CRANFIELD UNIVERSITY

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PROCESS MONITORING AND ADAPTIVE QUALITY CONTROL FOR ROBOTIC GAS METAL ARC WELDING

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PhD Thesis

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ABSTRACT

The aim of this research was to develop an adaptive quality control strategy for robotic gas metal arc welding of thin steel sheets. Statistical methods were used to monitor and control the quality of welds produced.

The quality of welds cannot be directly measured during welding. It can however be estimated by correlating weld quality parameters to relevant process variables. It was found sufficient to do this using welding current and voltage transient signals only.

The strategy developed was problem solving oriented with emphasis on quality assurance, defect detection and prevention. It was based on simple algorithms developed using multiple regression models, fuzzy regression models and subjective rules derived from experimental trials.

The resulting algorithms were used to

control weld bead geometry;
prevent inadequate penetration;
detect and control metal transfer;
assess welding arc stability;
optimise welding procedure;
prevent undercut;
detect joint geometry variations.

Modelling was an integral part of this work, and as a feasibility study, some of the models developed for process control were remodelled using "Backpropagation" Artificial Neural Networks. The neural network models were found to offer no significant improvement over regression models when used for estimating weld quality from welding parameters and predicting optimum welding parameter.

As a result of the work a multilevel quality control strategy involving preweld parameter optimisation, on line control and post weld analysis was developed and demonstrated in a production environment. The main emphasis of the work carried out was on developing control models and means of monitoring the process on-line; the implementation of robotic control was outside the scope of this work. The control strategy proposed was however validated by using post weld analysis and simulation in software.

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I dedicate this work to the memory of my late father

Chief Henry Olatunji Ogunbiyi

(1934-1995)

I praise God for his life

"All models are wrong, but some are useful"

George Box, 1979.

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NOTATION

Symbol	Definition	Unit
ε	Prediction percentage error	%
Bp	Bottom plate penetration	mm
CUR	Setup current for synergic welding	Amps
DCI	Dip Consistency Index	
dev	Prediction error nominal deviation	mm
F	Optimisation objective function	
gap	Gap size	mm
I_{bk}	Average of current transient data less than or equal to I_{mean}	Amps
I_{bkmin}	Threshold on I_{bkref}	Amps
I_{bkref}	Estimated refrence value for I_{bk}	Amps
I_{max}	Absolute maximum transient current in a window	Amps
I_{mean}	Average welding current (Arcwatch)	Amps
I_{meani}	Average welding current at "i" sampling interval	Amps
I_{min}	Absolute minimum transient current in a window	Amps
I_{ps}	Average welding current (Power source)	Amps
I_{ref}	Refrence welding current	Amps
Lavg	Average leg length	mm
Lb	Bottom plate leg length	mm
Lmax	Maximum leg length	mm
Lmin	Minimum leg length	mm
Lmn	Estimated minimum leg length	mm
Ls	Side plate leg length	mm
P	Penetration to plate thickness ratio	
Pen	Minimum plate penetration	mm
Pr(arc)	Possibility measure for bad arc start and weld quality	
Pr(Bp)	Possibility measure for inadequate penetration of bottom plate	
Pr(Sp)	Possibility measure for inadequate penetration of side plate	
Pr(spatter)	Possibility measure for spatter generation	
Pr(und)	Possibility measure for undercut presence	
pt	Plate thickness	mm
S	Setup welding speed	m/min
SE	Standard error of a regression model	
SI	Stability Index	
SO	Setup standoff	mm
SO_i	Estimate of standoff at "i" sampling interval	mm
SO_{ref}	Reference standoff	mm
Sp	Side plate penetration	mm
T	Throat thickness	mm
TI	Transfer Index	
TSI	Transfer Stability Index	
V_{bk}	Average of voltage transient data less than or equal to V_{mean}	Volts
V_{bkmin}	Threshold on V_{bkref}	Volts
V_{bkref}	Estimated refrence value for V_{bk}	Volts
V_{mean}	Average welding voltage (Arcwatch)	Volts
V_{min}	Minimum voltage	Volts
V_{ps}	Average welding voltage (Power source)	Volts
V, V_{set}	Setup voltage	Volts
WFS_{ign}	Ideal WFS required to give good arc ignition	m/min
WFS_{min}	Minimum wire feed speed	m/min
WFS, WFS_0	Setup wire feed speed	m/min

Chapter 1

Introduction

Due to competitive pressures on productivity, quality and safety, robots are increasing being used in many industrial applications including welding. In particular robots are widely applied in batch or volume production of sheet steel parts for white goods and automotive industries. Although robotic applications in welding are expected to give consistent performance, the process tends to be sensitive to changes in its environment, which can lead to defective welds.

The main factors influencing defects in robotic welding are inconsistent joint geometry, shape and position error caused by the cumulative effect of processing operations such as cutting, bending and so on before welding[1,2].

To accommodate these problems it is possible to equip welding robots with sensors to monitor the process. The information from the sensors is sent to a controller that adapts the welding parameters as necessary to ensure that consistently acceptable quality welds are produced. It must be pointed out that in many cases the existing sensors are costly and may restrict process flexibility. Before an attempt can be made to improve this situation the desired quality objectives must be reviewed.

1.1 Quality

Quality is the totality of features and characteristics of a product or service that bear on its ability to satisfy a given need[3]. In gas metal arc welding, this includes the weld size, surface appearance, mechanical property and types of defects present.

Weld quality is normally assessed and controlled manually. This involves[4]:

1. establishing satisfactory welding parameters by procedure trials and testing;
2. selecting and maintaining the same parameters/procedure in production;

3. monitoring by final inspection and nondestructive testing to ensure that the required results are being achieved;
4. correcting for deviation from stated quality requirement by repair and rework.

Final inspection may involve selecting random samples from a batch of finished welds and checking the dimensions and attributes identified as critical to the weld quality against some standard quality criteria. The result of the quality test is taken as representative of the whole batch.

Corrective action, involves making the decision of whether to reinspect the batch, repair or scrap defective welds, increase sample size or change the welding procedure(s). The decision is normally based on statistical quality control techniques[5,6]. The average levels of rejected and defective welds produced over several samples are analyzed using attribute charts such as Pareto charts to check for trends and shift in defect levels.

Whilst the quality control approach described above has been shown to be effective. It is costly, and it is difficult to visualise how the system can cope with a robotic system without the risk of giving false assurance of quality of the welds produced.

The quality of weld produced is usually unknown until the results of the inspection tests and statistical analysis becomes available. Unless production is stopped which is unlikely, there is the possibility that during this inspection lag time, more defective welds could be produced.

Another drawback is that, though the level of defects found may be small compared to the total volume of production, it could still be costly in terms of labour effort in inspection and rework.

The main objective of this project is to reduce the reliance on manual inspection by developing a real time quality monitoring and control strategy for automated welding systems.

Any attempt to control a process implies that all relevant characteristics defining the process are measurable. However, often weld quality parameters cannot be measured directly on-line and if measurable will require expensive hardware such as vision based systems.

In this work, the welding current and voltage transient signals are used to estimate weld quality through mathematical modelling and signal processing.

1.2 Identification of Quality Control Objectives

This research effort has benefited from the availability of confidential industrial data that helped to focus the control objective[7]. The company which supplied this data uses robotic welding to produce safety critical sub-assemblies for the automotive industry.

Statistical data on welding defects covering a period of five months of production of a typical component (a rear axle) was used to identify critical production and welding problems. The quality control procedure used involved taking samples for visual inspection and segregating defective units for detailed analysis. This involved destructive testing; 70 components were selected daily and the worst 20 components were picked for detailed analysis.

The main defects identified were gap filling, undercut, porosity, spatter, bead displacement, bead size and fusion problems. The highest defect rates were; undercut (77.1%), bead size (63.9%) and gap filling (59.75%). The defect' data shows that most of the defects are not critical and usually require no rectification (see Table 1.1). A scrap rate of 1.15% (mainly due to porosity) was reported.

An analysis of this data led to the division of the main control objective into the following sub elements:

1. control of weld bead geometry;
2. prevention of inadequate penetration;
3. control and detection of transfer mode;
4. assessment of arc stability;
5. prevention of undercut;
6. on line estimation of standoff;
7. on line detection of gap.

Table 1.1 An Example of Industrial Defect Statistics

WELDING No.		POROSITY 1	POROSITY 2	POROSITY 3	POROSITY 4	CRACKS 1	CRACKS 2	CRACKS 3	CRACKS 4	UNDERCUTS 1	UNDERCUTS 2	UNDERCUTS 3	UNDERCUTS 4
1	C												
	%												
2	C	40			40								
	%	2.77			2.77								
3	C			2	2								
	%			0.14	0.14								
4	C			2	2					678	16		694
	%			0.14	0.14					47.0	1.1		48.1
5	C			2	2					414	6		420
	%			0.14	0.14					42.6	0.41		43.0
6	C									1110			1110
	%									77.1			77.1
7	C												
	%												
8	C												
	%												
9	C									1100			1100
	%									76.4			76.4
10	C			2	2					978	12		990
	%			0.14	0.14					66.9	0.83		67.7
B-C	C	78	10	12	100					482	82		564
	%	1.60	0.20	0.24	2.04					9.8	1.67		11.47

WELDING No.		OVERLAPS 1	OVERLAPS 2	OVERLAPS 3	OVERLAPS 4	CRATERS 1	CRATERS 2	CRATERS 3	CRATERS 4	SPATTER 1	SPATTER 2	SPATTER 3	SPATTER 4
1	C												
	%												
2	C												
	%												
3	C												
	%												
4	C												
	%												
5	C												
	%												
6	C												
	%												
7	C									92			92
	%									6.40			6.40
8	C									92			92
	%									6.40			6.40
9	C									74			74
	%									5.14			5.14
10	C												
	%												
B-C	C												
	%												

WELDING No.		LENGHT 10 mm 1	LENGHT 10 mm 2	LENGHT 10 mm 3	LENGHT 10 mm 4	COVERING OF GAP 1	COVERING OF GAP 2	COVERING OF GAP 3	COVERING OF GAP 4	DISPLACEMENT OF BEAD 1	DISPLACEMENT OF BEAD 2	DISPLACEMENT OF BEAD 3	DISPLACEMENT OF BEAD 4
1	C									2			2
	%									0.14			0.14
2	C												
	%												
3	C					32			32	28			28
	%					2.20			2.20	1.9			1.9
4	C	510	74		584	118	8		126				
	%	35.41	5.14		40.5	8.20	0.55		8.75				
5	C	530	76		606	88	2		90				
	%	36.8	5.28		42.1	6.10	0.14		6.24				
6	C	6	4		10	26	8		34				
	%	0.41	0.28		0.69	1.8	0.55		2.35				
7	C	16			16								
	%	1.1											
8	C	86			86	4			4				
	%	5.97			5.97	0.28			0.28				
9	C	80	4		84	336	12		348	10			10
	%	5.55	0.28		5.83	23.3	0.83		24.13	0.7			0.7
10	C	148			148	108	4		112	36			36
	%	10.3			10.3	7.5	0.28		7.78	2.5			2.5
B-C	C	264			264	2160	752	22	2934	12	2		14
	%	5.38			5.38	44.0	15.3	0.45	59.75	0.24	0.04		0.28

C= CANTIDAD / QUANTITY
1= DEFECTOS NO REPASADOS
DEFECT WINTHOUT REWOK
2= DEFECTOS PARA REPASAR
DEFECT WITH REWORK
3= CHATARRA / SCRAP
4= TOTAL

MUESTRA TOTAL: 1440 PUENTES TRASEROS
MUESTRA TOTAL: 4906 B-C
TOTAL SAMPLE: 1440 REAR AXLES
TOTAL SAMPLE: 4906 B-C

1.3 Quality Control Strategy Overview

In this project it was aimed to produce a robust strategy for on-line weld quality control using statistical methods. In contrast to conventional statistical process control (SPC)[a], the deviation from required quality was prevented by controlling the process dynamically in response to changes in the process conditions.

The need to prove that the process is not in statistical control is not an overriding priority. The main objective was to ensure that acceptable welds were produced while avoiding critical defects such as undercut and insufficient fusion. Non-critical defects such as spatter and deteriorating arc stability were monitored and reported using conventional SPC. The necessary action and control limits usually referred to as thresholds are set using established process knowledge.

The quality control was treated as regression problem; predetermined relationships between the process parameters, workpiece parameters and final weld quality were developed. They consist of simple algorithms developed using multiple and fuzzy regression models with subjective rules derived from experimental trials.

The complete strategy was anticipatory in nature, this involved deciding in advance what control action should be taken for a disturbance type. This was designed and validated off-line.

The achievement of the control was split into two stages namely; procedural (off-line) and adaptive (on-line) control.

Procedural control is used here to describe the determination of the optimum process input parameters, which would give the required weld quality and minimise the risk of critical defects such as lack of fusion and undercut.

While, **adaptive control** is in this work taken to mean; ensuring acceptable weld quality by monitoring the process and workpiece parameters with sensors and fine tuning the optimum procedure according to the information received by the sensors.

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[a] **Traditional statistical process control follows the steps of detection, study and action. The control action (ie. process adjustment) is taken only when there is statistical evidence that the process is out of control.**

1.4 Thesis Organisation

This thesis contains ten chapters and appendices. The figures are placed at the end of each chapter and the tables are embedded within the text.

Chapter 1 presents the aim of the project and an overview of the control strategy and objectives.

Chapter 2 presents a literature review of gas metal welding process with emphasis on process monitoring, diagnosis techniques, adaptive control, procedure modelling and optimisation.

Chapter 3 describes the control strategy developed and identifies the requirement for process modelling, monitoring and experimental trials.

Chapter 4 summarises the experimental material and equipment used.

Chapter 5 deals with the results of the experimental trials and process modelling.

Chapters 6 and 7 describe the optimisation and quality control algorithm developed respectively.

Chapter 8 provides the comparison between Artificial neural network and Regression analysis for process modelling.

Chapter 9 discusses the results and possible industrial exploitation.

Chapter 10 concludes and suggest further work that could be carried out to enhance the work done.

The **appendices** contain experimental validation data and instruction on how to use the demonstration program developed from the results.

Chapter 2

Literature Review

Gas Metal Arc Welding (GMAW) is the most commonly used process in robotic welding of continuous seams. This chapter presents an overview of the GMAW process, focusing on those aspects relevant to the objective of this research. The emphasis is on providing an understanding of welding process phenomena to aid efficient modelling and control of weld quality.

2.1 The Process

The GMAW process uses the heat generated by an arc created between a consumable electrode and workpiece to melt and fuse the joint. The arc and molten metal are protected by an envelope of gas. The shielding gas protects the weld pool and arc from contamination of the surrounding atmosphere. In the welding of ferritic steels, the gas is usually a mixture of Argon, Carbon dioxide and Oxygen [8,9]. Figure 2.1 gives a diagrammatic representation of the process.

2.1.1 Metal Transfer

The manner in which the electrode is melted and the metal transferred greatly affects weld quality, defect formation, arc stability and positional capabilities of a welding procedure[10,11]. Norrish and Richardson[10] classify metal transfer into two namely "**free flight and dip** "

The process of free flight metal transfer occurs in three stages[12]:

1. a droplet of molten metal of a given size forms at the electrode tip;
2. the droplet travels towards the weld pool;
3. rupture of the bridge between the droplet and the electrode to complete transfer.

Dip transfer is characterised by the arc being periodically extinguished by the wire short circuiting in to the weld pool. This occurs when the electrode is fed towards the workpiece at a speed that exceeds the melting rate due to insufficient heating by the arc. This causes the end of electrode to dip into the pool causing a short circuit. The current then rises to a sufficiently high level to cause the end of the electrode to melt off due to resistive heating[13].

In free flight transfer, a continuous arc is maintained between the electrode and the workpiece while the metal is transferred through the arc in discrete droplets. Globular, spray and pulsed transfer all fall into this classification.

In globular transfer, there is sufficient heat from the arc to melt a drop of metal on the end of the electrode before it reaches the weld pool[13]. The droplet diameter is greater than electrode diameter and may cause spatter when it falls into the weld pool[13,14]. Globular transfer can be further divided into drop and repelled transfer[15]. Repelled globular transfer gives rise to erratic behaviour of the arc during the period the droplet is growing in size and may cause a very large crater to form in the work piece.

Spray transfer is characterised by droplets smaller than the electrode diameter detaching themselves at high frequencies from the end of the wire in a stream of fine droplets[14]. Spray can also be divided into projected, streaming, repelled spray, swinging spray and rotating spray transfer[15]. Figures 2.2 and 2.3 show dip and free flight transfer respectively.

According to Sicard and Levine[16] pulsed transfer occurs when the current is rapidly switched from a high to a low level. During the high-current pulse, metal is transferred across the arc, while during the low level or background current the arc is maintained but no metal is transferred[16]. Although it is now known that droplets initiated in the pulse may transfer during the background period.

2.1.2 Shielding Gases

The primary function of a shielding gas is to protect the molten metal from oxidation as it is transferred to the weld pool. Its composition influences weld fusion, arc stability, metal transfer, productivity and defect formation[17-20].

Three main concerns identified as crucially important in robotic welding shielding gas selection are spatter level, torch overheating and welding speed[20]. These in turn can lead to high cleaning cost, contact tip wear and reduced productivity.

The spatter level can be minimised by ensuring arc stability. Arc stability is enhanced by gases with low ionisation potentials[19]. This suggests that shielding gas should be rich in low ionisation potential gas such as Argon.

The thermal conductivity of the gas mixture is important. Weld fusion can be enhanced by high thermal conductivity gases, due to improved heat transfer to the work piece. Carbon dioxide has higher thermal conductivities than Argon. In addition carbon dioxide gives a higher heat input due to the high voltage requirement[20].

The increased heating effect provided by the addition of carbon dioxide promotes improved joint fusion, penetration and weld pool fluidity[19]. Also from a quality point of view, the stirring effects of the weld pool due to the globular transfer tendency associated with high thermal conductivity gases such as carbon dioxide can produce welds of greater integrity. Spatter level however increases with carbon dioxide, as the droplets are not detached smoothly[17]. Therefore, for robotic welding the shielding gas should be Argon based with 5-20% carbon dioxide (see Figure 2.4).

Oxygen is another important element of many shielding gas mixtures for gas metal arc welding of steel. When added to argon it improves arc stability and increases weld pool fluidity[19]. The typical oxygen content in a mixture is 1-5% by volume.

2.1.3 Arc Stability

Arc stability is the tendency of the welding arc to burn steadily in spite of the continuous (random) variations in welding parameters that are inherent in gas metal arc welding processes[21].

Phillipot[22] defines stability as the ability of the welding process to maintain:

1. a uniform heat input to a joint;
2. regular metal transfer without spatter;

3. smooth weld pool movements in a fixed position relative to the electrode;
4. stiff arc, ie flickering of the arc root does not occur.

In general, the more stable the welding arc the more tolerant the process is to defects[23]. Spatter is the main visible sign of instability. A stable arc generates low spatter while unstable arc generates larger levels of spatter depending upon the degree of process instability[24]. Spatter can lead to porosity because it adheres to the torch inducing insufficient gas shielding. The amount of spatter can be reduced by the correct selection of welding parameters[25].

Most work on assessing arc stability has concentrated on dip transfer. Spray transfer is a naturally stable process, while globular transfer is considered very unstable.

Statistical methods have been used to assess and/or quantify the stability of a welding arc. Standard deviation of a suitable parameter and/or combination (including ratios) of parameters is used as the measure of process stability. The smaller standard deviation the more stable the arc. In dip transfer, the stability is expressed as the standard deviation of the arcing voltage, short-circuiting current, arcing and short circuiting time[26,27].

Although calculating the standard deviation (**SD**) of process parameters, shows the sensitivity of the process to disturbances, it is not an absolute measure and is not suitable for assessing the arc over wide ranges of parameters.

Mita and Sakabe[28] state that when the welding current in dip transfer is low, the **SD** of welding parameters correlate well with arc stability but these correlations becomes poor as the welding current is increased. This led them to develop a novel method of assessing arc stability systematically using multiple regression analysis. A series of weld runs with different parameter combinations and process stability were assessed subjectively by an experienced inspector. The subjective index is then correlated using multiple linear regression with the **normalised SDs** of the welding parameter waveforms. The normalisation is achieved by dividing each parameter by the **SD** of the same parameters obtained from an optimum welding arc.

However most of the stability criteria above are intended for assessing the suitability of power source dynamics and different parameter settings and consumable types. They don't consider the physical nature of the welding process or resulting weld quality.

For example in dip transfer, metal transfer takes place during short-circuiting. Therefore metal transfer consistency and arc stability in dip mode are governed by the short circuit currents[29,30].

The amount of spatter produced is also proportional to the maximum current during the short circuit[29,31]. Dyurgerov[29] found that stable metal transfer and optimum stability is attained at a certain ratio between the short circuit and mean welding currents.

This ratio was used to define power source dynamic and process transient volt recovery characteristics by Lebedev et al.[32]. Lipei et al.[33] and Jennings[34] respectively also found that the ratio can be related qualitatively to the amount of spatter generated.

Lipei et al.[33], states that the ratio should be between 1.5-2 so as to allow the welding current to recover from the effect of short circuiting and keep the weld pool stable and prevent spatter while re-striking the arc.

If the short circuit to mean current ratio is greater than 2, the current output during re-ignition of the arc is so large that the molten pool is strongly depressed and neck rupture is "explosive" causing spatter. Jennings[34], however, set the maximum value at 2.35. There was no name given in the literature for this ratio and it was consequently called "Transfer Stability Index" by the present author.

2.1.4 Weld Pool Behaviour

Productivity and quality do not necessarily go hand in hand, most welding defects stem from productivity requirements and the weld pool physical behaviour. Defects such as undercut and fusion problems are associated with the way the molten metal flows behind the arc to form the weld bead and is affected by welding speed[35,36].

The metal flows from the front to the back of the weld pool under the influence of electro-motive forces. The eddy flows behind the arc will drive the liquid metal from the side surfaces of the groove by the travelling arc, to the centre line of the weld pool behind the arc[36]. The pool is then required to flow back to fill the groove.

The interval of time between the melting of a groove in the parent metal by the arc and its filling with molten weld pool metal is the main reason for the formation of undercut and a zone of lack of fusion. The longer the interval, the more likely it is that undercut and lack of fusion will develop[37]. The interval increases with travel speed since the metal is expelled more towards the rear of the weld pool causing the interval between the melting to become longer.

Weld pool dynamic equilibrium[37]

To achieve good fusion, the weld pool must be in dynamic equilibrium. Disruption of the equilibrium condition causes weld quality to deteriorate and defects to form. Figure 2.5 gives a schematic representation of pressures acting on a weld pool.
The basic condition for weld pool equilibrium and for normal weld formation can be represented in the form,

$$\boldsymbol{P_d = P_v - P_{zh.s}} \qquad \textbf{(2.1)}$$

where

P_v	*is the maximum pressure exerted on the base of the weld pool by the column of molten metal;*
$P_{zh.s}$	*is the pressure developed by the molten metal beneath the arc in the crater region of the weld pool;*
P_d	*is the pressure of the arc column and the flow of plasma and gas on the surface of the molten metal in the crater region of the pool.*

The process of maintaining weld pool equilibrium is self-regulating. Any changes in P_d or P_v results in alteration of the depth of the layer of molten metal beneath the arc and therefore $P_{zh.s}$. Dynamic equilibrium is achieved if the pressure of the molten metal in the pool exceeds the arc pressure. That is, $P_v > P_d$.

Equilibrium will be maintained until the difference between the alteration in the arc pressure and the alteration in the molten metal pressure exceeds the pressure of the layer of molten metal beneath the arc and this causes defects to form in the weld. That is, $P_v \leq P_d$.

Influence of current

P_d and P_v increase with current but P_d increases more rapidly than P_v. Therefore as the welding current is increased, to produce welds with no defects, the welding rate must be reduced. Further increase in current increases P_d till it becomes greater than P_v resulting in weld formation deteriorating.

Influence of welding speed

If welding rate is low, the depth of the layer of molten metal and the pressure $P_{zh.s}$ created by this will be relatively great. Under these conditions fluctuations in P_d and P_v are permissible without deterioration in weld formation. That is, the process is more tolerant; as the welding rate increases, the depth of the molten metal and the pressure $P_{zh.s}$ will decrease.

When welds are made at high speeds, there must be no great fluctuations in P_d and P_v; therefore, for the weld to form normally, the stability of the welding conditions and the conditions under which the weld is made must be maintained more accurately.

