Downhole Formation Data While Drilling'. SPE 12360. Production Technology Symposium, Lubbock,Texas.

25) **Estes, J. C.**,1971: 'Selecting the Proper Rotary Rock Bit'. SPE 3717. Journal of Petroleum Technology, Vol. 23, No 11, November, P.1395-1367.

26) **Galle, E. M. and Woods, H. B.**,1960: 'How to calculate bit weight and rotary speed for lowest-cost drilling'. Oil & Gas Journal, Vol. 58, No 46,November 14, P.167 -176.

27) **Galle, E. M. and Woods, H. B.**,1960: 'Practical ways to find proper bit weight and rotary speed'. Oil & Gas Journal, November 21, P.160 -167.

28) **Glowka, D. A.**,1985: 'Implications of Thermal Wear Phenomena for PDC Bit Design and Operation'. SPE 14222. 60th Annual Technical Conference and Exhibition, Las Vagas.

29) **Goldsmith, R.**,1985: 'Engineering Opportunities and Challenges in Drilling'. SPE14526. Journal; of Petroleum Technology, July, P.1141- 1148.

30) **Gray, G. R. and Young, F. S.**,1973: '25 Years of Drilling Technology:a Review of Significant Accomplishments'. SPE 4700. Journal of Petroleum Technology, Vol. 25, No 12, December, P.1347-1354.

31) **Guo, X. z.**,1988: 'A Preliminary Investigation on the Objective Function of Penetration Cost Applied to Optimised Drilling'. SPE 14849. SPE Drilling Engineering,

32) **Hagan, T. N.**,1983: 'Performance monitoring of blasthole drills - a means of increasing blasting efficiency'. Surface Mining and Quarrying, October, P.A173 - A179

33) **Hagan, T. N. and Aus, M.**,1983: 'Some recommended features of future drilling equipment - a blasting engineer's view'. Surface Mining and Quarrying, P.235-244.

34) **Howarth, D. F.**,1986: 'Review of Rock Drillability and Borability Assessment Methods'. Trans. Instn. Min. Metall, 95, October, P.A191-A202

35) **Lacy, K. ., Burchardt, B. J. and Buras, K. F.**,1983: 'A Computer Data Base System Design for Drilling Information Analysis'. 58th Annual Technical Conference and Exhibition, San Francisco.

36) **Langston, J. W.**,1966: 'A Method of Utilizing Existing Information to Optimise Drilling Procedures'. SPE 1262. Journal of Petroleum Technology, Vol. 18,No 6, June, P.677-686.

37) **Latva-Pukkila, P.**,1988: 'Computerized Drilling The Latest Development in Drilling Technology'. 21st Apcom Proceedings.

38) **Li, Y. F. and Lau, C. C.**,1989: 'Development of Fuzzy Algorithms for Servo Systems'. IEEE Control System Magazine, April, P.65-72.

39) **Lieghton, J. C., Brawner, C. O. and Stewart, D.**,1982: 'Development of a correlation between rotary drill performance and controlled blasting powder factors'. August, P.67 -73

40) **Lummus, J. L.**,1969: 'Factors to be Considered in Drilling Optimisation'. Journal of Canadian Petroleum Technology, October - December, P.138-146.

41) **Lummus, J. L.**,1970: 'Drilling Optimisation'. SPE 2744. Journal of Petroleum Technology, November, P.1379 - 1388.

42) **Lummus, J. L.**,1971: 'Acquisition and Analysis of Data for Optimised Drilling'. Journal of Petroleum Technology, November, P.1285 -1293.

43) **Lummus, J. L. and Field, L. J.**,1968: 'Non-Dispersed Polymer Mud:A New Drilling Concept'. Journal of Petroleum Technology, March, P.59 - 65.

44) **McDaniel, K. W. and Lummus, J. L.**,1971: 'Here's how to apply optimised-drilling techniques'. Oil and Gas Journal, 14 June, P.57 - 63

45) **Millheim, K. K. and Huggins, R. L.**,1983: 'An Engineering Simulator for Drilling: Part 1'. SPE 12075. 58th Annual Technical Conference and Exhibition, San Francisco.

46) **Mol, O., Danell, R. and Leung, L.**, 1987; 'Studies of Rock Fragmentation by Drilling and Blasting in Open Cut Mines'.

47) **Moore, P. L.**,1986: 'Drilling Practices Manual'. PennWell Books.

48) **Morel, E. H.**,1988: 'Optimisation of Gas Field Developments'. SPE 19033. Journal of Petroleum Technology.

49) **Outmans, H. D.**,1960: 'The Effect of Some Drilling Variables on the Instantaneous Rate of Penetration.'. SPE 8117. Petroleum Transactions AIME, 219, P.137-149.