Influence of welding position

Figure 2.6 shows the normal classification of welding positions in welding. They generally fall into two categories; downhand and positional. In downhand welding surface tension and gravity both act to retain the metal in the pool. While, the requirement in a positional weld is to ensure that surface tension retains the metal in place. The surface tension must be sufficient to overcome the force of gravity or molten metal will escape from the pool[38].

In the "vertical-down" direction, the arc supports the molten pool, thus preventing burnthrough and making it possible to deposit a larger volume of metal over a greater range of root gaps and travel speed[39]. That is, a relatively small change in P_d will increase P_v, this will tend to increase $P_{zh.s}$ with a consequent reduction in the likelihood of defects in thin section welds[37]. Some care is however needed to ensure that deposited metal does not run ahead of the arc, causing lack of fusion.

While in "vertical-up" direction, the molten metal tends to run down, the removal by gravity of this molten metal from the arc zone makes burnthrough more probable unless root gap, travel speed and pool volume are favourable[39]. This tends to produce a weld bead with a pronounced convex profile, which is difficult to fuse adequately[40]. A small change in P_d decreases P_v and $P_{zh.s}$ thereby increasing the possibility of defects.

When welding in any position, the size of the molten pool is controlled mainly by the level of welding current. The higher the current, the larger the molten pool[41]. In positional welds, the maximum current that can be used is limited by the size of the pool that can be supported by surface tension [41]. Hence, to maintain a small weld pool the welding conditions are limited to dip transfer or pulse transfer modes.

The stability of the process can be relaxed for positional welds as spatter will tend to fall away from the workpiece. As reported in section 2.1.3, the amplitude of the short-circuit current is proportional to the amount of spatter. Therefore, in the downhand position the amplitude of short-circuiting current is limited solely by the condition that the process must be stable[42].

While, in positional welds, the value of short-circuit current is constrained only by the conditions for metal transfer and the formation of the weld. The higher the short-circuit up to a specific limit, the greater the impulse transmitted to droplets of metal and the pool in the direction of the work, and this tends to retain them on vertical or overhead[42]. There is therefore a contradiction between the stability requirements regarding reducing the amount spatter and providing well-formed vertical and overhead welds.

Weld pool collapse

Weld pool collapse occurs when there is burnthrough of the joint caused by excessive arc power and the presence of a gap. The collapse occurs because of the failure of the molten pool holding firm as an unsupported layer under the effect of the arc pressure. The occurrence of burnthrough is usually preceded by a period of overpenetration.

Istolbov and Masakov[43] studied the formation and effect of burn-through in butt-welds with constant, convergent and divergent gaps. Two types of burn-through were observed:

1. **continuous burn-through** this occurred with comparatively wide gaps and it takes the form of uniform melting of the edges;
2. **discrete burn-through** appeared more frequently, and it consisted of periodically repeating holes and bridges.

2.2 The Robotic Arc Welding System

Robots are increasingly used for welding applications especially in the manufacturing of automobile parts and related applications. This is mainly due to the following factors[44]:

1. lack of qualified welders;
2. unhealthy working environment;
3. high product volume;
4. productivity and quality requirements;
5. need for flexibility[b].

The main features of a robotic welding system are shown in figure 2.7.

2.2.1 The Welding Robot

The robot is used to replace the manual welder holding the welding torch. It moves the torch along the weld joint at the right orientation and velocity relative to the joint[44]. The movements and actions of a robot are preprogrammed by an operator.

2.2.2 Power Source

The power source provides electrical energy for the welding arc. Power sources are required to give reliable arc ignition, have simple setting (for example, incorporating synergic control) and give a reproducible stable arc[45,46].

The performance of GMAW power sources are dependent on their static and dynamic characteristics[47]. These are defined as the slope and inductance respectively. These two parameters must be optimised and are usually fixed by the power source manufacturers.

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[b] **Due to product diversity, components requires multiple welds with varying sizes, lengths and in different welding position.**

The Static Characteristic

The static characteristic, describes the relationship between mean output current and the corresponding voltage available from the power source[48,49]. The slope of the characteristic has the dimension of resistance, that is, ohms.

It is however usually defined as the voltage drop per 100 amps of current rise. The common ranges are 2-4 volts per 100 Amps. The slope is used to control and limit the amount of the short circuit current attainable. The steeper the slope, the smaller is the available short circuit current[9,49].
The slope can therefore be used to reduce spatter in dip transfer welding. With little or no slope, the current will rise to very high current and explosive transfer might occur leading to spatter generation[9,49]. Too much slope however, would lead to arc ignition problems. Excessively low short-circuiting current could lead to stubbing with the peak current not high enough to detach the drop and the electrode can freeze to the weld pool[9,49].

The Dynamic Characteristic

The dynamic characteristic is defined by the secondary circuit inductance. Inductance is used to alter the rate of response of an electrical circuit. The dynamic characteristic influences the stability of welding process and is most significant, where the load is subject to rapid changes from an arc condition to a short circuit condition and vice versa[47]. The short-circuiting time and arcing time is determined by power source dynamics.

Inductance is used to control the rate of change of current and instantaneous relationship between current and voltage so that the short circuit may clear with minimum spatter[48]. The greater the inductance, the longer the current takes to reach its final value, and the less the rate of rise of current[49].

Increasing the inductance reduces the short-circuiting current and recurrence frequency, but increases the arcing time. This makes the weld pool more fluid, resulting in flatter, smoother bead. Too much inductance however will result in erratic starting and a sluggish unstable arc[9,48,50].

Low inductance gives rapid rate of rise, leading to explosive transfer and spatter. The short-circuit current is very high, a considerable energy is generated, the weld pool is repelled, the arc becomes considerably long and spatter is generated[51].

2.2.3 Power Source Control

The power source type used in GMAW is either a constant voltage (CV) or constant current (CC). A true constant voltage power source would maintain the preset voltage output (within its capability) at any current. While a constant current power source maintains current constant over a range of voltages. Constant voltage power source have in the past been the most commonly used power source for robotic GMAW welding.

It is important from a quality point of view to maintain the arc length constant, this may be achieved by self-adjustment of the arc voltage and arc length control.

Arc Self-adjustment

In a constant voltage power source, the arc voltage is established by setting output voltage on the power source. The power source supplies the necessary current to melt the wire at the rate required to maintain the preset voltage (or relative arc length). The wire is normally fed at a constant rate, this results in a self-correcting arc length system[9].

The welding arc is subject to fluctuation caused by the process itself and/or external disturbances[52]. If arc length changes, the current will change and the burn-off behaviour acts in a way that counteracts the change in arc length[4].

An increase in arc length causes an increase in arc voltage and power source reduces current to meet the demand for higher voltage. Since melting rate is current dependent the reduced current will result in reduced melting (that is, less wire is consumed) and the arc length is shortened. Shortening the arc will produce an increase in current, increased melting and again the arc length will return to its original value. Figure 2.8 shows an idealised self-adjustment of a welding arc over a step plate.

An additional self-adjustment mechanism occurs with resistive wires. The increase in the electrical stickout causes increased resistive heating and increased burnoff. This does not occur with high conductivity materials such as aluminum[4].

Arc Voltage Control

When using high conductivity materials such as aluminum, the arc length may also be maintained constant by regulating wire feed speed to keep arc length constant.

Arc voltage is directly proportional to the arc length. Therefore, arc voltage is used to estimate and control arc length. The control involves comparing the required and actual voltage and using the error to estimate a new value for wire feed speed[53,54].

Arc Length Control

Arc length control is used for larger diameter electrodes and welding application where a very rapid change in wire feed speed is not essential[9]. The arc length is maintained automatically, for any wire feed speed by regulating the arc voltage[9,48]. It is based on parametric relationship between the arc voltage and current (or wire feed speed).

2.2.4 Synergic Welding Control

Generating welding conditions for Gas Metal Arc welding can be difficult and time consuming especially in dip and pulse transfer. The setting of stable welding parameters requires skill and experience.

Welding parameter combinations are very critical to the final weld quality. Bad combinations will lead to defective welds caused by unstable arc and metal transfer. This has led to the development of synergic welding control algorithms.

Synergic welding stems from the need to make parameter selection easier with emphasis on good arc ignition, stable arc, and welding parameters. The principle is based on adjusting most of process parameters simultaneously from a single central control parameter[55]. For example, given a wire feed speed (WFS) value, the other required parameters are automatically set by the power source.

Synergic control algorithms are normally developed using statistical methods (mainly linear regression analysis) and preprogrammed in the power source control system. The wire feed speed is normally correlated with the steady state values of welding current and voltage. In order, to have control over mode of transfer, separate algorithms are usually developed for pulse, dip and spray transfer[48,55-57].

Most synergic models are consumable dependent but are based on simple linear regression trend of stable current, voltage and wire feed speed relationship. That is,

$$I_{mean} = a_1 + a_2 WFS \qquad (2.2)$$

$$V_{mean} = a_3 + a_4 I_{mean} \tag{2.3}$$

where

I_{mean}	*is the average welding current;*
V_{mean}	*is the average welding voltage;*
WFS	*is the wire feed speed;*
$a_1,..a_4$	*are the regression coefficients.*

The main limitation of synergic algorithms to date is that there is no global algorithm, especially one that combines dip and spray. Also, no consideration for welding position and sensitivity to certain defects. There is no control over the stability of the arc as stability requirement needs to be relaxed for positional welding.

The effect of variable standoff is often not considered. For example, the model coefficient may be determined with a single preset value of standoff. This may lead to instability in the process if a different standoff is used.

These drawbacks have led to some development of synergic welding algorithms mainly for dip transfer. Needham[58] in developing a synergic algorithm for control of dip welding considered the arcing time and cycle time ratio. He asserts that the average welding current is dependent on the ratio of the arc time to cycle time and independent of the short circuit frequency and power source inductance for a fixed open circuit voltage.

Popkov et al.[59] concluded that short circuit welding could be optimised by constraining the ratio of arcing time to cycle time to between 0.6 and 0.8.

However, in dip welding, the most stable transfer occurs when the amount of metal being transferred is minimum and the short circuit frequency is maximum. Manz[60] uses this idea to develop a unique synergic idea for manual welding with the objective of minimizing a factor "Z".

$$Z = \frac{WFS}{F_{sc}} \tag{2.4}$$

where

Z	*is the average length of electrode per transfer;*
F_{sc}	*is the short circuit frequency.*

2.3 Process Monitoring

Monitoring is the data acquisition (continuous or at a specified interval) and processing function used to confirm if a process is operating within some specified limits, outside which quality problems occur.

Blackeley[61] identifies the need for monitoring as:

1. welding procedure development;
2. process improvement;
3. evaluation of different power sources performance;
4. modelling: off line process control;
5. optimisation of welding consumable;
6. on-line fault diagnosis and quality assurance.

2.3.1 Data Acquisition System

VanDoren[62] defines a data acquisition system as an electronic instrument, or group of interconnected electronic hardware items, dedicated to measurement and quantization of analog signals for digital analysis or processing.

Data acquisition systems offer specialised computer programs written to digitise, store and analyze the input data normally obtained by using appropriate sensors[63,64].

Such systems usually consist of three main blocks[65]:

1. measurement hardware component	**sensors and signal conditioning hardware.**
2. digital hardware component	**computer and analog-to-digital (A/D) converters.**
3. signal processing component	**dedicated software algorithms.**

2.3.2 Sensing

The purpose of sensing is to obtain information about the process state and its environment using sensors. The information is converted to quality related information either directly or indirectly (via modelling).

The sensing functions are done via **contact-type sensors** such as mechanical probes equipped with electronic sensing devices that will show the relative vertical and cross-seam position of the joint (via deflection of the probe) in real time and/or through **non-contact sensors** such as optical/vision systems, acoustic systems and through arc techniques.

The sensing can be carried out at three levels namely:

1. Preweld sensing	**provides data on changes in joint geometry and seam position before welding;**
2. On-line sensing	**provides data on arc stability and weld quality directly or indirectly during welding;**
3. Post weld sensing	**assesses weld quality obtained after welding.**

2.3.2.1 Contact Sensing[66,67]

A typical contact sensor shown in Figure 2.9 is inexpensive and offers simultaneous seam tracking and welding ability using a mechanical probe that precedes the arc. The probe is equipped with a transducer, transmitting data to the robot controller to make corrections to the welding path as necessary.

Contact sensors require a joint geometry that is capable of smoothly guiding the probe (see Figure 2.10), this means that narrow butt joints or outside corner joints made of thin sheet cannot be sensed.

The main drawback is the high tendency for the probe to loose contact with joint, therefore limiting the welding speed. They are also subject to wear, are not compact and could limit access to certain joints. Contact sensing is therefore not very attractive for robotic welding.

2.3.2.2 Non-contact Sensing

Acoustic Sensing

The simplest hardware required to obtain an acoustic signal is a microphone and an Analog-to-Digital (A/D) converter.

A characteristic sound is emitted by the welding process as the electrical input into the arc varies. For every pulse of electrical energy entering the arc (metal transfer), a pulse of sound is produced[68]. Manual welders use the variation in the sound pulses to fine tune arc welding parameters especially at low current[68].

It has been proposed that acoustic signals can be used to sense[68,69]:

1. variation in arc length;
2. metal transfer;
3. penetration variation especially overpenetration and burnthrough;
4. joint geometry variation;
5. standoff variation;
6. arc instability;
7. gas flow rate variation.

The main drawback of acoustic sensing is that the sound signal is easily corrupted by the ambient noise from welding and other workshop equipment. The influence of these noises could be reduced however by using a very directional microphone, or noise cancelling techniques.

Visual Sensing

A welding robot with no joint sensing facility will make a weld where the joint is supposed to be rather than where it is. Vision systems are commonly used in robotic welding for the correction of preprogrammed welding paths and measuring joint and weld bead geometry[70].

The hardware requirement for visual sensing consists of charge couple device (CCD) camera, a structured light projector (laser), a camera control unit and powerful microcomputer system[71]. The image obtained is usually digitised using a frame grabber.

Vision systems are commonly used in two modes namely[72]; real time system and two pass system.

The real time systems view the joint ahead (eg 5mm) of the arc and provide on line information about the joint seam and geometry. This data is used to control the welding parameters as the robot welds.

The two pass systems view the joint on the first pass (preweld inspection) and necessary correction of welding parameters made and used to weld on the second pass (based on data collected during preweld pass).

Two pass systems have the advantage that sensors can be removed from the arc environment before welding, so avoiding the possibility of damage by fume and spatter. The real time systems can be affected by fume, spatter and the arc intensity leading to control error[67,70,73].

The main drawback of the two pass systems is that they are unable to compensate for errors that occur during welding. They can also significantly reduce the process productivity with the preweld inspection pass taking a significant time. The use of visual sensing can also restrict joint accessibility, sensing hardware being located near the welding head.

Other limitations include[70,73]:

1. The need for a large amount of computer memory for data storage;
2. The data processing algorithm is computationally intensive;
3. The hardware requirements are significantly more expensive when compared with other sensing alternatives.

The main benefit of visual sensing from a control point of view is its feedforward sensing nature. This means that joint variations are sensed and the process corrected before the torch reaches the error position on the joint and affects weld quality. Also, they are independent of the welding processes as there is no mechanical contact between the sensor and the workpiece[67].

Electrical Sensing

Electrical sensing involves using the dynamic response of the welding arc transient characteristics to process disturbances as a sensor. The technique is called through-arc sensing. The variations in welding current and voltage are used to detect and estimate the standoff, joint and bead geometry variation.

The hardware requirement is a current probe (eg. Hall effect), a voltage probe and an Analog-to-Digital (A/D) converter.

The benefits of electrical sensing include[66,74-76]:

1. no additional sensing device around the torch required therefore present no access problem;
2. sensors relatively inexpensive;
3. do not interfere or constrain the process and/or welding technique;
4. applicable to any arc welding process.

The thru-arc sensing technique is however sensitive to process stability. Its efficiency is also affected by welding arc phenomena that occur due to differences in consumable, such as wire composition, shielding gas type and welding conditions.

For example, the parameters of welds carried out in Argon rich atmosphere may be constant with respect to time[77]. Argon stabilises the arc but also minimises the measurable process of random effect[78]; while, carbon dioxide welding parameters are of stochastic character with considerable scatter of instantaneous values and unstable process behaviour[77,78].

2.3.3 Signal Processing

The emphasis of the current research is on using electrical signals for process monitoring and control. Signals in general can be classified into two groups namely deterministic and stochastic signals.

Stochastic signals are those whose behaviour is highly unpredictable, that is, occur randomly[79]; while, deterministic signals are those that have known characteristics and that can be explicitly described by mathematics[79,80].

Stochastic signals are signals affected by random noise, where the noise content is negligible, the process may be regarded as deterministic. The welding current and voltage signals in their unsmothened states are stochastic.

A deterministic signal can be formed from a stochastic signal provided amplitude or time classes of the signal are formed over a sufficiently long period[80]. The period for which data is collected (ie sampling time), should be such that the mean value of a definite portion of the signal is equal to the overall average of the total signal. This enables statistical analysis to be performed on the signal[64,80].

Large amounts of data are usually collected during monitoring, most of this information is not useful for process control. The raw data needs to be reduced to make analysis simpler, faster and save on storage capacity.

The most common data processing approach is to break the sampled transient data into its basic statistical features such as mean, minimum, maximum etc. This significantly reduces the data without losing important information, and filters out irrelevant information[81].

This process is called feature extraction and is a very important element of process monitoring and defect detection. The fundamental assumption is that the logical combination of the features extracted is sufficient to provide quality control and diagnostic information about the process[81].

2.3.4 Process Diagnosis

Process diagnosis is concerned with assessing the state of a process on the basis of sensory data. It involves signal processing, feature extraction and classification.

Diagnosis involves differentiating between normal and abnormal process variation for defects and fault detection. This requires some understanding of the process cause and effect relationship.

The basic requirements for process diagnosis are[82,83]:

1. **establish** weld quality and **knowledge** of process "normal" behaviour;
2. **define** the "faulty" behaviour; that is identified defect types and establish the pattern of variation for each defect;
3. **availability** of at least one **easy to measure** process feature correlating well with a particular defect.

The diagnosis methods which have been used include statistical process control, model-based diagnosis, pattern recognition and artificial intelligence[84-86].

2.3.4.1 Statistical Process Control

Statistical process control (SPC) is the application of statistical methods in determining if a given process is operating within the specified limits[87]. SPC aims to monitor process average level and process spread.

It is a monitoring strategy that focuses on the process rather than on the product[88]. It involves gathering samples during the manufacturing process and measuring those against a predetermined standard.

It is based on the premise that a certain amount of inherent variation (random) exists in every process that does not affect the quality of the process output. This is used to develop a control chart which is used to differentiate between normal variation and abnormal variation. The most common control chart is X-bar chart (also known as Shewart Chart) for monitoring process average level.

The control limits on the chart, as a rule, are set at three times the standard deviation of the random variation. To enhance the monitoring and decision making capability of X-bar charts, additional limits are usually set on them. These are often twice standard deviation limits, called the warning limits. If a sample is outside the control limits or too many samples are outside the warning limits the process is considered to be "out of statistical control". However, this type of chart is not very good at detecting small changes. To increase its sensitivity an additional limit of one times standard deviation can also be added[89].

Table 2.1 shows a more detailed decision rules that are widely used to decide if a process is out of control.

Table 2.1 **X-Bar Chart Decision Rules**

The process is out of control if[88,89]:

1. one point is outside the 3 standard deviation (**SD**) limits;
2. two out of three consecutive points beyond 2-**SD** limits;
3. four out of five consecutive points 1-**SD** or beyond centre line (process average);
4. eight consecutive points on one side of centre line;
5. unusual or non-random behaviour such points run up, run down and cyclic behaviour;
6. one or more points between control and warning limits;
7. six consecutive points increasing or decreasing;

An alternative to Shewhart chart is Cumulative sum (CUSUM) control chart. It involves the plotting of cumulative sum of the process average or its deviation from a target value. It is more sensitive to small shifts in process mean[90].

2.3.4.2 Model Based Diagnosis[82,91,92]

Most processes have multiple inputs and outputs, requiring deduction to be made from several process parameters in order to make a quality control decision. Model-based diagnosis is a simple technique that achieves this by relating the relevant process parameters to quality. It uses mathematical models to monitor the process and detect any changes.

Model based diagnosis is done by comparing process actual output with an established process models prediction.

That is,

$$\delta = Y - E(Y) \qquad (2.5)$$

where

$$E(Y) = f(X_1, X_2, \ldots X_i) \qquad (2.6)$$

and

Y	*is the actual process output;*
$E(Y)$	*is the predicted (expected) process output;*
$X_1, \ldots X_i$	*are the process input parameters ;*
δ	*is the difference (prediction error) between actual and expected output.*

The diagnosis is based on the size of the difference (ie. the residuals) which ideally should be zero if the process is operating normally. Due to modelling error, support using heuristic and rule based methods may be unavoidable. Then decision zones are setup using threshold techniques.

However, the efficiency of model based diagnosis depends on the sensitivity of process parameters to the fault conditions. The models are developed using "normal data" only because usually the amount of knowledge of normal conditions is far larger than that of abnormal conditions.

2.3.4.3 Pattern Recognition[85]

Pattern recognition involves learning or establishing the normal and abnormal process behaviour by preparing templates that show typical behaviour. The templates are then used for diagnosis. If process data match a template the condition is recognised.

This approach is similar to model-based diagnosis, in looking for a match. The main difference is that the pattern recognition approach is very rigid and cannot readily describe dynamic variation in the process.

The fixed recognition pattern means that it would be expensive and difficult to collect and standardise all possible fault conditions in a process. The method should therefore only be used for diagnosing selected, mainly critical behaviours.

The modelling tools used in pattern recognition include artificial neural networks, fuzzy logic and regression methods. An example of pattern recognition use in welding, can be seen in Smith and Rider[93]. The authors used pattern recognition for defect prediction based on deviation of tungsten inert gas (TIG) orbital welding variables from established control limits.

2.3.4.4 Expert Systems

Expert systems are computerised knowledge based systems that are capable of providing expert advice. Expert systems are clones of human experts and are used to solve specific problems[94]. They use rules developed from scientific facts and the underlying process causes and effects relationship. They are widely applied in welding to develop procedures and evaluate the likelihood of defective welds at the procedure planning stage[95-97].

2.3.4.5 Hypothesis Testing

Disturbances due to process environment would influence the process output and its transient behaviour. This would be manifest in the form of increased variability. However, a clear-cut correlation does not always exist with any process features. It might be necessary to develop a hypothesis using process theoretical and practical knowledge on how to detect them. Then testing them for validity by simulating the defects and using any combination of the methods described above for diagnosis.

2.3.4.6 Selecting Thresholds

The emphasis of all the diagnosis methods is on identifying critical parameters and their appropriate pre-determined limits (ie thresholds) to separate normal from abnormal process behaviour.

The limits are determined from experimental trials and/or process knowledge of perceived optimum condition. The main concern in setting thresholds is the need to balance between false alarm and sensitivity of detection.

Process knowledge is required to setup and manage thresholds. If tightly specified, will result in an increase rate of false diagnosis. While if too loose, will result in low sensitivity to fault detection.

From a welding point of view the possibility of not detecting faults present (ie. diagnosis or control failure) should be minimised. This could lead to the temptation to make the threshold limits tight; hence increasing the risk of detecting non-existing faults ie. false alarm.

2.4 Through Arc Sensing

Through arc sensing is used to provide real time information about standoff and joint geometry variations. It is only used when the arc is on and not before. Therefore for through arc sensing to be effective the joint must first be precisely located.

Wire touch sensors are effective for locating weld seam positions using "touch and feel" technique[98,99]. The sensing is done with the tip of welding wire, cut to a known length.

Touch sensors also use high voltage and low current to define the centre line and starting point of a joint as the robot goes through a preprogrammed search routine.

2.4.1 Standoff and Joint Width Estimation

Conventionally, through arc sensing involves the weaving of the torch across the joint to control the welding torch height and trace the weld joint[100-103]. Therefore to be efficient it can only be used with joints with well-defined sidewall such as lap, tee or groove weld joint types.

The standoff and joint width estimation from the arc signal is normally carried out, using differential control and template matching algorithm. The algorithms are summarised below. Wells[66] and Cook et al.[103] give full details in their publication.

Template Matching[66,103]

This algorithm is based on continuous measurement of the arc voltage or current taken as the arc torch weaves across the joint. The joint profile is obtained from this data.

This profile is then continuously compared against an ideal template[c] and error signal generated. Two error signals are derived, namely **centring error signal and width error signal.**

The centring error signal is used for keeping the arc on the joint. It is obtained by comparing the signal to template match on one side of the weave with that on the other side of the weave pattern. While, the width error signal is obtained by comparing the template and signal over the full width of the weave pattern.
The resulting deviation (ie the error signal) can then be fed back to carry out real time control of welding systems using a proportional controller.

Differential control[66]

The differential control is computationally simpler than template matching. The arc signal is sampled at the sidewalls and centre for each weaving cycle.

Weaving the torch across the joint forces the contact tip-to-workpiece distance to change and therefore the current for GMAW processes. The difference between the current sidewall samples is proportional to the cross-seam (torch-to-joint centre line, ie. misalignment).

The change in vertical distance has been shown to be proportional to the difference between the centre sample and the reference centre current. The variation in joint width is proportional to the difference between the sum of the sidewalls samples and a reference value.

However thru-arc is not limited to welding involving weaving only. Sugitani et al.[104] reported on a system for seam tracking and torch height control based on a high speed rotating (welding tip of the wire) arc.

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[c] **The ideal template signal normally empirically determined from a predetermined number of prior weave cycles.**

2.4.2 Gap Detection and Joint Geometry Variation

Most of thru-arc sensing involves monitoring joint dimension when weaving. The joints are usually made of thick plate and designed with a wide groove. However, for thin materials, it has been difficult to use through arc techniques to monitor joint dimension. There are very few published works on the use of the welding arc for thru-arc sensing of joint geometry[105-107].

Koves[105] used thru-arc sensing for gap detection in short-circuiting welding of butt-weld. The strategy used was to begin with an optimum welding condition and to investigate the influence of gap width variation on the welding signals. The variation in gap sizes makes the arc unstable and the degree of instability was correlated to gap size.
The main conclusion of his work is that with an increasing gap, the frequency of short circuits decreased considerably, with a greater increase of arc burning time.

Inoue et al.[107] although studying the effect of arc sound on burnthrough in gas metal arc welding, also studied the behaviour of welding current in joints with gaps. In small gaps the welding current is fairly constant. In gaps with high risk of burnthrough, the current is found to decrease significantly with the current returning to its original state after burnthrough.

Davis[106] used thru-arc sensing for on-line gap detection in 90 degree fillet welds. The work involved weaving and the welding signal was acquired using a data acquisition system designed at Cranfield.

The minimum detectable gap size reported was 1.7mm and 1.5mm for spray and dip transfer respectively. The presence of gap was reflected in the welding signal by drop in values of background current. In this case background current was the average value of transient current value less than total mean current in a known interval.

The work was restricted only to the effect on arc signal when a gap is encountered, nothing was specified about the quality of weld produced or whether the welding condition used was bridging the gap.

2.4.3 Monitoring Metal Transfer

Metal transfer affects weld quality and arc stability. The mode of transfer can be detected using visual signals, acoustic emissions and welding current and voltage transient signals (ie. thru-arc sensing)[108-118].

Visual Signal

The main advantage of the visual method is that the direct observation of the arc allows droplet transfer to be classified with a very short sampling time.

Rhee and Kannatey-Asibu[109] studied metal transfer using digital high speed video analyzer and arc shadow graphing system. The drop position was determined on each video frame using an X-Y position detector.

Madigan, et al.[117] uses the fluctuation in arc light intensity to detect droplet transfer and its frequency. The fluctuation in arc intensity is caused by changes in arc length due to droplet detachment. The arc intensity is proportional to arc length.

The limitations of the visual method for metal transfer mode detection is that it requires complex experimental setup and can only be used for welding processes where the arc gap can be seen.

Acoustic Signal

The arc sound fluctuation can be correlated to the mode of transfer. To increase the precision of correlation, the audio sound is often synchronised with visual images of the transfer[116].

The benefit of acoustic sensing for transfer mode detection is that simple experimental setup and short sampling time are required. The main drawback is that the signal is easily corrupted and it is incapable of droplet size and shape determination.

Current and Voltage Signals

Through-arc sensing for metal transfer is the most desirable, due to the simplicity of sensors required. Metal transfer occurs in two stages "melting" and "detachment" which is reflected in the electrical circuit transient response provided the power source being used has low noise characteristics.

Adam and Siewert[115] used statistical analysis, fourier transforms, amplitude frequency histograms, peak-searching algorithms and smoothing procedures to process these fluctuations and classify the metal transfer mode (see Figures 2.11 and 2.12).

The fourier transform of dip transfer current signal shows a main frequency corresponding to the droplet transfer frequency as well as low-frequency characterising the switching of the power source during short-circuiting[115].

The globular transfer fourier transform is characterised by a well defined and relatively sharp main peak representing the transfer frequency, the width of the peak is a measure of the variation of the repetitive signal over time, a uniform droplet rate will result in a narrow peak. This means that the stability of globular transfer can be controlled. The fourier approach has a low sensitivity to spray transfer[115].

The standard deviation of the current signal can also be used to classify transfer mode. Spray and dip transfer have low and high values of standard deviation respectively. It cannot however, be used to detect globular transfer effectively from its adjacent transition zones[115].

The plot of amplitude histograms showing the time-weighted distribution of voltage amplitudes for dip transfer give two main peaks corresponding to dip and arcing. Globular transfer has a main peak at the average voltage and two smaller ones representing the voltage spikes below and above the average value. There is only one peak in spray[115].
The histogram may be standardised by calculating peak ratios. The ratio is about 1 for dip transfer, 0.1 in globular mode and 0 in spray mode.

Liu et al.[112] used the ranges of arc voltage variation(ΔV) to classify transfer mode. The classification was as follows:

noise	$\Delta V<0.5$
spray	$0.5<\Delta V<1$
globular	$1<\Delta V<8$
dip	$\Delta V>8$

The main drawback of through-arc sensing of metal transfer mode is that, relatively long sample time is required. It is also difficult to characterise mixed mode transfers.

2.5 Causes of Defects and Control Actions

Defects are unsatisfactory process and weld bead conditions that could result in unacceptable quality. To monitor and/or prevent defects efficiently, it is important to have some understanding of their causes and necessary corrective actions. A summary of causes and control actions for defects critical to welding of thin sheet material are outlined below[119].

2.5.1 Incorrect Bead Size and Profile

Bead dimension and profile are the main quality indicator in many welding applications. An over sized weld will increase the production cost. While an undersize weld will fail to meet its required load carrying capability.

Defects associated with bead profile such as bead asymmetry[d], excessive reinforcement, excessive convexity or concavity may adversely affect the dynamic performance of the joint[119].

Some possible causes of bead geometry defects are:

1. long standoff[e];
2. low deposition rate (ie. low wire feed speed and high welding speed);
3. high deposition rate (ie. high wire feed speed and low welding speed);
4. torch-joint misalignment;
5. presence of gap[f].

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[d] Bead asymmetry is a condition of unequal leg in fillet welds which could lead to penetration problems and insufficient throat.

[e] The combination of low wire feed speed and long contact tip-to-workpiece distance can lead to bead asymmetry due axial displacement of wire away from joint seam.

[f] The bead size is reduced due to the flow of molten pool into gap under the influence of arc pressure.

The following possible remedies have been suggested:

1. review procedure;
2. check robot program path;
3. use of sensors(vision or through-arc) to:
    - i) locate joint and weld start and finish;
    - ii) track and detect changes in joint geometry.

2.5.2 Undercut

Undercut is a geometric defect that occurs when the weld metal solidifies too rapidly before the groove created by arc is fully filled[35]; leading to reduced strength of the joint (the plate is thinner at the undercut)[119].

The probable causes of undercut are:

1. high voltage;
2. high current (wire feed speed);
3. high welding speed;
4. torch-joint misalignment;
5. presence of gap;
6. large weld size[g].

The following corrective actions are suggested:

1. review welding procedure;
2. use sensors(vision or through-arc);
3. use multi-pass for heavy section welds.

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[g] **Big weld size leads to excessive heat build-up per unit length.**

2.5.3 Standoff Variation

Standoff variation is not a "fault condition"; but it influences the occurrences of other problems such as insufficient penetration, porosity, bead asymmetry, arc and metal transfer instability.

The probable causes of standoff variation are[120]:

1. movement in contact tip to weld pool surface (due to gap and torch-joint misalignment);
2. changes in wire pickup point (due to worn contact tip);
3. workpiece distortion due to high heat input;
4. welding robot program setup error.

The effects of standoff variation may be countered by:

1. make procedure tolerant to standoff variation;
2. use sensors(vision or through-arc)[h].

2.5.4 Burnthrough and Overpenetration

Burnthrough is a critical defect causing the rejection of components in thin sheet welding[121]. It normally takes the form of the melt through of the parent metal by the welding arc. Burnthrough occurs when the heat input is too high or when the gap in a joint is greater than the specified or tolerant one. It is normally preceded by overpenetration.

Overpenetration defines a condition where the weld metal penetrates the full thickness of a joint without burning through.

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[h] **If joint is properly located the effect can be controlled by through-arc sensing.**

The probable causes of burnthrough and overpenetration are:

1. high current;
2. high voltage;
3. low speed;
4. fitup problems;
5. torch-joint misalignment.

The following corrective actions are suggested for prevention of burnthrough and overpenetration:

1. review procedure or use a procedure that includes weaving[i] for welding parts that are prone to gaps;
2. use sensors (vision or through-arc);
3. adapt procedure to suit gap.

2.5.5 Inadequate Penetration and Lack of Fusion

Penetration is the distance that the fusion zone extends below the original surface of the parts being welded[122]. Inadequate penetration is a condition where the weld metal fails to reach a specified depth of a joint[123].

Lack of fusion is the failure to fuse adjacent weld metal and base metal[124]. It is caused by failure to raise the temperature of the base metal to its melting point (ie fusion temperature).

The probable causes of inadequate penetration and lack of fusion are:

1. current too low;
2. irregular wire feed ie slippage;
3. speed too slow (ie. weld pool too large causing arc cushioned by molten metal therefore preventing plate heating);
4. speed too high (weld metal not sufficiently heated up);

---

[i] Weaving makes procedures more tolerant to fitup problems but at the expense of productivity.

5. standoff too long or varying;
6. torch-joint misalignment.

The following corrective actions are suggested:

1. review procedure;
2. adapt procedure to reduce the effect of standoff variation.

2.5.6 Porosity

Porosity refers to the presence of cavities in the weld metal, usually caused by gases becoming entrapped by solidifying metal[123,124]. It may be a cosmetic problem, but when excessive can affect weld strength. It may appear scattered uniformly throughout the weld, in small isolated patches or concentrated at the root.

The probable causes of porosity are:

1. inadequate or excessive shielding gas flow;
2. arc instability;
3. high welding speed;
4. long standoff leading to loss of gas shield;
5. voltage too high, ie. long arc;
6. leaking gas line;
7. nozzle blocked by spatter, resulting in shielding gas turbulence;
8. draughty welding environment, resulting in disturbance of shielding cover.

The following corrective actions are suggested:

1. optimise welding parameter to ensure stability;
2. good quality assurance of consumable handling;
3. clean nozzle regularly; obstruction by spatter can cause turbulence;
4. use slower welding speed.

2.5.7 Spatter

Spatter is the physical result of arc instability occurring mostly in welding in dip and globular transfer modes. It is usually a cosmetic problem but can result in expensive post weld cleaning (repair) if not acceptable in an application.

The probable causes of spatter are:

1. poor wire feed speed, voltage combination (voltage too high or too low for wire feed speed);
2. worn contact tip;
3. inappropriate power source characteristics.

The following corrective actions are suggested:

1. optimise welding parameters to ensure stability;
2. optimise power source characteristics.

2.5.8 Gap

Gap is not a defect, but a joint geometry variation that could influence defects such as burnthrough, undercut and spatter. It can also lead to a reduction in the effective bead dimension, such as leg length in fillet welds.

The probable causes of gaps are:

1. imprecise pre-weld processes;
2. inconsistent workpiece dimension.

The following corrective actions are suggested:

1. check all pre-weld equipment for wear;
2. use sensors (vision or through-arc);
3. adapt procedure to suit gap size.

2.6 Effect of Welding Parameters on Weld Quality

The quality of thin sheet welds is measured in terms of bead geometry and penetration depth. The quality of welds produced can be ensured by monitoring and controlling the process parameters directly reflecting weld quality.

The quality of welds depends on key process parameters; namely welding current, arc voltage, welding speed and standoff. These parameters have to be optimised to achieve quality. The way they are reported to affect some of quality characteristics are summarised below.

2.6.1 Effect of Welding Variables on Penetration[8,122]

The depth of penetration increases in an almost linear way as the welding current level increases but decreases relatively linearly as speed increases.

The relationship between penetration and voltage is fuzzy, because voltage also influences arc stability. An unstable arc will not give consistent fusion. Therefore, voltage cannot be used as a control variable for penetration.

Cary[122] states the welding current should be considered first when a change of penetration is required. However, due to productivity and economic reasons, it is desirable to weld at the highest speed possible. It is therefore not desirable to use travel speed or voltage as the major control variables for penetration. The voltage must be set to give a stable arc and metal transfer.

2.6.2 Effect of Welding Variables on Bead Geometry[8,122]

Bead geometry depends on the support that the joint configuration gives to the weld pool. The bead dimension can be divided broadly into bead (reinforcement) height and width.

The relationship of welding current to bead height is relatively linear, this is based on the amount of weld metal deposited. The amount of metal deposited increases with current for a fixed travel speed. The speed can be used to control bead height at a fixed current, at low speed the mass deposited is large and vice-versa. However, as travel speed increases, the mass of metal will be spread over a longer length reducing tolerance to defects (see section 2.1.4.1).

The arc voltage has a linear correlation with weld bead width. Increasing the arc voltage makes a bead wider, the bead reinforcement will reduce because the same volume of weld metal is involved. Note that the voltage can only be used as control variable up to a limiting value that depends on current level and arc stability.

The travel speed has a relatively linear relationship with bead width. The current does not have a linear relationship. Therefore, current was not used in this work to control weld width.

2.6.3 Effect of Standoff on Welding Variables[8,41,122]

The standoff is the distance between workpiece and contact tip (see Figure 2.13). Standoff variation leads to variation in heat input and mass input. This in turn leads to variation in bead geometry, penetration and process stability.

Increasing standoff increases the resistance in the circuit, causing the electrode temperature to be raised due to resistance heating. Therefore less welding current is needed to melt the electrode.

The output voltage of a constant voltage power source is the sum of the voltage across arc and voltage drop in extension. Therefore as standoff increased, actual voltage across the arc is lowered, leading to a reduction (not very significant) in bead width and increase in bead reinforcement.

Standoff affects penetration through its effect on welding current. Increasing standoff will reduce penetration. Excessive standoff will lead to bead misalignment due to the wire curvature and increase the risk of pore formation due to ineffective shielding. Tuthill[41] suggests that stickout should not be greater than fifteen times wire diameter.

2.6.4 Effect of Welding Variables on Appearance[8]

A weld with good appearance is a weld with the required profile and no visible defects. However, it is the welding speed that influences appearance most. The risk of undercut and porosity increases with speed and voltage. As welding speed increases weld metal buildup occurs due to rapid cooling of the weld pool edges increasing the tendency towards undercutting along the edges of the weld bead.

If the gas flow rate is held constant, increase in travel speed will cause the gas shielding pattern to be pulled back causing dragging in of air. This could lead to loss of shielding, causing arc instability and porosity.

There is a limit on welding parameters settings in relation to bead appearance. Excessive current produces convex weld beads and poor bead appearance. Too high an arc voltage (ie. very long arc) will result in excessive spatter, porosity, wide and irregularly shaped weld beads. Too low arc voltage (ie. very short arc) will result in narrow and convex beads with excessive spatter and stubbing.

2.7 Process Modelling

The effectiveness of a process control system is totally dependent on the models and algorithms handling the dependence between the process input and output variables[125].

A model is the mathematical representation of a process or part of the process operation. The models could be theoretical, empirical or semi-empirical equation(s) providing quantitative and/or qualitative relationship between the main process parameters and its outputs[126].

Theoretical models are developed from first principles based on the process scientific and physical facts. They are usually computationally intensive due to the complexity of the resulting equations but are valid over a wide operating region[126].

Empirical models are derived from the relationship between process input and output variables using usually regression analysis. They are subject to the conditions of an experiment trials and are not valid outside the range of the experiment. They provide a fast approach to model building without the need for extensive and accurate knowledge of all process variables[126].

Semi-empirical models are developed with regard to established fact or knowledge of the process. They combine the advantages of theoretical and empirical models to achieve modelling accuracy. They offer a standardised process modelling strategy, even when the basic principles of the process are not understood.

2.7.1 Experimental Design

Experimental design is the process of planning experiments such that appropriate data are collected to meet desired process objectives[127]. The objectives range from process analysis to developing models for process control and establishing correlation between process input and output.

The most important part of planning an experiment is identifying the variables that affect the process response and establishing a practical range relevant to the problem under study.

This requires a careful specification of variables, constraints and practical considerations[128]. Thought must be given to how the response will be measured and the probable accuracy of these measurements.

The variables in an experimental design are general divided into two groups namely, the "independent" and "dependent" variables. The parameters directly controllable, such as machine settings and raw materials are called independent variables[125]. The response of the process output, such as bead geometry and defects are called dependent variables[125].

There are two approaches to experiment design. The planned and intuitive sequential experiment. The planned approach is usually based on full or fractional factorial designs. While in a sequential experiment a trial and error approach is used, and various input variable combinations are selected using process knowledge.

Factorial design implies that in each complete trial or replication of the experiment all possible combinations of factor levels are investigated[129,130]. It provides a systematic way of performing the least number of experiments to obtain a maximum amount of information in a multivariable environment. Factorial design is orthogonal by nature, that is, no correlations exist between process independent variables. Therefore, experimental errors are normally distributed.

However, it is only effective for a process studied over a small range. The experiment is normally planned around a working point[131]. The main purpose is to determine the effect of variables on process output and to check the existence of interaction between the variables.

Factorial design is now being used routinely in welding applications. It is mostly being used to evaluate how tolerant a procedure is to changing welding parameters[132].

If the objective is to develop a model spanning a process operating range, factorial design might be restrictive as the physical combination of some welding parameters might lead to defects and instability. Therefore, it is not always possible to use factorial experimental design. Its structure can however be used for initial experimental plan and then adapted to avoid (ie. change for better) unsatisfactory parameter combinations.

2.7.2 Regression Analysis

Regression analysis is a technique used to estimate the underlying mathematical function given a "finite" number of possible (experimental) data points[133]. The modelling process consists of two stages, the development of a model structure and estimating of the model parameters[133,134].

The most common regression method is multiple linear regression. Linear in the sense that the response variable is linear in the unknown parameters. The most common model structures are[135]:

1. First-order polynomial model

$$y=\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots\ldots+\beta_k x_k \qquad (2.7)$$

2. Second-order polynomial model

$$y=\beta_0+\sum \beta_{kk} x_k+\sum \beta_k x_k^2+\sum \beta_{k-1,k} x_{k-1} x_k \qquad (2.8)$$

3. Intermediate model

$$y=\beta_0+\sum \beta_{kk} x_k+\sum \beta_{k-1,k} x_{k-1} x_k \qquad (2.9)$$

4. Multiplicative model

$$y=\beta_0 x_1^{\beta_1} x_2^{\beta_2}\ldots x_k^{\beta_k} \qquad (2.10)$$

5. Exponential model

$$y=Exp\,(\beta_0+\sum \beta_{kk} x_k) \qquad (2.11)$$

where

y	*is the model output;*
$x_1,x_2 \,..x_k$	*are controllable (or independent) variables;*
$\beta_0,\beta_1....\beta_k$	*are the regression coefficients to be estimated from the data;*
k	*is the number of independent parameters.*

The multiplicative and exponential models are not linear, but they can easily be transformed into a linear form by a logarithmic transformation.

The regression coefficients are estimated using least square methods. The least square estimates of $\beta_{0,1..k}$ are the values that minimise the function below:

$$\Psi = \sum_{i=1}^{n} (Y_i - y_i)^2 \qquad (2.12)$$

where

Y_i	*is the actual ith output;*
y_i	*is the fitted model ith output;*
n	*is the number of response (observations).*

The main drawback of least square method however is that it is very sensitive to outlier points; caused by poor experimental design.

Johnson[136] outlines the benefits of regression analysis as follows:

1. it can handle nonnumerical attributes;
2. it can be made to test for interactions;
3. it can handle factorial and unplanned experiments data;
4. it can handle lots of variables (up to 30).

Box and Hunter[137] stress the need to use established technical knowledge in model development. Modelling should not be seen as statistical exercise but as a system design.

Therefore, when building a model, a compromise must often be made between the simplicity of the model and the accuracy of the result of the analysis[138]. This requires making decisions about which physical variables are negligible and which are crucial to the accuracy of the model[138].

In prediction oriented problems, the inclusion of variables that don't contribute to the regression model inflates the error of prediction. It is better to exclude variables that are not contributing significantly (or known from knowledge) to the process output in the regression. However, deleting too many variables could lead to "underfitting" and including too many variables to "overfitting".

One way to eliminate this problem, is to have control over as many independent input variables as possible during the experimental stage. This can be done by linking the process variables together by their influences and interactions. This indicates the benefit of synergic welding or one knob control welding.

Checking Regression Models Adequacy

Most regression analysis is done automatically in software. The question therefore is how to check model adequacy.

The models must be used within the limit of experimental data used. To make the model robust and insensitive to misuse, its structure must be logical and reflect practical understanding of the process.

The evaluation of regression models has focused mainly on the magnitude of summary statistics. These statistics are now performed within most applied software. Figure 2.14 shows the printout from a typical software package which is commonly used for regression modelling (Statgraphics™).

R^2 known as **coefficient of determination** is the principal measure of a model's quality[139]. It is a measure of how well the equation developed fits the experimental data. It is always between zero and one.
It is defined by the relationship:

$$R^2 = \frac{SSR}{SSTO} \tag{2.13}$$

where

$$SSTO = \Sigma Y_i^2 - \frac{(\Sigma Y_i)^2}{n} \tag{2.14}$$

$$SSR = \Sigma y_i^2 - \frac{(\Sigma Y_i)^2}{n} \tag{2.15}$$

and

SSR	*is the sum of squares due to regression;*
SSTO	*is the total sum of squares.*

The overall significance of the model is evaluated by F-Ratio

$$F = \frac{R^2 (n-k)}{(1-R^2)(n-k)} \tag{2.16}$$

where

n *is the number of observations*;

k *is the number of parameters in the model.*

The calculated F ratio is compared with the expected value from an F ratio distribution table. If the F ratio calculated exceeds the expected value at the significant level specified, then the hypothesis is accepted that the regression parameters are not all equal to zero and that R^2 is significantly different from zero. The P-value gives significant level of this value.

The adequacy of the model is further tested by checking the residuals[j] for non-random distribution pattern; through the scatter plots of the residuals against the fitted values and independent variables.

2.7.3 Fuzzy Regression

Some weld quality criteria cannot be measured quantitatively. They have to be classified as "true or false" (eg. undercut is or is not present) but usually we have to deal with the range between "true and false" (ie. the seriousness or level of defects).

Fuzzy logic allows intermediate grades between "true and false". Fuzzy logic is a mathematical model for capturing ill-defined process relationship[140]. It provides a mathematical framework to capture the uncertainties associated with human cognitive processes, such as thinking and reasoning[141].

The use of fuzzy logic has been reported to be very successful for many welding applications[142-147]. The theory of fuzzy logic is beyond the scope of this project.

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[j] **Residual is the difference between the actual data and the fitted value.**

Regression analysis can be used to model nonnumerical attributes coded in binary form[136]. The regression model involving binary data is now referred to as fuzzy regression. Tanaka et al.[148] and Chen[149] introduces the idea. It provides a means for fitting data when the relationship between the independent and dependent variables is imprecise or the amount is insufficient[148].

A multiple linear regression model has been used to define a fuzzy linear function of a multiple input system according to[148,149]:

$$y_i \rightarrow [0,1] = F(x_1, x_2, \ldots\ldots, X_k) \tag{2.17}$$

where

y	*is the model output;*
x_1, x_2 ..x_k	*are controllable (or independent) variables;*
k	*is the number of independent parameters.*

In conventional regression analysis, residuals are attributed to experimental and measurement errors. However, in fuzzy regression, residuals are assumed to represent the imprecise phenomena of the process. The output of the model hence defines the possibility distribution of the response variable.

It should be noted that the fuzzy models need not be strictly linear. In an approach that falls under the concept of fuzzy regression; Doherty and McGlone[150] used a nonlinear model for modelling the risk of undercut.