50) **Pearse, G.**,1989: 'Hydraulic Drills'. Mining Magazine, July, P.48-55.

51) **Peck, J. and Pollitt, D.**,1990: 'Lithological Recognition Based on Rotary Blasthole Drilling Performance Monitoring'. Advances in Mining Equipment Performance Monitoring, McGill University,Montreal,Canada.

52) **Peck, J. and Scoble, M.**,1989: 'Drilling Intelligence and Automation'. Vol. 2, No. 2.

53) **Peck, J., Scoble, M. J. and Hendrick, C.**, 'Monitoring While Drilling Production Blastholes: Applications in Surface Mining'.

54) **Pfister, P.**,1985: 'Recording drilling parameters in ground engineering'. Geodrilling, October, P.8-14.

55) **Remson, D.**,1985: 'Planning Technique - Key to Drilling Efficiency'. SPE 13467. Journal of Petroleum Technology, September, P.1613-1621.

56) **Rowsell, P. J.**,1987: 'Drill Performance Monitoring'. Unpublished B Eng. Dissertation, University of Nottingham.

57) **Samaniego, F. and Cinco-Ley, H.**,1983: 'Pressure Transient Analysis for Naturally Fractured Gas Reservoirs: Field Cases'. SPE 12010. 58th Annual Technical Conference and Exhibition, San Francisco.

58) **Scoble, M. J., Peck, J. and Kennedy, D.**,1989: 'Drill Monitoring Investigations in a Western Canadian Surface Coal Mine'. Second Large Open Pit Mining Conference.

59) **Sheikloeslami, B. A., Miller, D. M. and Strong, R. E.**,1984: 'A Practical Method for Evaluating Rig Performance'. SPE 11364. Journal of Petroleum Technology, March, P.489-494.

60) **Simpson, J. P.**,1971: 'Drilling Fluids -Today and Tomorrow'. SPE 3714. Journal of Petroleum Technology, November, P.1294 -1298.

61) **Simpson, M. A.**,1984: 'Calculator program optimises bit weight, rotary speed, reducing drilling cost.'. Oil & Gas Journal, Vol. 82, No. 17, April 23, P.71-78.

62) **Teale, R.**,1965: 'The Concept of Specific Energy in Rock Drilling'. Int.J.Rock.Mech.Mining Sci., 2, P.57-73.

63) **Thorogood, J. L.**,1987: 'A Mathematical Model for Analysing Drilling Performance and Estimating Well Times'. SPE 16524/1. Offshore Europe 87, Aberdeen.

64) **Unknown**,1985: 'Computer Controlled Drilling'. International Mining, October, P.21-25.

65) **Unknown**,1986: 'Advances in Exploration Drilling Technology'. International Mining, January, P.32-35.

66) **Vynne, J.**,1990: 'How to Improve the Drill and Blasting Efficiency in Open Pit Mines'. Advances in Mining Equipment Performance Monitoring, McGill University,Montreal,Canada.

67) **Walker, S. H. and Millhiem, K. K.**,1989: 'An Innovative Approach to Exploration and Drilling: The Slim-Hole High-Speed Drilling System'. SPE 19525. 64th Annual Technical Conference and Exhibition, San Antonio.

68) **Wampler, C. and Myhre, K.**,1990: 'Methodology for selecting PDC bits cuts drilling costs'. Oil & gas Journal, January 15, P.39-44.

69) **Warren, T. M.**,1983: 'Factors Affecting Torque for a Tri-Cone Bit'. SPE 11994. 58th Annual Technical Conference and Exhibition, San Francisco.

70) **Welch, R. H.**,1982: 'The Role of Synthetic Diamonds in Drilling'. Sixth Australian Drilling Association Symposium.

71) **Wijk, G.**,1989: 'The Stamp Test for Rock Drillability Classification'. Int. J. Rock Mech. Min. Sci & Geomech Abstr., Vol. 26,No 1, P.37-44.

72) **Winters, W. J. and Warren, T. M.**,1987: 'Roller Bit Model With Rock Ductility and Cone Offset'. SPE 16696. 62nd Annual Technical Conference and Exhibition, Dallas.

73) **Wright, D. N. and De-Barra, C.**,'Selection of diamond bit type for hard rock drilling'. Industrial Diamond Review.

74) **Young, F. S.**,1969: 'Computerised Drilling Control'. SPE 2241. Journal of Petroleum Technology, Vol. 246.

75) **Zhang, H.**,1988: 'New Methods for Drill Bit Evaluation and Selection'. Chinese Journal:Petroleum Drilling & Production Technology, Vol 10, No 3, June

76) **Zhou, Z.**,1988: 'Effect of Bottom Hole Pressure Differential on Penetration Rate'. Chinese Journal: Petroleum Drilling and Production Technology, No 2.