2.7.4 Artificial Neural Networks

The use of multiple linear regression method for modelling a process that is largely nonlinear could result in an over simplified representation of the process. Artificial Neural Networks are increasingly being used for process modelling in order to overcome the problem of over-simplification.

Artificial neural networks are a complex system that combine a network of highly interconnected processing elements or neurons that are arranged into structures called layers (see Figure 2.15)[151].

The increasing application of neural networks is attributed to the nonlinear mapping and learning properties which are central to their use in modelling and control[152]. They require no programming and can operate on both quantitative and qualitative data.

However, they do not lend themselves to mathematically accurate and precise applications, such as calculating process average, feature extraction on signals, summation, multiplication and so on[153].

Artificial Neural Networks (ANN) are best applied to problems for which generalisation is a more important success criterion than precision, that is, when the true boundaries are not exact[154].

Bailey and Thompson[153] identify the properties of situations for ANN application:

1. conventional approaches are inadequate ie poorly understood system that cannot be described by rules or equations;
2. problem requires qualitative or complex qualitative reasoning;
3. solution is derived from highly-interdependent parameters that have no precise qualification;
4. data is readily available but multivariate and intrinsically noisy and/or prone.

The major limitations of neural networks are the lack of standard procedures for specifying network size, training parameters and validation[155,156].

The building of ANN is largely trial-and-error. However, many researchers such as Smith and Dagli[156], Cherkassky and Lari-Najafi[133], Srirengan and Looi[157], White[158] and Schoner[159] are taking advantage of statistical techniques in neural network applications. Statistical inference tools are being used to design and train the networks.

Neural Network Training

Artificial neural network modelling involves training the networks to produce desired responses. Training of neural networks is simply the problem of finding a set of weights which allows the network to carry out the desired computation. This involves presenting the network with training data[152]. There are two methods for training a network. These are supervised and unsupervised training methods.

In supervised learning, the network is presented with a set of input and target output patterns. The network compares its output to the target and adapts itself according to the learning rule. The training algorithm commonly used is called "back propagation"[160,161]. In unsupervised learning, no output pattern is required, the network is simply presented with the set of training inputs. The network creates its own internal representation of the input data according to the statistical associations (ie to form clusters) in the input patterns[160,162]. The method used for this is self-organised learning or competitive learning algorithms; an example of such a network is a Kohonen map.

Backpropagation Algorithm

Back-propagation is the most popular training approach used in artificial neural networks and has successfully been applied to many practical problems.

Its area of application includes process control, diagnosis, prediction and decision making[163-166]. The "back-propagation" algorithm is an iterative gradient algorithm designed to minimize the error between the actual output of the network and the desired output[162,166]. The algorithm makes the weight changes to follow the steepest path towards the point of minimum error.
The basic training algorithm[162]:

Step 1: initialise weights[k] and offsets
Step 2: present input and desired outputs
Step 3: calculate actual output
Step 4: update weights
Step 5: goto Step 2

The algorithm updates the network weights at each training cycle according to the rule[167,168]:

$$W(n+1) = W(n) + \eta G(n) + \alpha\,[W(n) - W(n-1)] \tag{2.18}$$

where

W	*is the weight vector;*
n	*is the number of iterations;*
η	*is the learning rate coefficient;*

---

[k] The initials are either fixed or generated from random numbers.

α	*is the momentum factor;*
G	*is the gradient of the error function.*

The Neurons[151,154,169]

A neuron is a simple processing/storage unit that has several inputs and an output. Each neuron processes the input data through the network layer by layer to generate the output. Figure 2.16 shows the processing operation in a neuron.
The algorithm that a neuron carries out is:

$$y_i = f(x_i) = \frac{1}{(1+e^{-\beta x_i})} \tag{2.19}$$

where

$$x_i = \sum_{1=0}^{n} W_{ij}s_{ij}+I_{ij} \tag{2.20}$$

yi	*is the output of a neuron; the range of y is (0,1) for x(-∞,∞);*
x_i	*total activation for a neuron;*
f(x)	*is the sigmoid (non-linear) transfer function;*
ß	*is the gain of the sigmoid function;*
S_{ij}	*is the input coming either from other neurons or from external world;*
W_{ij}	*is the weight's vector; each associated with each of the neuron inputs;*
I_{ij}	*is a bias; a set value (usually set to 1) input into each neuron;*
n	*is the number of neuron.*

Network Size

The network size is defined by the number of hidden layers and the number of nodes on each layer. The network size affects the ability of the network to generalise. This is the ability of a network to respond correctly to data not used to train it.

The selection of network size is normally trial and error. Hush and Horne[169] recommended starting with the smallest possible network and gradually increasing the size until the performance begins to level off. The number of hidden neurons is set heuristically. A suitable initial size is seventy five percent of the number of neurons in the input layer[153].

Muller and Reinhardt[170] advocate starting with a large network and then applying a pruning technique that destroys neurons that are not contributing to the model. Most neural network software carry out this function automatically, if required.

The number of hidden layers is also chosen heuristically, if one hidden layer is insufficient then it is common to move to the use of two or more. Villiers and Barnard[171] found in an experimental study, that networks with one and two hidden layers perform similarly; however, networks with two hidden layers are more prone to fall into local minima.

The optimum network size is the one that gives the best generalisation[1] from the available training data. Cherkassky and Lari-Najafi[133] stressed that this must be viewed from a statistical perspective.

As the network grows larger, the number of parameters defining a neural network increases. This would cause the training data to become sparsely distributed in the network parameter space. The data becomes less representative of the of the problem, reducing the predictive capability of the network[169,172].

Srirengan and Looi[157] empirically established that to avoid overfitting and overtraining, the total number of weights ie. connections, must be less than the total number of input parameters.

Selecting Training Parameters

Once the size of the network has been decided then the training parameters have to be selected. The training parameters in the backpropagation method are learning rate, momentum and gain. These are again chosen by trial and error.

The learning rate and momentum determine the amount by which the weights are updated. The learning rate regulates the relative magnitude of weight changes during learning. The momentum acts as a low-pass filter on the weight updates, thereby tending to resist erratic weight changes[173].

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[1] Generalisation is the ability of a network to respond correctly to data not used to train it.

This helps to make a network train faster by adding a fraction of the last cumulative average weight change to the next one[174]. This ensures that the weight change moves almost in the same direction; increasing momentum would increase training, however too large a value can cause instability.

The learning rate must be chosen to reflect the test data. The magnitude of the error gradient increases with the number of patterns in the training set. Therefore the learning rate must be decreased as the training data becomes bigger to prevent instability[167].

Eaton and Olivier[167] gives an empirical equation for selecting learning rate:

$$\eta = \frac{1.5}{\sqrt{N_1^2 + N_2^2 + \ldots + N_m^2}} \qquad (2.21)$$

where

N_1 *is the number of patterns of type 1*;

m *is the number of different pattern types.*

Gain also makes a network train faster. However, too large or small a value increases the learning time and the chance of reaching a local minima[175]. With low gain, the error will remain constant at about fifty percent. This can be avoided by simply increasing the gain.

If the gain is set too large, the errors of some training sets will approach one hundred percent. The others will decrease and remain at low values. This is the worst case of local minimum error; the solution is to start training again with a lower gain.

This behaviour is a result of the tendency to find solutions that generate mostly correct outputs close to the target output but have few outputs that are very far from the target outputs[176].

Eaton and Olivier[167] give a numerical equation for calculating the appropriate gain given the learning rate and momentum.

$$Gain = \frac{\eta}{1-\alpha} \qquad (2.22)$$

where

η *is the learning rate coefficient*;

α *is the momentum factor.*

It was however suggested that a fixed value of 0.9 could be used for momentum for any back-propagation networks.

Network Training Stopping Condition

Stopping conditions for network training are critical. This is usually specified as tolerance error below which training is stopped. The problem is that, there is no guarantee that the obtained network is optimum. Sometimes, it is better to stop the learning process before the error function becomes very small to avoid over training[163].

A strategy for doing this involves training a network at different level of tolerance error. When the network has trained, validate if satisfactory stop, if not reduce the tolerance error and continue training.

Validating the Trained Network

There is no theoretically sound method for verification of neural network systems. Unlike regression analysis, neural network model accuracy cannot be easily assessed.

Trial and error testing is normally used. Typically, about twenty to thirty percent of the training data are reserved for testing the fully trained network. The proportion correctly identified and/or predicted by the trained network is used as a measure of model adequacy[160].

2.8 Procedure Development

2.8.1 Statistical Approach

Procedure development is the process of selecting input variables (ie. equipment settings) that result in a process with the preferred combination of output characteristics[177].

Traditionally a welding procedure is developed by trial and error and a presumed good/working condition quality is confirmed by repeating a small number of runs[130].

The tolerance box technique was developed to provide a more systematic method of setting process parameters[130]. It is based on the construction of a database containing a range of welding parameters that would give good quality welds within given dimensional tolerance (maximum and minimum) for a given situation[178]. The major problem with tolerance box is the volume of data collected.

Procedure development has advanced with advantage being taken of computer based statistical and numerical approach to predict and optimise welding procedures[178]. Palotas[179] reported a computer-aided "welding technology design system" developed at the Technical University of Budapest. The system uses algorithms developed via statistical methods to develop procedures for consumable and non-consumable welding processes.

Galopin et al.[180,181] used regression models and optimisation techniques to develop software to generate welding procedure conditions for metal core arc welding of single V-groove joint with backing.

Chan et al.[182], Chandel et al.[183,184], Paton et al.[185], Dudovetski et al.[186,187] and Kasatkin et al.[188] all use regression algorithms for computing the size and shape of gas metal arc welds giving the welding parameters, such as voltage, current, welding speed, wire diameter and electrode extension.

While empirical models are widely used for predicting weld geometry defined by filler metal addition into the joint[182-188]; Daggett[189] reported difficulty in modelling and predicting penetration in dip transfer welding.

Penetration and fusion depend on energy input that varies with wire feed and welding speed. Figure 2.17 shows how different travel speeds at the same energy input affects fusion area and penetration. Welding at the higher travel speed means increased melting efficiency; more of the available heat is used to melt the base plate and a smaller proportion is used to raise the temperature of the surrounding plate[190]. This leads to increased fusion and penetration.

To model fusion, Bradstreet[190] relates the cross-sectional area of the fused metal (A_t) to the product of the effective heat input and the cube root of the travel speed.
That is,

$$\log A_t = \alpha \log (HI\, S^{1/3}) + \beta \qquad (2.23)$$

where

A_t *is the cross-sectional area of the fused metal;*
HI *is the effective heat input;*
S *is the travel speed.*

Although the model (Equation 2.23) was for submerged arc welding, it offers a valuable modelling structure for fusion and penetration because it represents the physical nature of the process.

Persson and Stenbacka[191]; welding 6mm plate using dip transfer established that weld metal cross sectional area is a direct linear function of arc power[m], while the depth of penetration is directly proportional to the square root of arc power for a fixed welding speed.

Kutenov et al.[192] used a threshold approach for modelling and controlling penetration to prevent lack of fusion and burn-through. The intermediate region between these two defects is the normal penetration, whose boundaries are established for each specific case. Although it was not stated in the publication, it is clear that this approach was adopted due to the difficulty in modelling penetration accurately.

The authors[192] developed a model for penetration in terms of the welding conditions and using the model as a sensor three threshold rules were developed:

---

[m] **Arc power is the product of the welding current and voltage.**

if **Pen < Pcrl** then **there is lack of fusion**
if **Pcrl<=Pen<=Pcr2** then **penetration normal**
if **Pen >Pcr2** then **burnthrough**

where Pen *is the predicted penetration and* Pcrl and *Pcr2 are the minimum and maximum threshold values for normal penetration.*

2.8.2 Neural Network Approach

Artificial neural networks have found growing application in welding, especially in defect diagnosis, process monitoring, seam tracking, bead dimension estimation, and procedure development[193-198].

The apparent advantage of using neural networks for modelling welding process stems from the fact that the arc welding processes is a nonlinear and highly coupled multivariable systems[196].

Cook et al.[197] used backpropagation neural networks to estimate bead geometry from tungsten arc welding signals. However, when used for procedure development that is, predicting the welding parameters given required bead dimension, some unexpected results were obtained.

Their results suggested that dense training data in the region of anticipated welding condition is needed to avoid unexpected results. This illustrates the inflexibility of neural networks compare to convention statistical approach.

The American Welding Institute[198] has also developed a neural network system for weld model geometry flux cored arc and gas tungsten arc welding. The outputs of their network include spatter, bead dimension, penetration, undercut and ease of slag removal.

Probably the most promising aspect of neural networks is that they can be used to replace conventional expert systems for defect diagnosis. Artificial neural network based diagnosis systems require no rules, only representative data of the process and its possible fault patterns[165,166].

The network then learns to recognise the patterns and when presented with a completely new pattern, it will either[199]:

1. find the closest match to the new example among the previously trained patterns, or;
2. classify the new example as an interpolative "blend" of previously trained pattern.

The second property makes the backpropagation neural network very valuable for diagnosis and classification applications.

2.8.3 Optimisation Technique

Optimisation is important because many different combinations of input variables could result in the same output target value, but with considerable difference in the operating conditions. It helps to identify the best operating conditions for the required objective.

To optimise a process, the objectives must be expressed mathematically in terms of variables that are easy to control. Latour[200] outlines the requirement for optimisation as follows:

1. select proper independent variables;
2. formulate model requirement;
3. formulate objective functions;
4. select optimisation algorithms appropriate to the nature of the problem(s);
5. define parameters and process physical limits.

Optimisation, in welding can therefore be used to identify settings of process parameters that make the product's performance close to target values in the presence of multiple quality characteristics. The success of this however depends on having good models for predicting the quality characteristics.

Several objectives are required to be satisfied in welding such as bead size, defect free weld (ie no undercut, no burnthrough etc.) and maximum heat input requirement.

Doherty and McGlone[150] developed an interactive computer program for generating welding conditions for close square butt submerged-arc welding of steel plate. The program predicts a series of potential procedures in order of decreasing output rate; the objective is to maximise of welding travel speed subject to the user specified process constraints.

Shepherd[72] also developed a simulation program that uses an iterative strategy for selecting welding parameters that will satisfy the required weld bead shape. The author noted that the size of the iteration step is very important, if too large there was risk of missing optimum results while if too small it will produce many iteration steps and takes more computation time. The iteration was stopped when all possible conditions were assessed or time allowed to reach a solution elapsed (that is, the program was time truncated).

Galopin et al.[180] used a direct search method to predict welding procedure by minimising the sum of the absolute relative deviation from desired penetration and fusion area. That is,

$$F = \frac{|P-P_0|}{P_0} + \frac{|A-A_0|}{A_0} \tag{2.24}$$

where

F	*is the objective function;*
P_0	*is the required penetration;*
P	*is the predicted penetration;*
A_0	*is the required fusion area;*
A	*is the predicted fusion area.*

Lho and Na[201] also used similar technique but their objective function was expressed as the weighted sum of squares of the difference between the predicted bead dimension and the required ones. That is,

$$F = \sum_{I=1}^{n} \alpha_i \left(1 - \frac{y_{(i)p}}{y_{(i)r}}\right)^2 \tag{2.25}$$

where

F	*is the objective function;*
$y_{(i)p}$	*is the predicted quality parameter;*

$y_{(i)r}$ *is the required quality parameter;*

α_i *is the weighting factor between zero and one.*

It is perceived that the sum of α_is would be equal to one but its individual value depends on the quality parameter criticality; for example having a bigger weld than required is not as critical as having lack of penetration or burnthrough.

Oddy and Chandel[202] and Hunter et al[203] generate welding procedures by solving process equations (models). This is equivalent to solving simultaneous equations, with the number of models solved equal to number of specified parameters. This approach however requires the setting of reasonable requirements otherwise a welding procedure that is not feasible within the process range could be predicted.

Dubovtskii[187] generated welding condition using a multi-criteria optimisation scheme; the optimisation criteria used includes minimisation of the cost of producing 1mm of weld, maximisation of welding speed, minimisation of spatter losses and dimension accuracy of the bead size required.

The result of the optimum conditions for a range of bead size, wire diameter and joint gap width for fillet and butt welds are then generalised in the form of a second-order polynomial model. The optimum models are then used for selecting welding parameters given initial conditions and are fitted in the form shown below.

$$X_i = f(C) \tag{2.26}$$

where

X_i *is a welding parameter which could be current, voltage or speed;*

C *is the initial condition specified which includes bead size required, gap width, wire diameter and plate thickness.*

Paranhos[178] used a linear programming method to optimise welding procedure. Linear programming is a technique used extensively in operation research. They are of value in the formulation of many (though not all) problems concerned with the efficient use of limited resources by maximising or minimising a linear objective function;

$$Z = \sum_{i=1}^{n} c_i x_i \tag{2.27}$$

subject to linear constraints;

$$b_j * \sum_{j=1}^{m} a_{ij} x_i \tag{2.28}$$

where

Z	*is the objective function;*
x_i	*is the real variables (x_i=>0);*
c_i	*are constants;*
n	*is the number of real variables;*
b_j	*are the constraints to be satisfied;*
*	*denotes <, =<, =, => or >;*
a_{ij}	*are constants;*
m	*is the number of constraints.*

It should be noted that in linear programming the solutions, the objective function and constraints are all linear.

The weld quality requirements cannot all be modelled or defined precisely, some " fuzziness" is required in transforming the multiple objectives into a single objective using a numerical approach. It is not easy to define or measure phenomena such as undercut and arc stability.

An optimisation criterion that can deal robustly with imprecise characteristics, is a technique called simultaneous multivariable optimisation method developed by Deringer and Such[204]. The structure of the technique is very useful for welding applications.

There is no restriction on the type or number of performance criteria and no need to combine criteria into a single objective function. It is not strictly necessary to have linear functions and the final objective function offers a modular structure.

The technique involves ascribing a value to indicate how desirable an estimated response variable is. This involves transforming each response output under consideration to a desirability value "d_i", which is always between zero and one. That is, the function is a decision variable.

The value of d_i increases as the desirability of the corresponding response increases. The individual d_i's are then combined using geometric mean to give the overall assessment of desirability D. That is,

$$D = (d_1 * d_2 * d_3 * \ldots . * d_k)^{\frac{1}{k}} \tag{2.29}$$

where

k *is the number of objectives.*

The most important element of this technique is that if any d_i is equal to 0, that is, not desirable then D will also be 0. It should be note that the objective function could also be additive. The transformation of quality variable into desirability value d_i is obtained by using two approaches depending on quality objective.

One-sided Transformation

This is used when the objective is to maximize Y_i (or minimize Yi which is equivalent to the maximisation of $-Y_i$).

The desirability value is,

$$d_i = \left(\frac{Y_i - Y_{i,\min}}{Y_{i,\max} - Y_{i,\min}}\right)^r \tag{2.30}$$

where

$Y_i <= Y_{i,min}$ *will make* $d_i=0$ *and* $Y_i => Y_{i,max}$ *will make* $d_i=1$;

$Y_{i,min}$ *is the minimum acceptable value of* Y_i, *while* $Y_{i,max}$ *although not a constraint would be the value of* Yi *above which there is no additional advantage or benefit.*

Two-sided Transformation

This is used when the response variable has to be kept between a minimum and maximum level. That is,

$$d_i = \left(\frac{Y_i - Y_{i,\min}}{C_i - Y_{i,\min}}\right)^s \left(\frac{Y_i - Y_{i,\max}}{C_i - Y_{i,\max}}\right)^t \qquad (2.31)$$

where

C_i *is the value of* Y_i *desired. If the value of* Y_i *falls outside the specified range* d_i *should be set to zero;*

and

r, s *and* t *are transformation constants. They could have values between* 0.1 *and* 10. *The default values are* r=1 *and* s=t=10.

2.9 Adaptive Control

A lot of published works are available on adaptive control of arc welding processes but most focuses on classical control theory. However in line with the stated objective, only published work with statistical emphasis are of relevance to this research effort.

Statistical methods are widely used for analysing and improving the output quality of manufacturing processes[205]. Statistical process control (SPC) technique has been used successfully for decades to detect changes in manufacturing process. This follows the steps of detection, study and action. The control action (ie. process adjustment) is only taken when there is statistical evidence that the process is out of control.

However, traditional statistical process control will fail in high productivity (ie. automated) manufacturing environments due to the increasing lag time between detection and process adjustment as the volume of production increases therefore instantaneous detection of process disturbances is important and necessary[206].

This leads to the combination of adaptive control concepts and statistical methods that has been called "algorithmic statistical process control" by Tucker et al.[207]. The objective being to reduce predictable quality variations by using adaptive control techniques and statistical process control to detect and remove the root causes of unexpected variations[207].

The components of the resulting technique includes process modelling, model identification and estimation, process optimisation, control-rule design and process monitoring[207].

Adams[208] defines adaptive control as the act of using observations and knowledge of a process behaviour to make decisions and to manipulate operational variables to cause the process to behave in a more desirable fashion.

With reference to the welding process, the objective of adaptive control is principally to achieve consistent weld quality. Control actions are required to be implemented with the intention of cancelling the effect of disturbances on the welding process before they affect output quality and the stability of the process. This however depends on the ability to detect and/or measure the disturbances.

This would involve the development of models that describe the relationship between the process input and output quality characteristics and the effect of disturbance effects on them.

Malin[209] and Sicard and Levine[16] stress that adaptive control systems for welding must try to emulate a welder since the objective of welding automation is to replace the action of the welder by a machine. The characteristic of a manual welder control action is shown in Figure 2.18. The welder's control method is subjective, skill intensive and experience biased.

A welder listens to the sound of the arc to optimise welding parameters and assess the arc and metal transfer stability, especially in short circuiting welding. The welder also views the weld pool to gain an indication of fusion characteristics and the intensity of the arc is used to gauge the arc length. Sensors are now employed to emulate the welder's sensing function. Published works has shown that the focus was initially on vision systems[16] but section 2.3.2 in the present work gives details of sensing methods used in arc welding.

The ease of setting up a control system emulating a welder depends on the control structure being used. Paton and Podola[210] both proposed hierarchical control structure for automatic welding processes. This consist of three control levels namely local level; supervision and integration level; and user interface level.

The local level consists of control systems that ensure setup parameters stability eg. automatic voltage control, synergic control in power sources and touch sensors in robots. The supervision level monitors the process and controls the setup parameters using process knowledge. The user interface level provides interaction between the process and operator. The level is software based and deals with procedure development from the specified joint requirements.

Figure 2.19 shows the adaptive control architecture for welding systems developed by Sicard and Levine[16]. This contains sensory processors, trajectory controller, weld process controller and weld task planner.

The sensory processors processes vision data to obtain desired parameters such as joint geometry, weld pool width etc. The trajectory controller and weld process controller controls the torch path and its orientation and welding process variables. The weld task planner contains a decision module (process models) that predicts welding parameters that will produce welds that meet the user's quality criteria and also supplies all of the data to each module in real time.

It is important to stress that adaptive control basically involves developing appropriate models that relate process inputs to its outputs. These models are then used for process control. The basic requirement is to achieve the control objective within established process and equipment constraints.

Adaptive quality control would therefore involves ensuring output weld quality by monitoring disturbances and process parameters according to prevailing conditions in such a way as to direct the welding results towards a quality target. The increasing demands for process flexibility and product diversity suggests a very flexible and deterministic control strategy.

The control can be carried out by either or combination of look-up tables and algorithm strategy[72]. Look-up tables contain scheduled procedures relating to range and type of disturbances and corrective actions preprogrammed in the process controller memory. They are very simple and quick to implement. However look-up tables are time consuming to construct, wasteful of computer memory and lack generality; being unique to each joint and disturbance type.

The algorithm strategy is based on mathematical (empirical) models correlating the procedure inputs to outputs. However, depending on the required response time to control the process, the algorithm method may be too slow for real time operation, comparing unfavourably with the look-up table.

A compromise strategy is to construct a look-up table with very few points and the intermediate values being determined by interpolation[72,157]. The most common approach however is algorithm based control.

Hunter and Bryce[203] used an algorithm approach based on regression models relating welding parameters to bead features for on-line control of the flux-cored arc welding process of fillet welds in flat welding position. This involves compensating for on-line change in standoff by adjusting the wire feed speed, voltage and travel speed. The control models are of the form:

$$WP = \alpha + \beta SO \tag{2.32}$$

where

WP *is the welding parameters which are speed; wire feed speed and welding voltage;*

SO *is the standoff measured online by capacitive distance transducers;*

α,ß *are constants obtained by solving the regression models, their values depend on the size of desired bead features.*

Shepherd[72] used regression analysis to develop control models for self shielding flux cored electrode welding parameters. The author developed first-order regression models that relate standoff and electrode position on the joint to the joint geometry (root face thickness and root gap). The models give appropriate value of standoff and position based on the measured joint geometry. The geometry was measured with a vision system. The voltage was expressed as a function of standoff; the wire feed speed and welding speed were kept constant.

In extension to the work carried out by Shepherd[72], Street et al.[211] express the welding voltage as a first-order function of travel speed, wire feed speed and standoff.

Smartt et al.[212] used a proportional controller to control the weld heat and mass input independently for gas metal arc welding. The strategy involves calculating appropriate weld speed, wire feed speed and an expected value for welding current. The expected current value is compared with the measured current and the difference used to calculate corrections for welding speed and wire feed speed.

Sugitani et al.[213,214] developed a multivariate adaptive strategy for controlling weld penetration depth and bead height based on the detected joint geometrical error. The parameters used for control are welding current, arc voltage, wire feed speed and welding speed.

Probably the most important work on the adaptive control of arc welding processes carried out to date are the four control concepts developed by Sugitani et al.[215] for Gas Metal Arc Welding of V-groove joints with a backing plate.
The concepts were summarised below:

Concept 1 **Regulating welding speed according to geometrical variation.**

The welding speed is adapted according to gap size using:

$$S = A_{wire}\frac{WFS}{(A_0+\Delta A)} \tag{2.33}$$

where

S	*is the welding speed;*
WFS	*is the wire feed speed;*
A_{wire}	*is the cross sectional area of welding wire;*
A_o	*is the cross-sectional area of weld bead at* Gap=0;
ΔA	*is the change in area due to geometrical variation.*

This method for adapting the procedure for increasing gap has the effect of increasing the heat into the joint and reducing the amount of liquid in the pool thereby superheating the liquid and reducing the surface tension pressure (see Section 2.1.4). The arc pressure would remain unchanged because current is not changed.

Concept 2 **Regulating the welding speed and current together according to geometrical variation.**

The welding current is adapted using:

$$I = I_o - \beta_1 Gap \tag{2.34}$$

where

I	*is the new welding current;*
I_o	*is the current used at* Gap=0;
β_1	*is a constant given in advance and kept constant during welding;*
Gap	*is the size of the gap.*

Because the wire extension (see Figure 2.13) is expected not to vary the wire feed speed is changed according to changes in current I, using the burn-off equation:

$$WFS = \alpha_2 I + \beta_2 l_{so} I^2 \tag{2.35}$$

where

l_{so}	*is the wire extension;*
WFS	*is the wire feed speed;*
I	*is the new welding current;*
α_2, β_2	*are constants.*

To keep the arc length constant the welding voltage must be adjusted whenever current and/or wire feed is adjusted. The model for controlling voltage is complex; the simplified version is given below:

$$V = \alpha_3 + \beta_3 WFS \tag{2.36}$$

where

V	*is the welding voltage;*
WFS	*is the wire feed speed;*
α_3, β_3	*are constants.*

This approach also increases the heat input into the joint but both the arc pressure and surface tension reduce.

Concept 3 **The welding heat input per unit length of weld bead Qw (J/mm) and wire feed speed are kept constant irrespective of geometrical variation.**

The welding speed is first calculated according to the variation using equation 2.33. Then, the welding current is calculated from the heat input using:

$$I = \frac{Q_w S}{\eta V} \tag{2.37}$$

where

Qw	*is the welding heat input;*
S	*is the welding speed;*
η	*is the arc efficiency;*

The wire extension is then regulated with current, by reversing equation 2.35 (the burn-off equation). This implies changing of the contact to workpiece distance, which is the sum of wire extension and arc length.

This control approach has the effect of reducing arc pressure and increasing the surface tension.

Concept 4 **The arc heat input per unit length of weld bead Qa (J/mm), welding current and speed are kept constant irrespective of geometrical variation.**

This is realised by regulating wire feed speed and voltage.
The wire feed is calculated using equation 2.38 and the voltage using Equation 2.36.

$$WFS = \frac{S(A_0+\Delta A)}{A_{wire}} \tag{2.38}$$

The wire extension is regulated with wire feed speed by reversing equation 2.35. This approach reduces heat input while no significant changes in arc pressure and surface tension. This makes Concept 4, the most tolerant to geometrical variation.

2.10 Summary

A review of the literature indicates that there is a need for compact non-invasive sensor based systems for monitoring and control of robotic gas metal arc welding. Whilst various approaches have previously been investigated there appears to be no complete solution to the problem.

The aim of the current work is to devise and test a suitable system with particular emphasis on the welding of sheet steel in the automotive industry. The concept developed is described in Chapter 3.

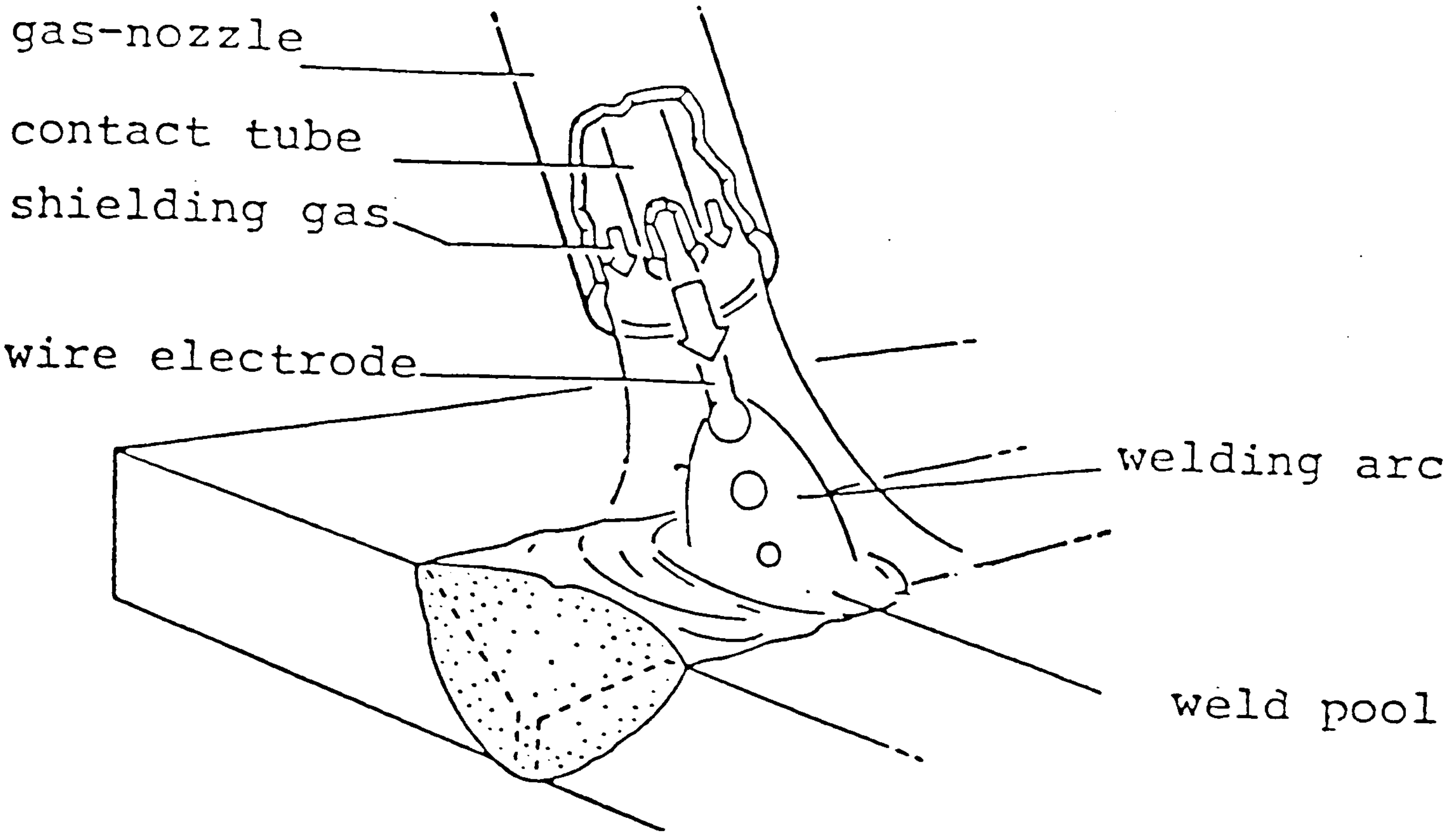


Figure 2.1 The GMAW Process[23]

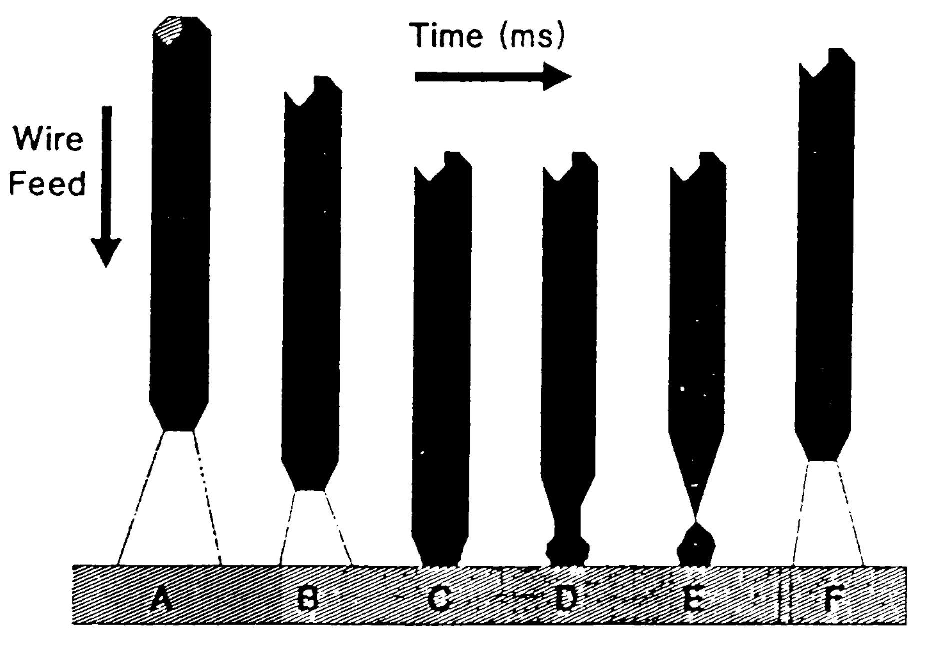


Figure 2.2 Dip Transfer[4]

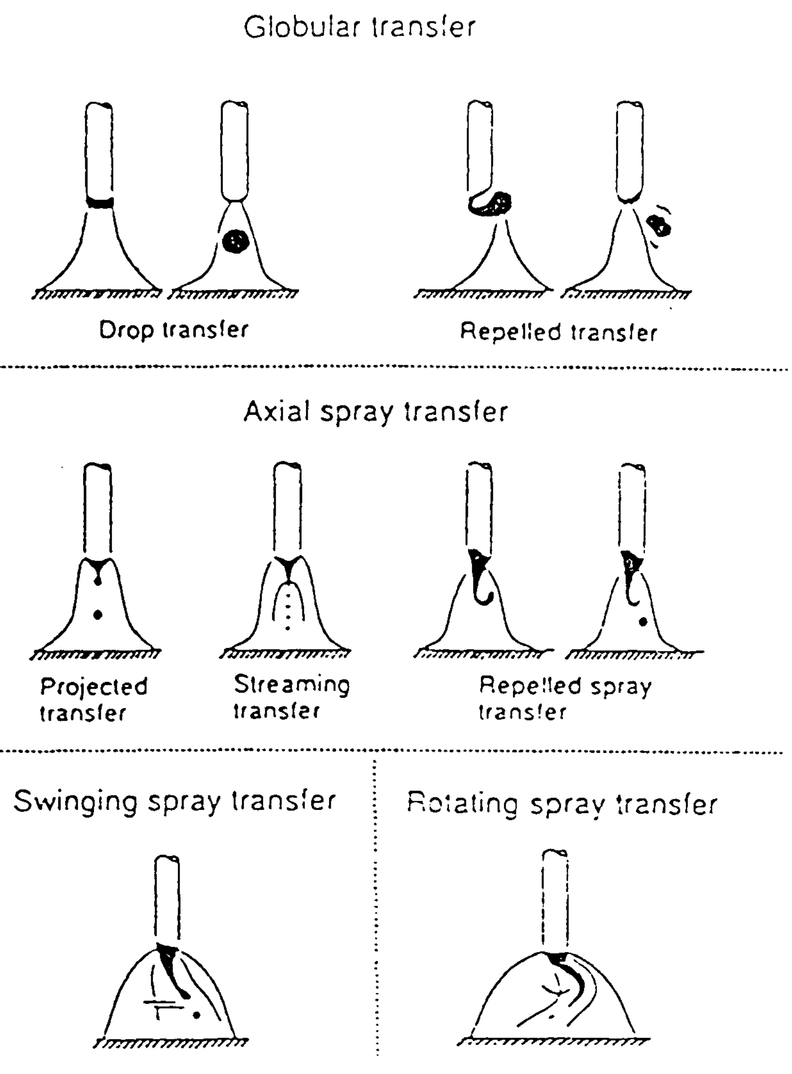


Figure 2.3 Free Flight Transfer[15]

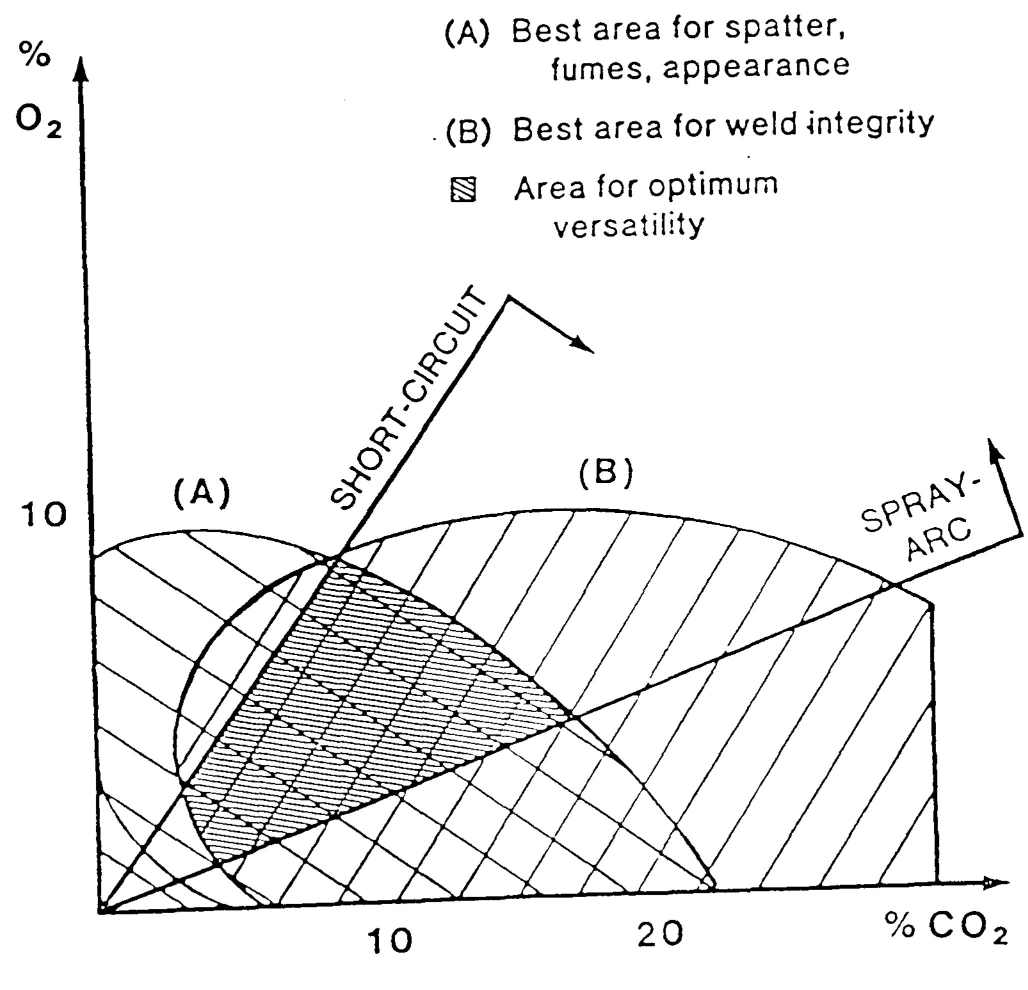


Figure 2.4 Guide to Shielding Gases and Metal Transfer[20]

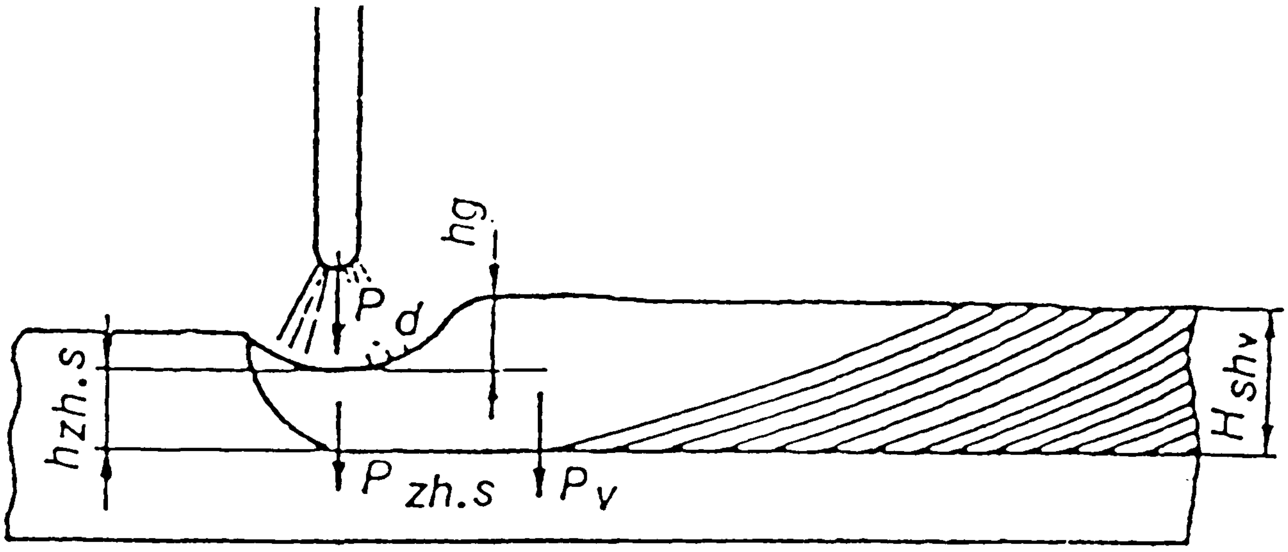


Figure 2.5 Pressure Acting in a Weld Pool[37]

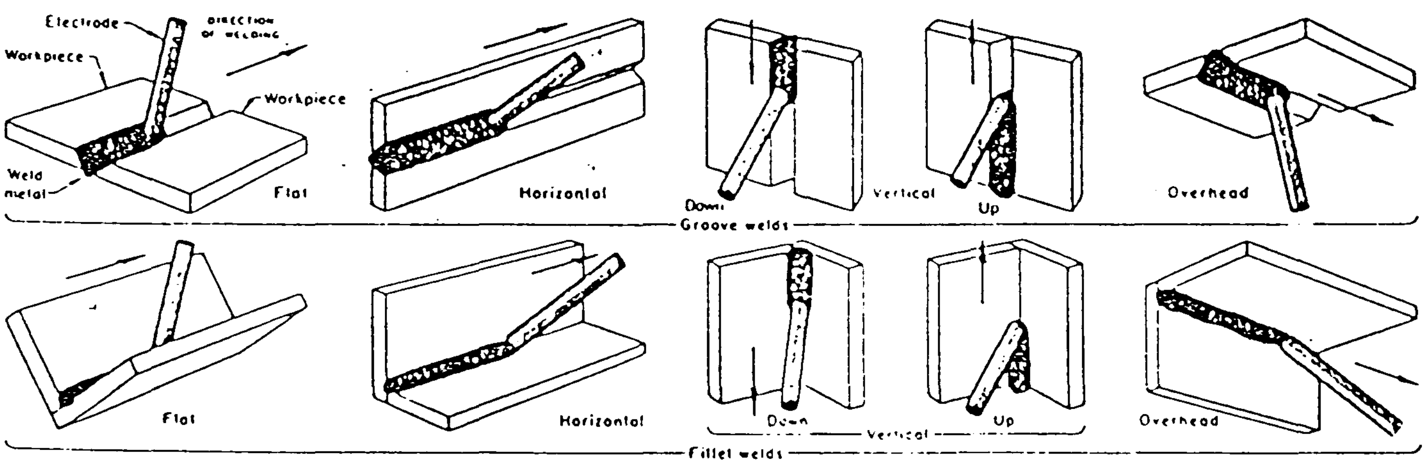


Figure 2.6 Welding Positions[9]

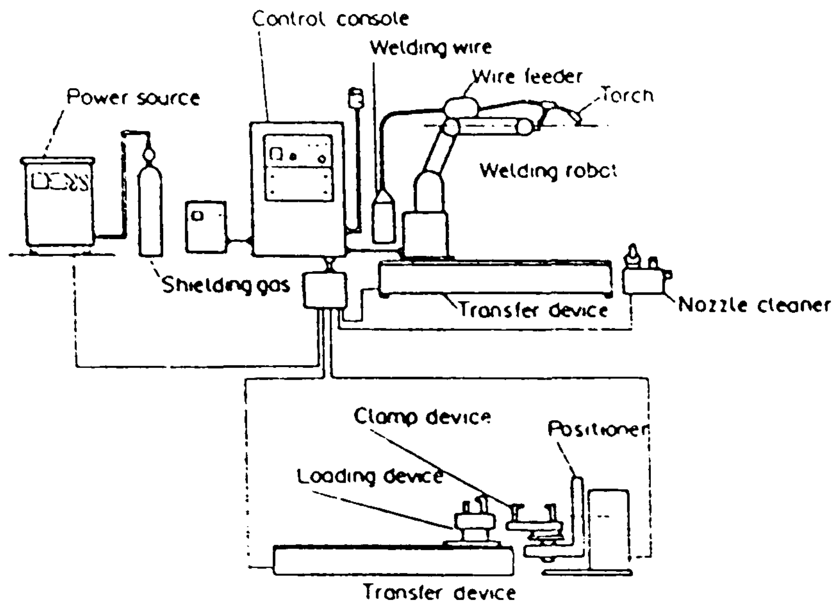


Figure 2.7 Typical Features of a Robotic Welding System

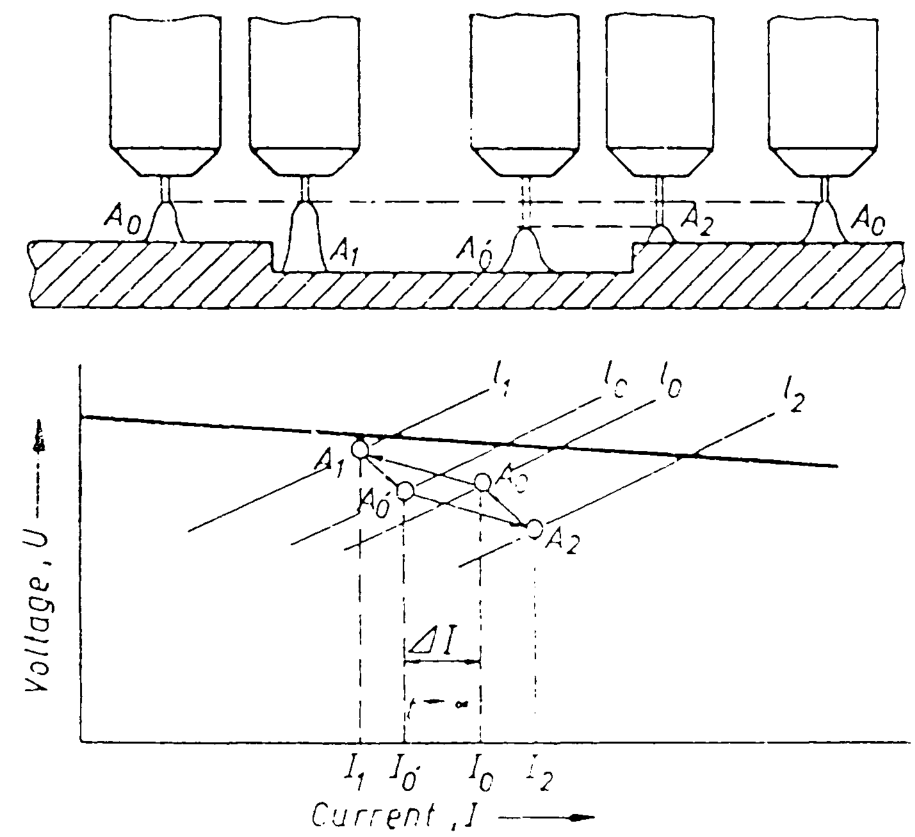


Figure 2.8 The Welding Arc Self-adjustment Process[52]

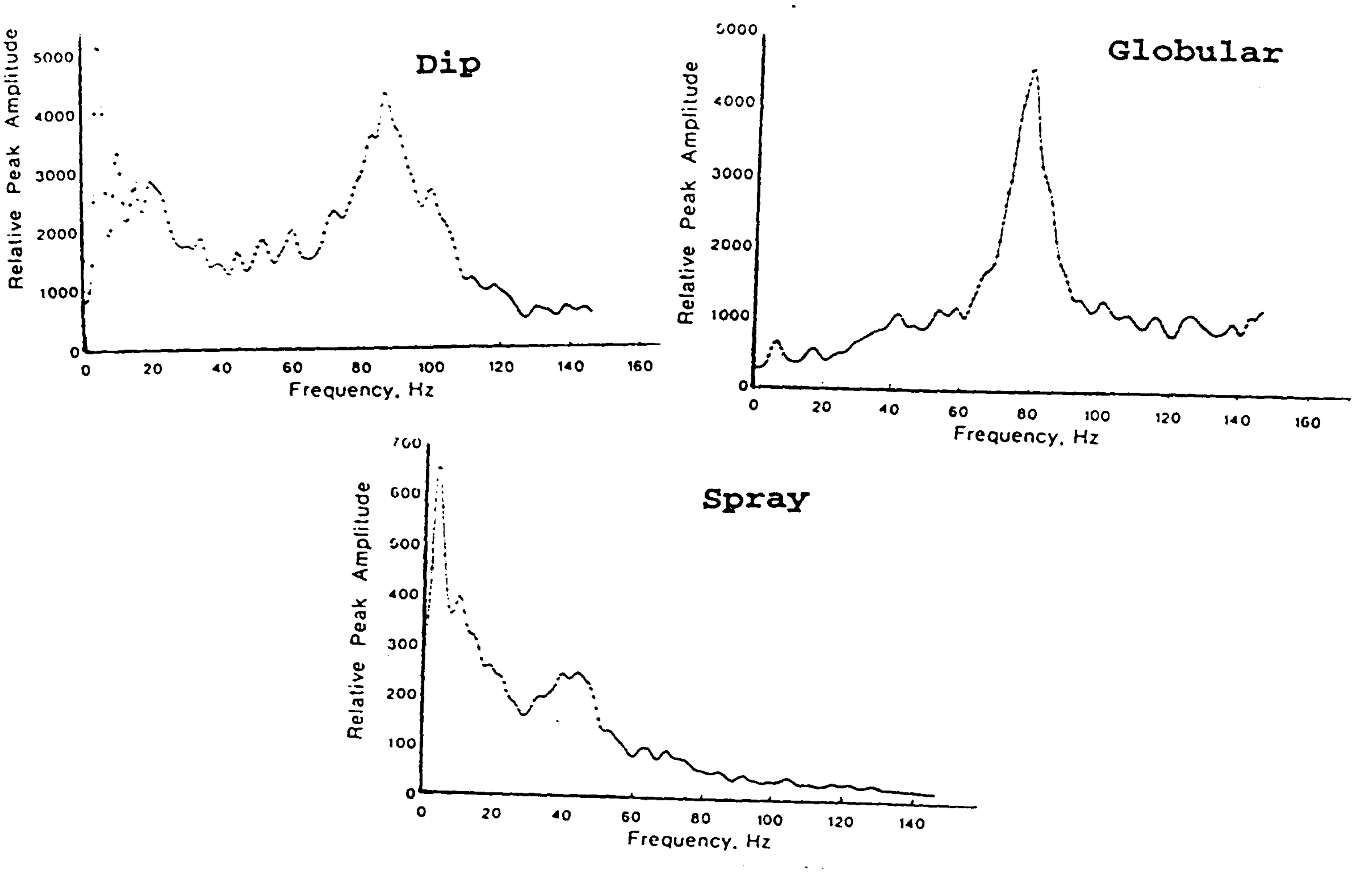


Figure 2.11 FFT of Transfer Mode[115]

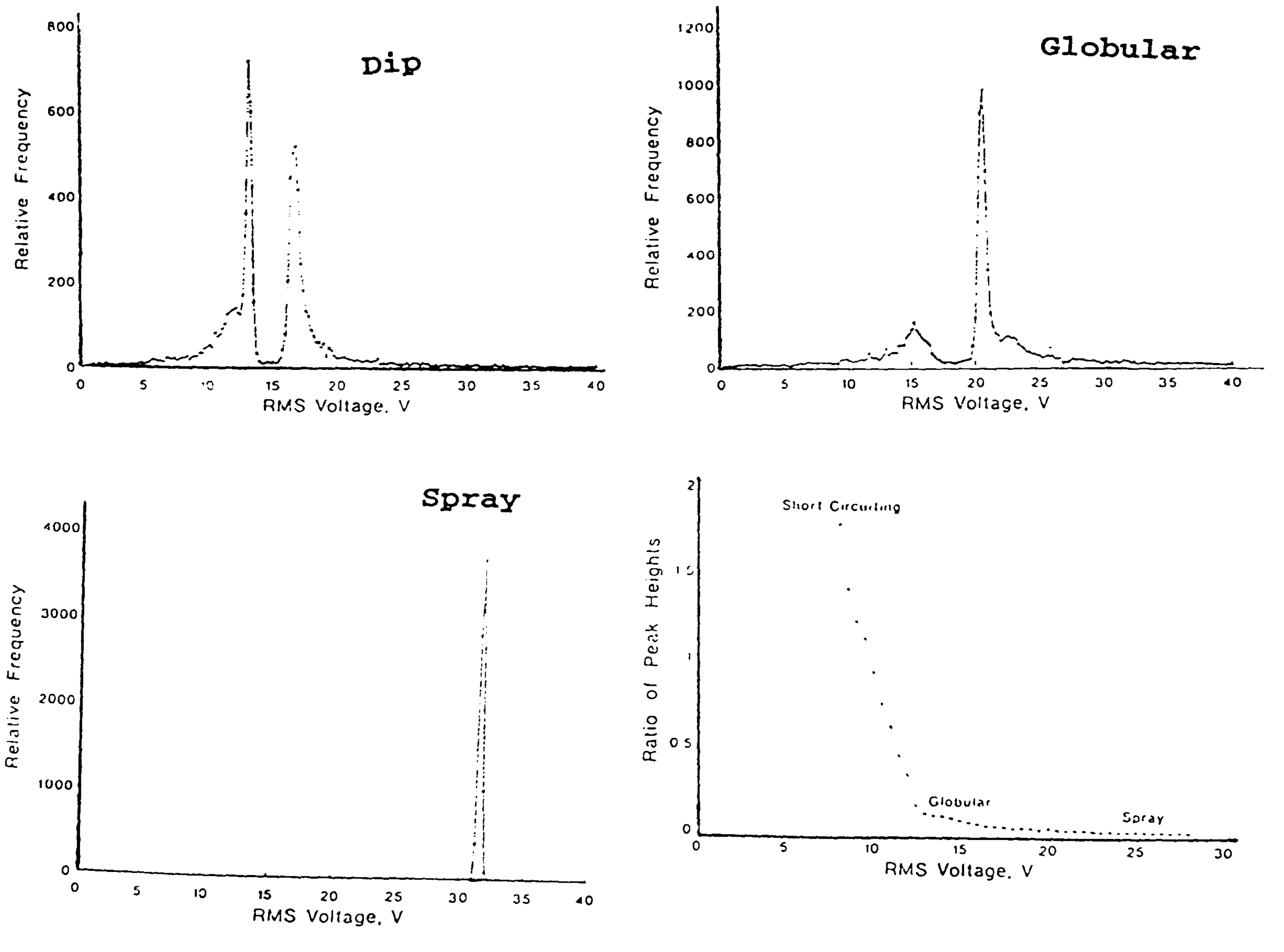


Figure 2.12 Amplitude Histogram for Metal Transfer[115]

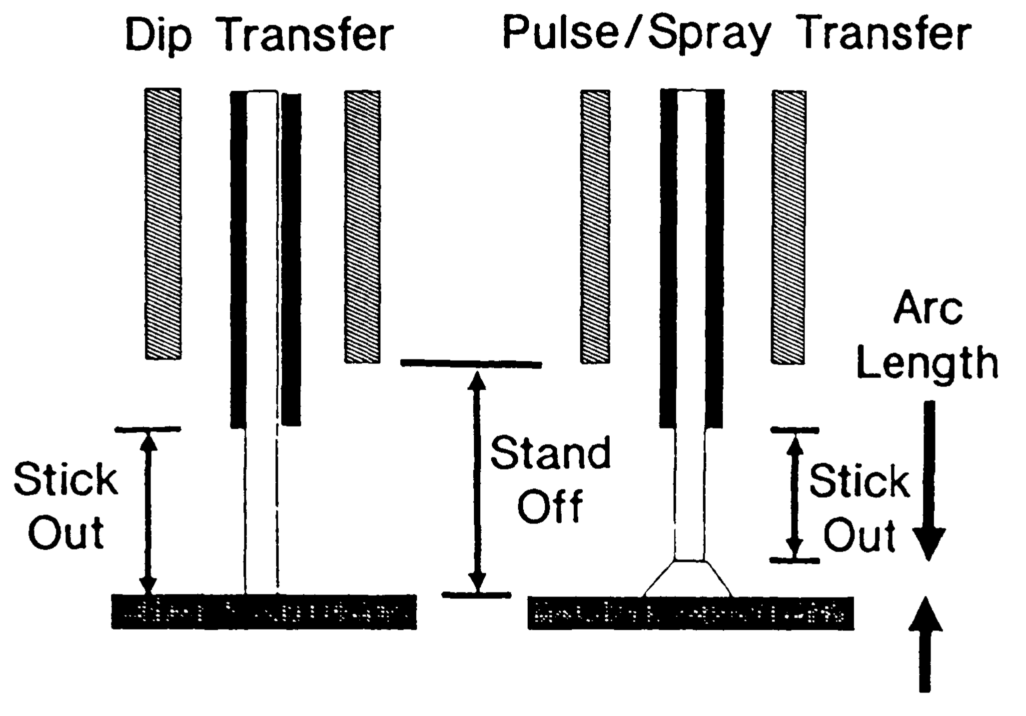


Figure 2.13 Definition of Standoff[4]

Multiple Regression

```
Dep. var.: LOG DIPC.Ls                  ÜÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÔÜ
                                        Ü                                  Ü
Ind. vars.: LOG DIPC.WFS/DIPC.S         Ü Analysis of variance             Ü
                                        Ü Conditional sums of squares      Ü
                                        Ü Plot residuals                   Ü
                                        Ü Summarize residuals              Ü
                                        Ü Plot predicted values            Ü
                                        Ü Probability plot                 Ü
                                        Ü Component effects plot           Ü
                                        Ü Influence measures               Ü
                                        Ü Corr. mat. of est. coeffs.       Ü
                                        Ü Generate reports                 Ü
                                        Ü Confidence intervals             Ü
                                        Ü Interval plots                   Ü
                                        Ü Save results                     Ü
                                        Ü                                  Ü
Weights:                                ÜÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÉÜ

Constant: Yes    Vertical bars: No      Conf. level: 95
```

Model fitting results for: LOG DIPC.Ls

Independent variable	coefficient	std. error	t-value	sig.lev
CONSTANT	0.127964	0.155957	0.8205	0.42
LOG DIPC.WFS/DIPC.S	0.512847	0.059484	8.6216	0.00

```
R-SQ. (ADJ.) = 0.8209  SE=        0.099389  MAE=        0.081154  DurbWat=  3.09
Previously:    0.8542             0.425275              0.319648            2.68
17 observations fitted, forecast(s) computed for 1 missing val. of dep. var.
```

Analysis of Variance for the Full Regression

Source	Sum of Squares	DF	Mean Square	F-Ratio	P-val
Model	0.734264	1	0.734264	74.3320	.00
Error	0.148173	15	0.00987817		
Total (Corr.)	0.882437	16			

```
R-squared = 0.832087                          Stnd. error of est. = 0.0993
R-squared (Adj. for d.f.) = 0.820893          Durbin-Watson statistic = 3.091
```

95 percent confidence intervals for coefficient estimates

	Estimate	Standard error	Lower Limit	Upper Lim
CONSTANT	0.12796	0.15596	-0.20453	0.460
LOG DIPC.WFS/DIP	0.51285	0.05948	0.38603	0.639

Figure 2.14 Statgraphics Regression Analysis Printout

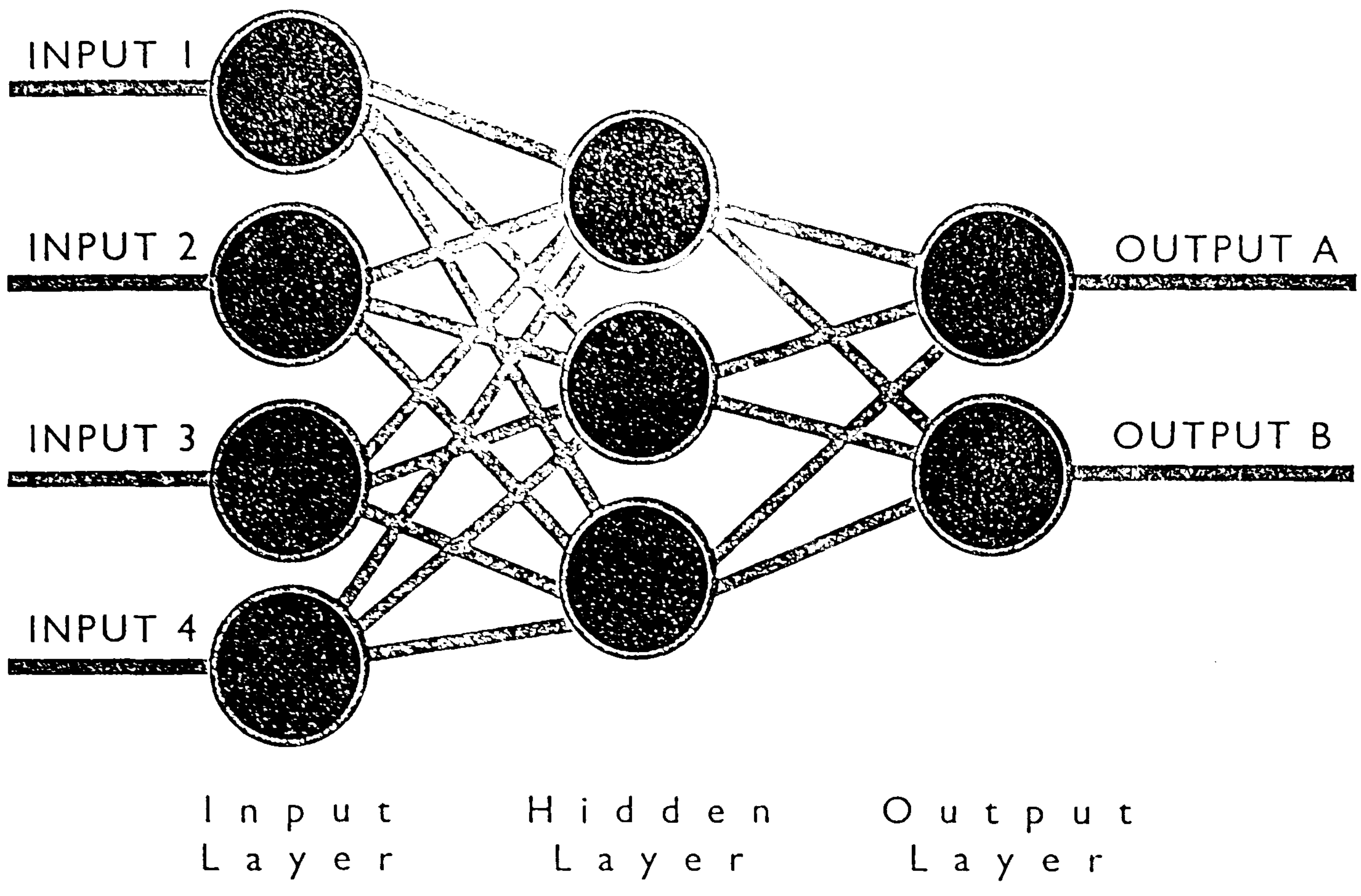


Figure 2.15 Artificial Neural Networks

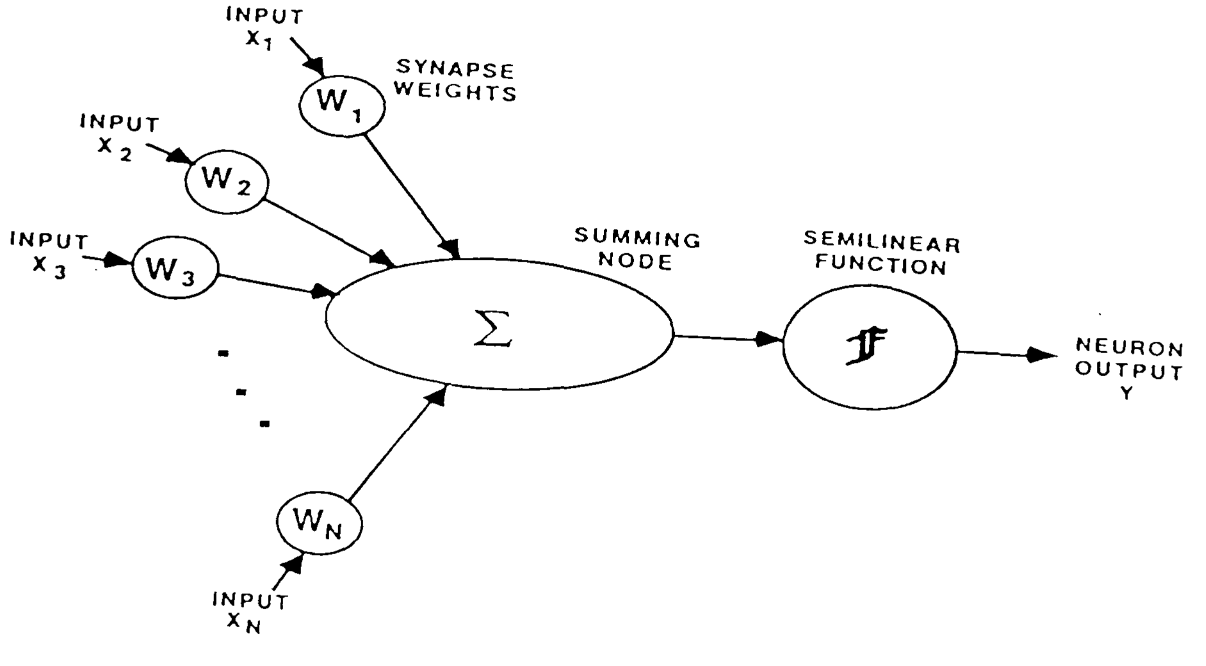


Figure 2.16 Model of a Single Artificial Neuron

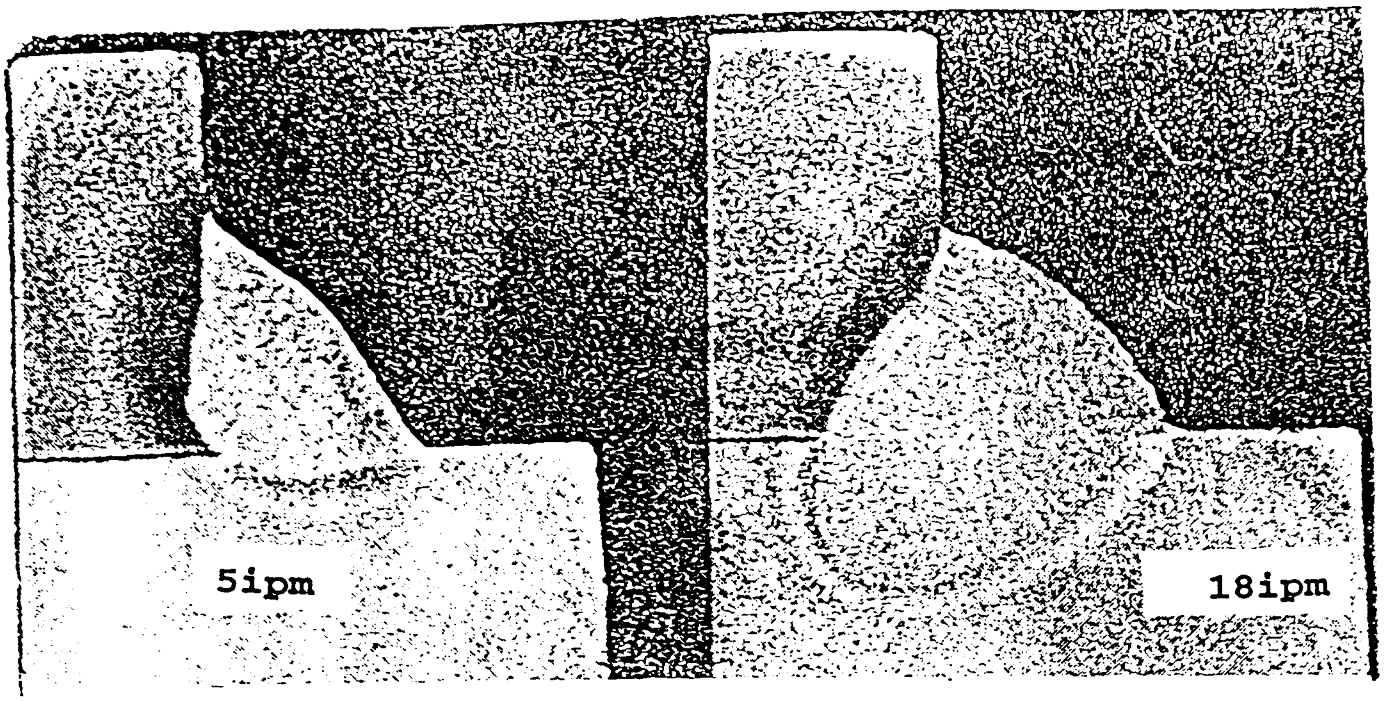


Figure 2.17 **Influence of Welding Speed on Fusion and Penetration at a fixed Heat Input**[190]

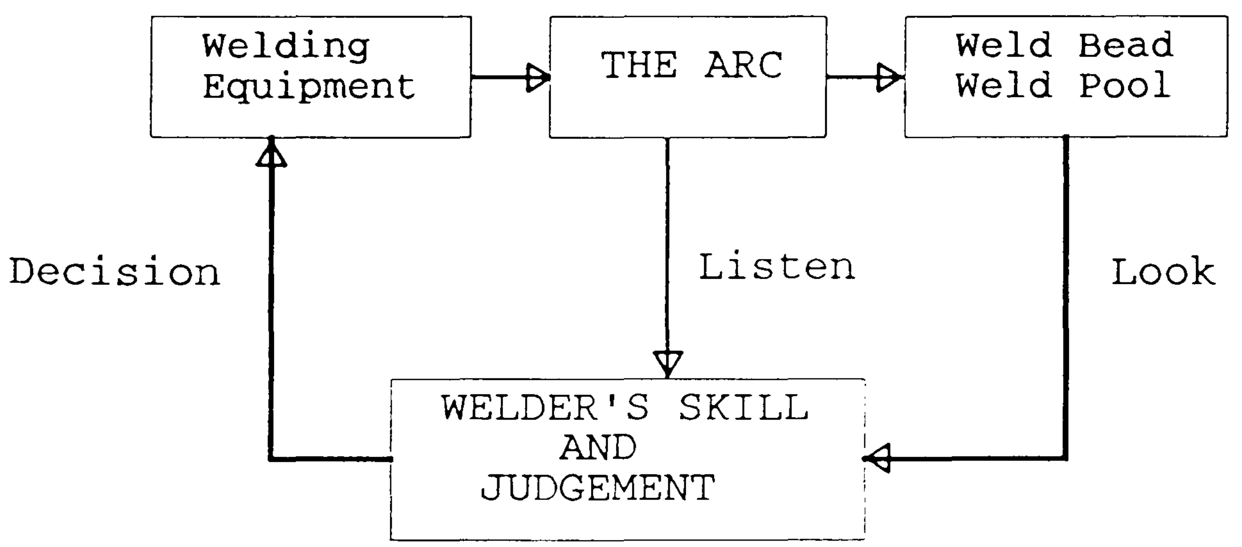


Figure 2.18 A Welder's Control Method

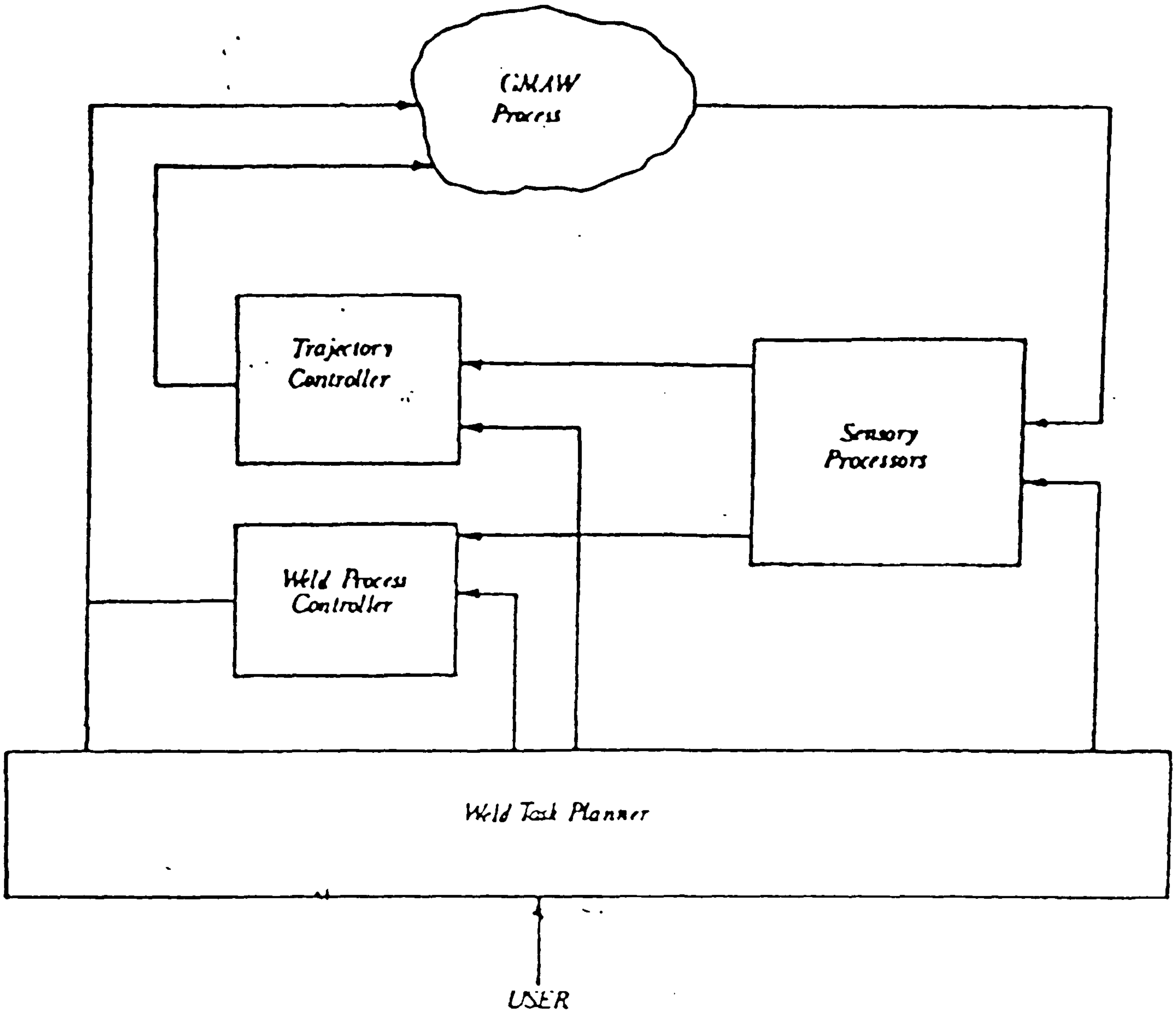


Figure 2.19 Sicard and Levine Control Architecture[16]

Chapter 3
Monitoring and Control of Weld Quality

The primary aim of any welding process control system is to consistently produce adequate quality welds by preventing critical defects such as undercut, lack of fusion and burnthrough.

This objective can only be achieved by monitoring and controlling the process parameters that affect weld quality. This chapter gives an overview of the concept developed and assumptions made to achieve this.

3.1 The Quality Control Strategy

The strategy proposed is empirically based and dependent on the deterministic nature of the process. The main quality problems were identified and corrective procedures established.

With reference to section 1.2, the following objectives are identified as important for quality control:

1. control of weld bead geometry;
2. prevention of inadequate penetration;
3. control and detection of transfer mode;
4. assessment of arc stability;
5. prevention of undercut;
6. on line estimate of standoff;
7. on line detection of gap.

The control was implemented by a combination of procedural (ie. off-line) and adaptive (ie. on-line) control methods. **Procedural control** is the identification and off-line optimisation of welding parameters, that would give a required weld quality.

While **adaptive control** is a means of ensuring acceptable weld quality by monitoring and fine tuning the optimised welding parameters. The objective being to prevent and/or reduce the damaging effect of any process disturbances on final weld quality output.

Control of Bead Geometry

The bead geometry would be mainly controlled by off-line optimisation of welding parameters to give required weld size with minimum risk of defects while ensuring appropriate level of productivity. It is assumed that adaptive control would not be required unless there is variation in standoff and joint geometry (ie. gap).

Prevention of Inadequate Penetration

Adequate weld penetration would be ensured via off-line optimisation of welding parameters. Further control is assumed not to be required unless there is significant variation in standoff and joint geometry.

It would be assumed that to maintain consistent penetration the welding current is maintained at a fixed level for a varying standoff[189,216,217]. While if there is gap present, the arc power would be reduced to prevent burnthrough. The joint would be filled using the dip transfer mode. The welding speed would be adjusted as appropriate to control bead size.

Control and Detection of Metal Transfer Mode

The mode of metal transfer is determined by the wire feed speed and voltage combination. The welding voltage and current transient parameters were used to detect transfer mode.

Synergic algorithms can be used to select voltage. However, robotic welding involves welding in different positions (see Figure 2.6) and subject to varying quality and process constraints (see Section 2.1.4). The conventional algorithms usually don't take this into account (see section 2.2.4). It should be noted that synergic algorithm in pulse welding usually controls the current; this is however not within the scope of this work.

A novel synergic algorithm was developed, which in contrast to established synergic concepts takes into consideration the effect of standoff, joint geometry and welding position. The models developed for detecting metal transfer mode and assessing arc stability were used to develop a new synergic control algorithm.

The algorithm offers the scope for controlling mode of metal transfer, transfer stability and minimises spatter generation by selecting appropriate voltage for each wire feed speed. It should be noted that welding position needs to be pre-defined by the user in the software developed during the work.

Assessment of Arc Stability

In contrast to established principles which use descriptive statistical measures such as standard deviation of welding waveform features for arc stability assessment, a new approach using the parametric ratio of welding current and voltage waveform was developed using a rule based approach.

Prevention of Undercut

The risk of undercut was minimised by off-line optimisation of welding parameters.

On-line Estimation of Standoff and Control of its Effect

It is well established that standoff variation can be estimated from the welding current. It has been established from published work and experimental trials that this variation mainly affects penetration with only slight effect on bead dimension such as leg length and throat thickness.

There are two ways to control the effect of standoff variation. The torch can either be moved to the right level or the arc welding parameters can be adjusted. It is assumed that controlling the wire feed speed to maintain the welding current at a reference value will give consistent penetration. The bead size would be kept constant by controlling the welding speed.

On-line Detection of Gap and Control of its Effect

The presence of gap reduces the weld size because the molten metal is forced into the opening created by the gap. Therefore, bead size must be increased to ensure proper coverage (bridging) as gap size increases. To reduce the damaging effect of gap, the

Table 3.1 and Figure 3.2 both identify relevant process parameters for gas metal arc welding of thin sheet. These parameters have been further classified as directly (DC) or indirectly controllable (IC), uncontrollable (UC), application dependent (AD), measurable (M) and predictable (P).

The welding parameters (WP) are defined as the parameters required to setup a welding procedure. The disturbance parameters (DP) are defined as factors that could affect the quality of welds produced if not detected and accounted for by changing welding parameters.

The quality parameters (QP) are those parameters that define the quality features of the weld produced. The transient parameters (TP) are the on-line measurement of the welding current and voltage waveforms captured using a data acquisition system.

Directly controllable parameters (DC) are those that can be varied on-line during welding to effect change in the quality and transient parameters. Indirectly controllable parameters (IC) are those that can be controlled on-line but only indirectly through the directly controllable parameters, for example the wire feed speed can be used to control the welding current.

Application dependent parameters (AD) are those that are fixed prior to welding and which do not vary during welding such as plate thickness, gas type, joint design etc. Uncontrollable parameters (UC) are those that cannot be modified on-line during welding such as gaps in joints.

Predictable parameters (P) are those that are difficult to measure on-line but are predictable by their effect on and/or relationship with the transient and welding parameters. Measurable parameters (M) parameters are those measurable using appropriate sensors.

It should be noted that the parameters identified above are focused on the industrial problem and sensors available.

welding current (wire feed speed) and speed must be reduced as gap size increases.

There are two ways of controlling the effect of gap. The first; is to assume a minimum level of gap and select a procedure that would produce good weld irrespective of gap being present. This could however lead to oversize bead, therefore increasing production cost.

The second approach involves detecting and estimating gap size and adapting the welding parameters according to the gap size. The presence of gap was detected using through-arc sensing but its size cannot be precisely stated. A monitoring look-up table and estimation model were therefore developed for gap sensing.

3.2 Quality Acceptance Criteria

The relevant application area for this work is the welding of thin mild steel sheet within the range used in the automobile industry. The typical joint types are fillet and lap configuration. The main welding position is horizontal vertical.

The main quality acceptance criteria, are the bead dimensional accuracy, the type and seriousness of any defects present. In general, welds are expected to have good appearance, minimum undercut and no burnthrough.

The welds are normally specified in terms of leg length. This is usually the average length of both legs or in some cases it is taken as the minimum leg length.
Figure 3.1 shows typical industrial weld quality specification for fillet welds from different industrial sources. These specifications are used to assess the quality of the welds produced in this project.

3.3 Identification of Process Parameters

To control a process, it is important to identify all its relevant parameters. These consists of input and output parameters. The input into the welding process are the welding and disturbance parameters. The output consists of the quality and transient parameters.

Table 3.1 Identification of Process Parameter

Input Parameters

Welding Parameters [WP]		Disturbance Parameters [DP]	
wire feed speed	DC, M	gap variation	UC, P
voltage	DC, M	standoff variation	DC, P
welding speed	DC, M		
standoff	DC, M		
welding position	AD		
plate thickness	AD		

Output Parameters

Quality Parameters [QP]		Transient Parameters [TP]	
bead geometry	P, IC	current	M, IC
penetration	P, IC	voltage	M, IC
undercut	P, IC		
spatter	P, IC		

3.4 Process Modelling Requirement

The most important components of any control concept are models which relate the process parameters together. In this work, the models required to define the process were mainly developed using multiple regression analysis. Three model types are identified as necessary for overall process control:

Type 1: Models relating quality parameters to welding parameters;

Type 2: Models correlating transient parameters to disturbances parameters (including process stability);

Type 3: Models correlating transient parameters and quality parameters.

3.5 Experimental Data Requirement

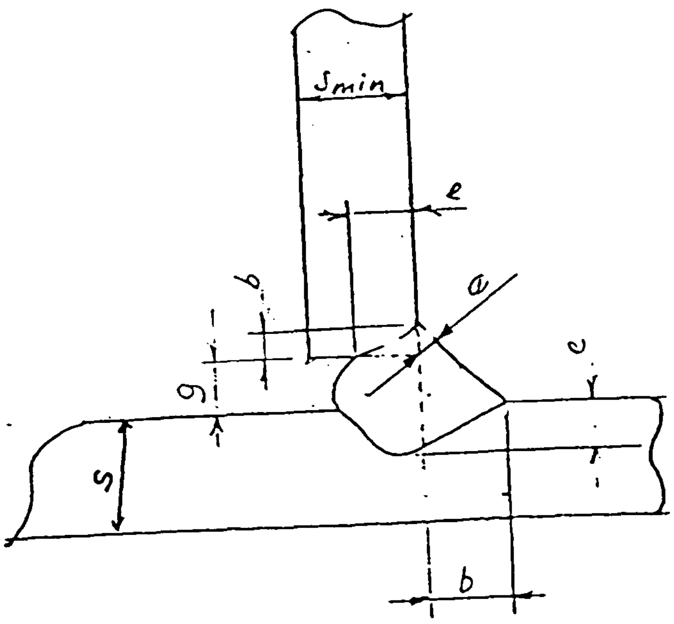
Experimental trials are required to produce data that would be used to estimate the regression model parameters. For each experimental run the welding and transient parameters are recorded. The bead geometry measured using a vision system after each weld has been sectioned and etched.

3.6 Process Monitoring Requirement

The quality and disturbance parameters cannot be directly measured on-line. They can however be detected and/or estimated from the transient signals collected using computer based data acquisition system.

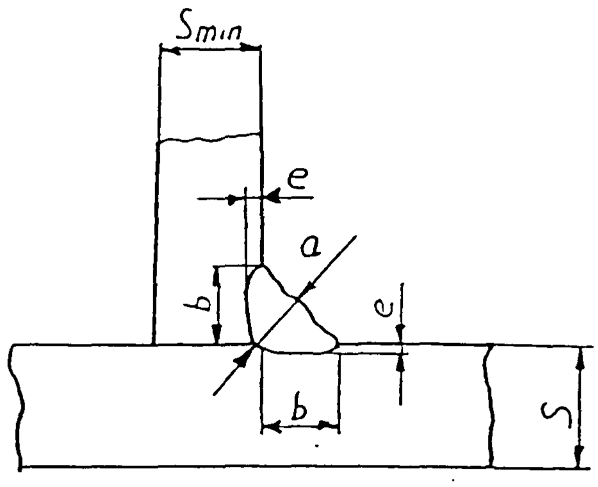
In order to do this it is necessary to develop dedicated algorithms for processing the information from transient signals, depending on monitoring objectives. The objectives includes stability assessment, metal transfer mode detection, standoff estimation, gap detection and estimation.

(a) Inauxa Specification



g	gap	
e	Penetration	0,12 x S_{min}
a	Throat thickness	0,7 x S_{min}
b	Leg length	0,7 x S_{min}

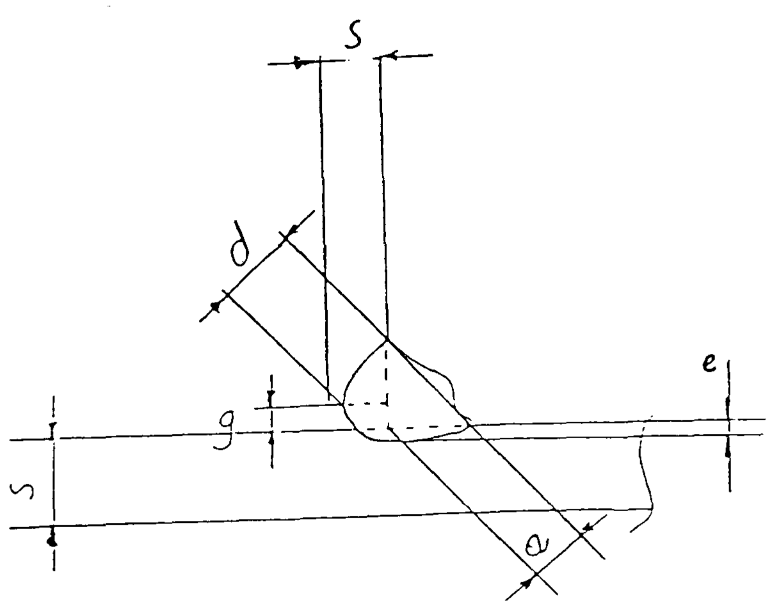
(b) GM Specification



Throat thickness:	$a \geq 0.7\, s_{min}$
Length of side wall fusion:	$b \geq 0.7\, s_{min}$
Depth of side wall fusion:	$e \geq 0.12\, s_{min}$

s_{min} is minimum plate thickness.

(c) Volvo Specification



g	gap	Allowed gap Larger gaps	0mm - wire diameter Alter welding parameters or robot program
e	Penetration		0,1 x S_{min}
a	Throat thickness		0,8 x $S_{min}/\sqrt{2}$ = 0,9 x S_{min}
d	Depth		d_{min} = a

Figure 3.1 Fillet Weld Quality Specification

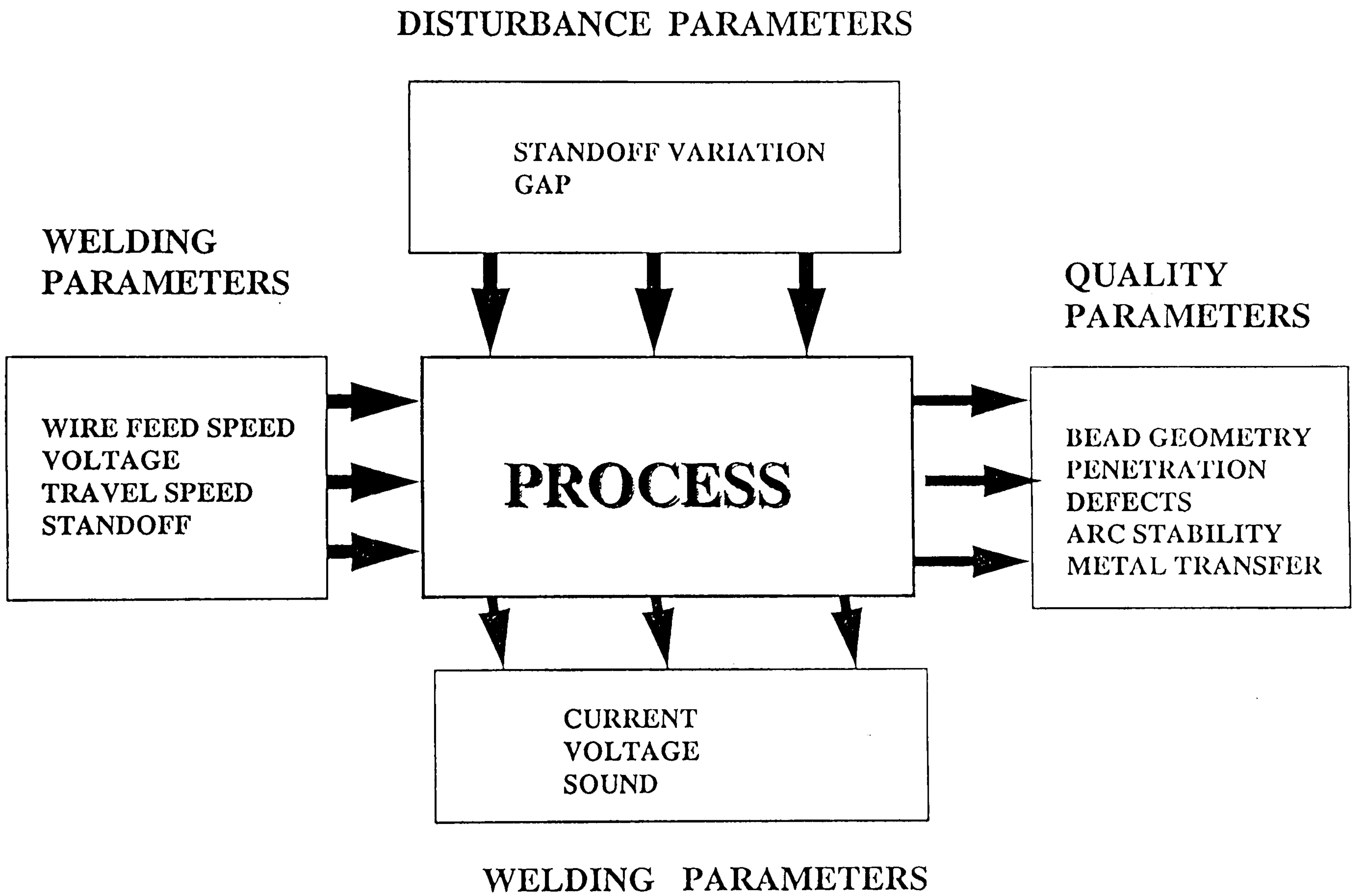


Figure 3.2 Parameter Identification

Chapter 4
Experimental Equipment and Materials

The main equipment used was a Migatronic Commander BDH 320 power source (includes Migatronic KT 12 external wire feed unit), Panasonic Robot AW-7000 (6-AXES Articulated arm welding robot) and Computer based Monitoring system (Arcwatch^{TM}). Figure 4.1 shows the picture of the experimental setup.

4.1 The Welding Robot

The robot used was Pana Robo AW-7000. It is a 6 axes articulated arm welding robot that offers easy communication (gives arc on/off command) with power source and arbitrary travel (welding) speed setting.

4.2 The Power Source

The power source is a 100kHz inverter based power source with 80 volts open circuit voltage and current range of 5-320amps. It is a constant voltage power source and uses **integral control** to maintain set up parameters constant throughout a weld.

It has on board a **self diagnosis** system for equipment related problems. It can detect errors in power supply, the inverter, overheat error, gas error, low pressure gas supply and wire feed motor overload. It cannot however detect failed arc ignition.

The power source operates in two modes, namely synergic and manual mode. In **synergic mode**, a current value is specified and the wire feed speed and voltage are automatically set by the power source based on the set value. While, in **manual mode** the welding voltage and wire feed speed are directly specified by the welder. Both modes were used in the experiments reported here.

4.3 The Monitoring System

The monitoring system used (Arcwatch^{TM}) was developed at Cranfield University by Dr. K Chawla. It is a PC based monitoring system, consisting of an industrial 486 computer, a signal conditioning unit, a 12 bit 12 channel Analog-to-Digital converter plug-in board and a dedicated data acquisition software package.

The software written in C programming language, allows the user to vary the data acquisition parameters such as sampling rate (between 1Hz and 200kHz), sampling interval (up to 64seconds), sample (data points) size (default size is 512 but could be 256, 1024 or 2048 data points) and calibration factors. It uses various established numerical and statistical methods to analyze and display graphically the acquired data.

4.4 The Sensor Specification

The sensors used in the experimental study are summarised below. The wire feed speed, welding current and voltage were measured.

Current Sensor

The welding current was measured using an Hall effect probe. The specification of the sensor used (RS Catalog No. 256-174) is given below:

Rating	400-500 Amps
Calibration accuracy at 23 deg C	±1% per range
Zero offset (23 deg C)	±0.1% per range
Zero offset (0-60 deg C)	±1% per range
dI/dt (transient) following	>200kA/s

Voltage Sensor

The welding voltage was measured directly by connecting a sensing lead (high voltage probe (full scale 106.8 volts) from workpiece and the back of welding torch.

Wire Feed Speed Sensor

A tacho generator was used to measure wire feed speed directly (independent of the wire feeder motor). A Data Harvest Wire speed Tacho (Product No: 8020 and Full scale 24m/min) was used.

4.5 Checking the Sensors Calibration Factors

The output of all the sensors is in the form of a voltage, which is proportional to the measured signal level. To convert to the appropriate physical reading, the measured voltage is multiplied by a constant, referred to as the calibration factor.

The calibration factors used in this work are:

Wire feed speed	19.8
Voltage	106.8
Current	406(509.7)

The robot specified speed and actual welding speed measured were compared and found to be consistent (see Figure 4.2). The wire feed speed measured using Arcwatch was consistent with the calculated values and specified (ie power source input) wire feed speed. (see Figure 4.3). The power source was equipped with internal digital meters to measure the average current and voltage. These were found to be consistent with Arcwatch measurements (see Figures 4.4 and 4.5).

4.6 Experimental Materials

The experimental material specifications were:

Wire diameter	1mm	
Wire type	Oerlikon BS 2901.A18	
Plate thickness	1.6 and 3.2mm	
Plate Material	Mild steel	
Shielding gas	BOC Argonshield 5 ie Ar5%$CO_2$2O_2.	
Joint type	Tee fillet	
Welding position	Horizontal Vertical (2F)	
Test plate dimension	Flange	76 by 250 mm
	Web	51 by 250 mm

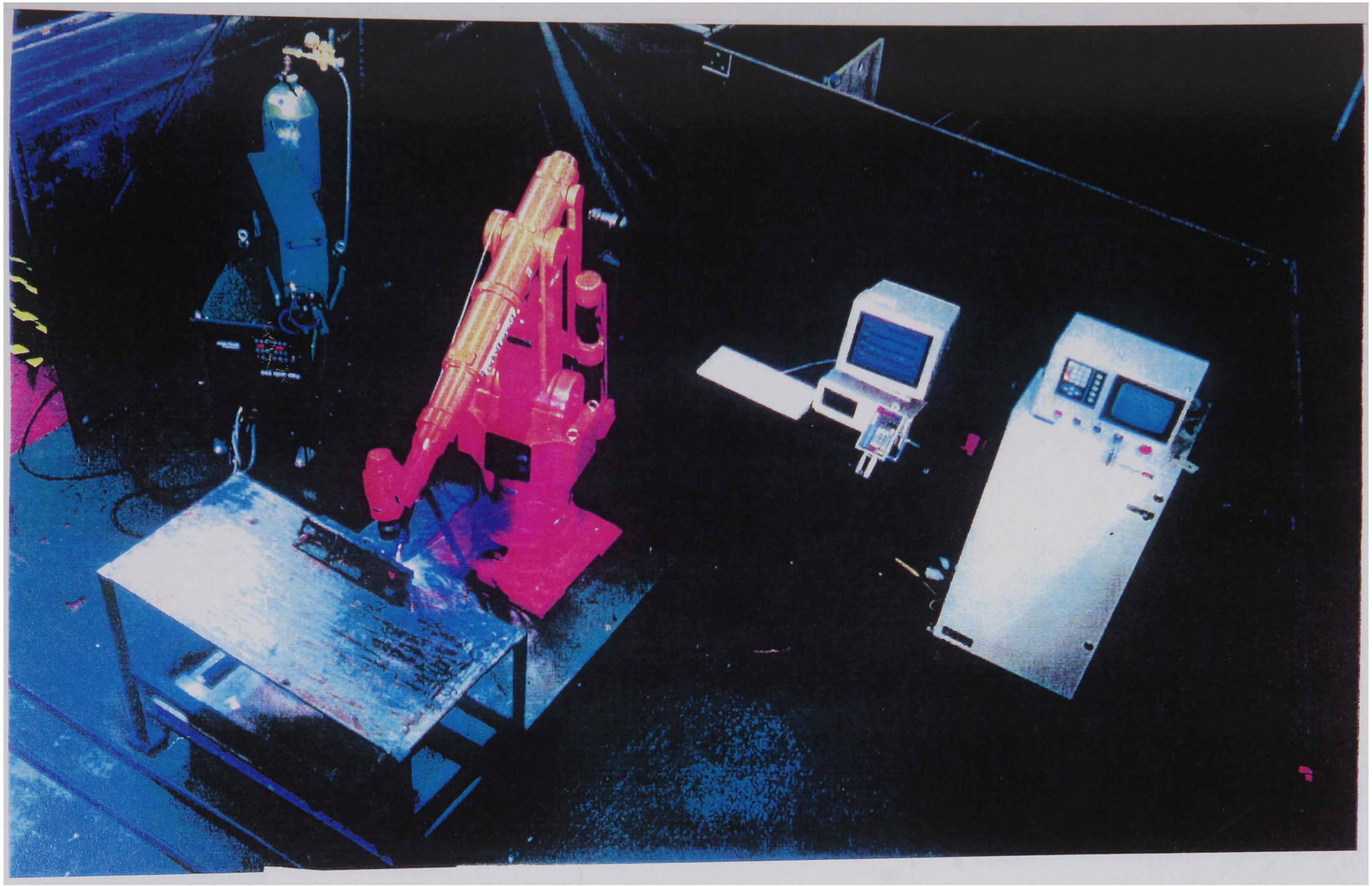


Figure 4.1 Photograph of the Experimental Setup

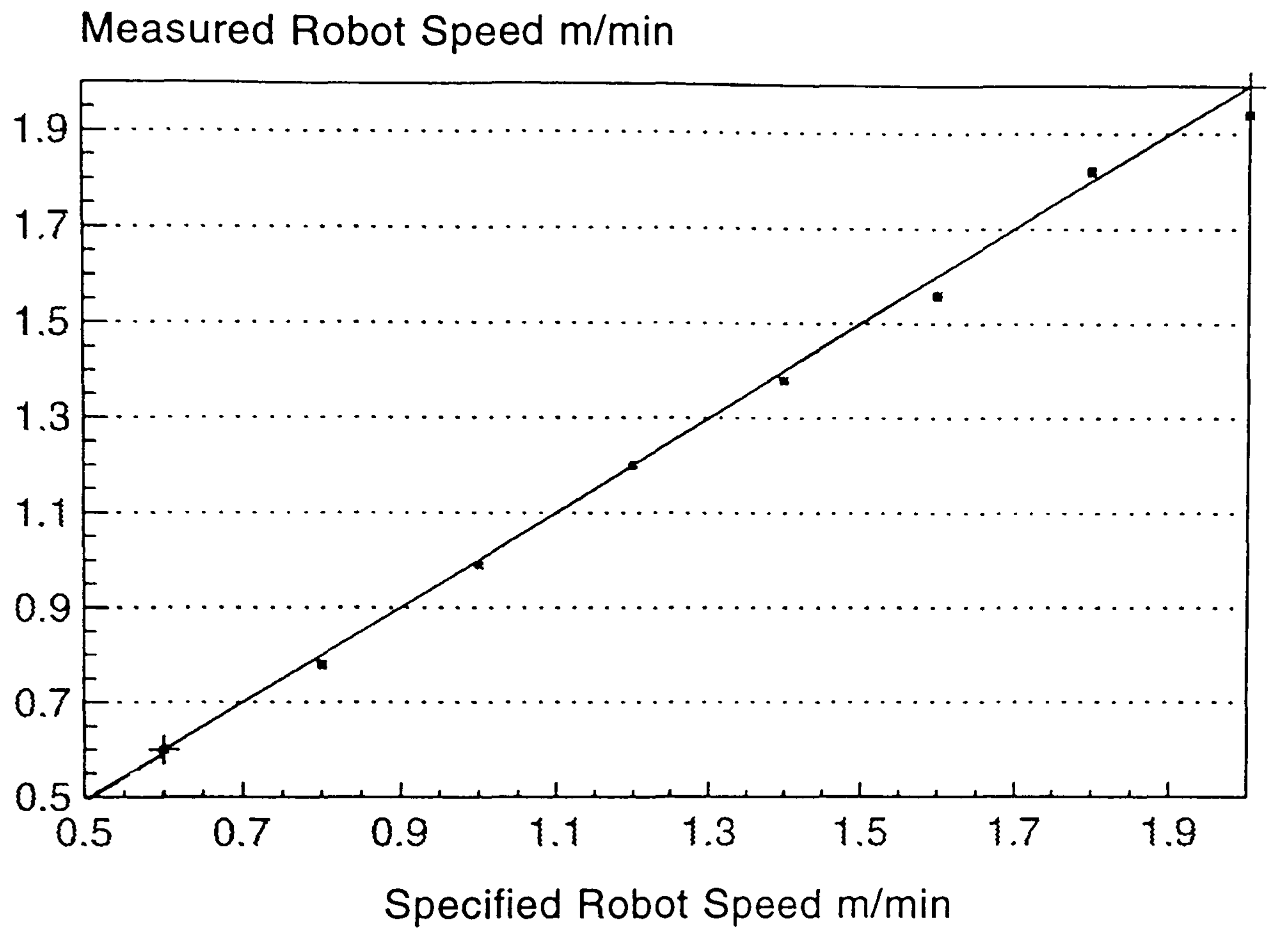


Figure 4.2 Welding Speed Calibration

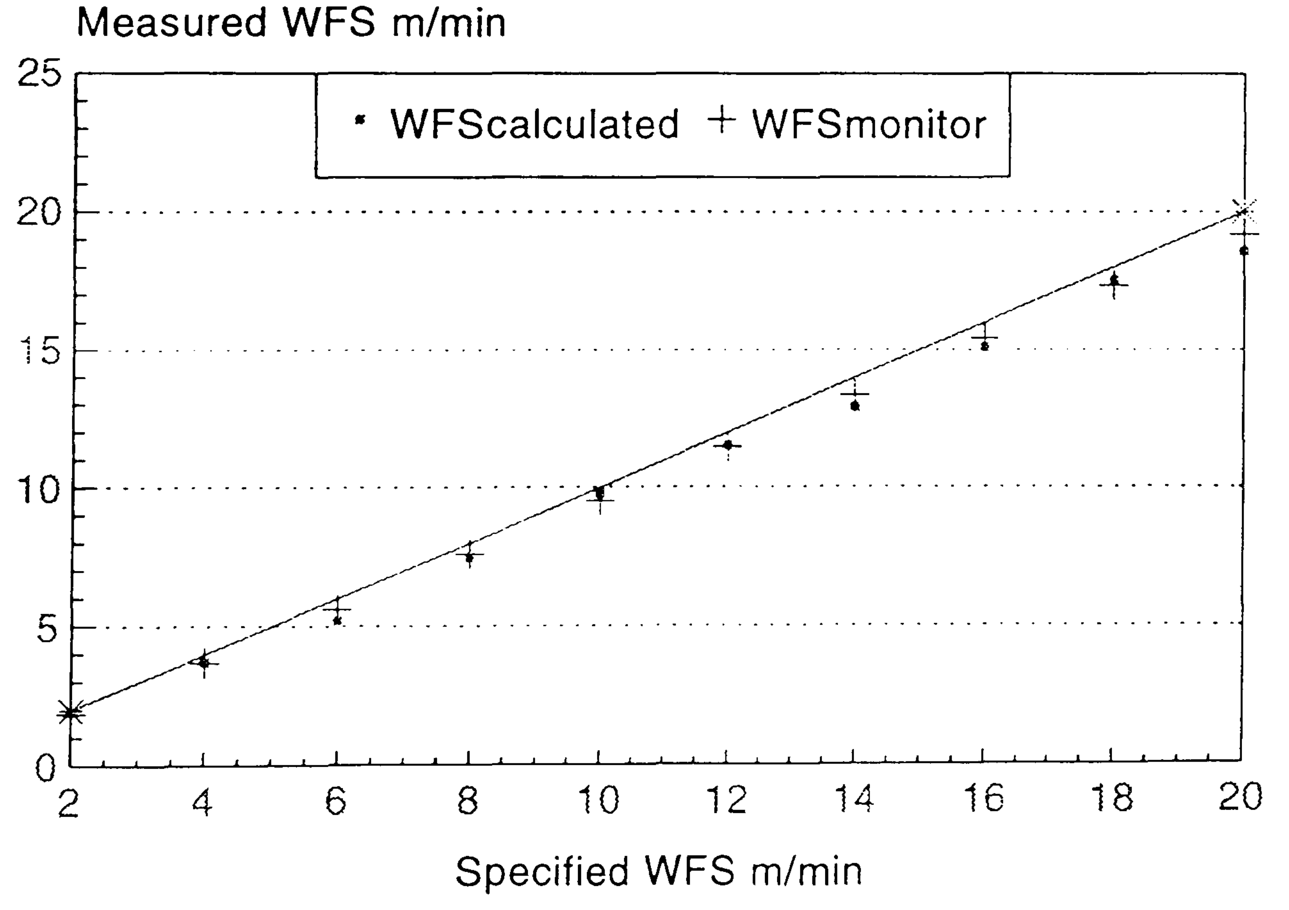


Figure 4.3 Wire Feed Speed Calibration

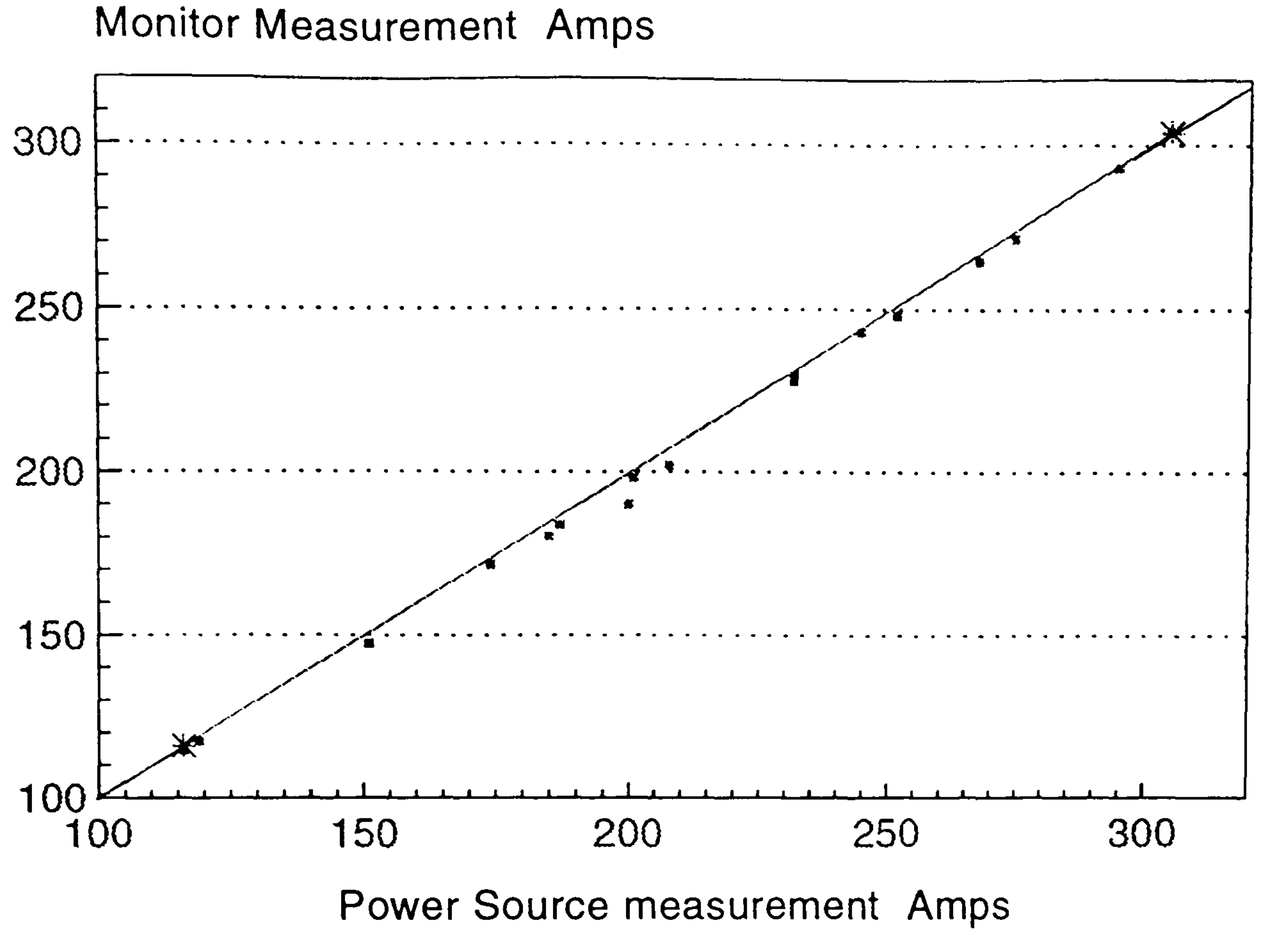


Figure 4.4 Welding Current Calibration

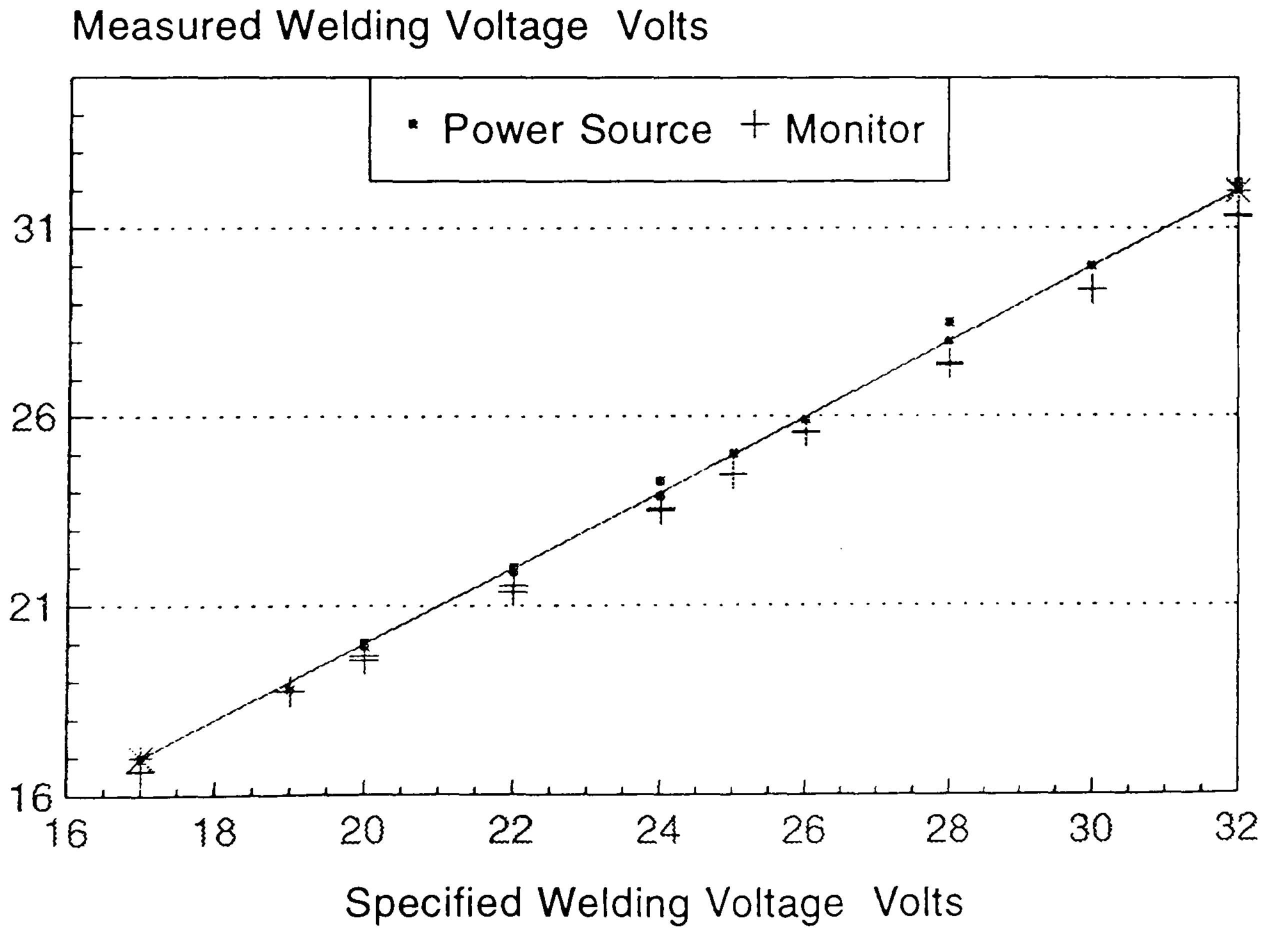


Figure 4.5 Welding Voltage Calibration

Chapter 5

Experimental Study and Process Modelling for Quality Control

5.1 Introduction

The experimental study in this work was carried out using the Migatronic BDH 320 power source. Both synergic and manual mode were used. Previous work by Feldthusen[218] on fillet welds in horizontal vertical welding position was used as the starting point. Feldthusen only used the synergic welding program (Program 4) provided by the power source manufacturer (Migatronic, Denmark).

The effects of process parameters on weld quality (mainly bead dimensions) were investigated using 2^k factorial analysis. The main process inputs are current, speed, standoff, misalignment and gap. The resulting experimental data were used to develop process models.

Feldthusen reported difficulty in modelling penetration and undercut. The difficulty can be traced to process parameters not properly identified. All of the models presented incorporate gap and misalignment, which are not usually independent parameters. They are also the major sources of quality disturbances in automated welding.
Undercut was treated as a quantitative variable rather than as a qualitative variable. Defects should be treated as discrete phenomena, that is, they are either present or absent.

From a statistical point of view the models are valid, but no consideration appears to be given to practical process situations. A logical modelling approach is required with clearly defined objectives. Process modelling of multivariate systems like welding processes requires the integration of various models which each define some aspects of the process.

5.2 Developing Models Relating Quality Parameters to Welding Parameters

5.2.1 Synergic Mode Models

Experimental Data

The objective was to collect experimental data that would be used to develop dedicated models for welds done using the BDH 320 synergic program 4. The experiment was carried out in two stages. The first stage was used to collect data for modelling risk of undercut and inadequate penetration. The second stage; was used to collect experimental data for modelling bead dimension. Figure 5.1 shows the nomenclature adopted in this project to define bead geometry.

Modelling Risk of Undercut and Inadequate Penetration

The objective was to develop models for assessing the risk of undercut and inadequate penetration. The models are developed under the assumption that penetration is either adequate or inadequate and undercut present or not.

9 weld runs corresponding to the treatment combinations associated with a 1/3 fraction of 3^3 factorial design are made on 1.6mm plates. The welding conditions and response is shown in Table 5.1. The responses obtained are the presence of undercut and penetration. The shielding gas flow rate was fixed at 15 l/min and torch was set to bisect the joint at 45°.
The Volvo fillet weld quality specification shown in Figure 3.1(c) was adopted. The standard requires penetration to be more than ten percent of the thickness of the thinnest plate. Therefore, the experimental data was coded as follows:

IF Sp and/or Bp is LESS THAN 10% of plate thickness
THEN Pr(Sp) and/or Pr(Bp) equals 1
ELSE Pr(Sp) and/or Pr(Bp) equals 0
IF undercut is present THEN Pr(und)=1 ELSE Pr(und)=0

The coded values Pr(und), Pr(Sp) and Pr(Bp) represent the possibility (that is, risk) of having unacceptable undercut, inadequate side and bottom plate penetration respectively.

Table 5.1 **Experimental and Response Data for Undercut and Penetration**

RN	CUR	SO	S	Undercut	Sp	Bp
A1	175	14	1.6	present	0.30	0.27
A2	125	14	1.2	none	0.55	0.33
A3	95	14	0.8	none	0.12	0.32
A4	125	17	0.8	none	0.64	0.46
A5	175	17	1.2	none	0.42	0.75
A6	95	17	1.6	present	0	0
A7	125	20	1.6	none	0.21	0
A8	95	20	1.2	none	0.15	0
A9	175	20	0.8	present	0.46	0.31

where

CUR Synergic Current, Amps
Sp Side plate penetration, mm
Bp Bottom plate penetration, mm
SO Standoff, mm
S Welding Speed, m/min

Modelling Bead Dimensions

The objective was to develop models for predicting bead dimensions; the dimensions were limited to leg lengths, throat thickness and penetration depths.

A full 3x3 factorial experiment (27 runs) was used to design the experiment. Since the objective was to develop models that would be used for quality control, the welding setup conditions are changed as necessary to ensure a reasonably good fusion from each parameter combinations (see Table 5.2). The shielding gas flow rate was fixed at 15 l/min and torch was set to bisect the joint at 45°.

Table 5.2 Experimental and Response Data for Bead Dimensions

RN	CUR	SO	S	Ips	Vps	Imean	Vmean
A10	95	12	0.8	127	16.9	126.9	16.12
A11	135	12	0.8	177	18.5	177.8	17.52
A12	175	12	0.8	217	20.1	216.3	19.0
A13	95	12	1.2	120	16.9	116.4	16.04
A14	135	12	1.2	176	18.5	173.2	17.43
A15	175	12	1.2	214	20.1	214.9	18.65
A16	116	12	1.6	151	17.7	155.4	16.52
A17	135	12	1.6	172	18.4	174.7	17.52
A18	175	12	1.6	216	20.1	214.3	18.84
A19	95	15	0.8	117	16.9	116.9	16.22
A20	135	15	0.8	168	18.5	168.7	17.58
A21	175	15	0.8	204	20.0	202.8	19.06
A22	130	15	1.2	154	18.2	156.9	17.34
A23	145	15	1.2	171	18.8	170.2	18.04
A24	175	15	1.2	202	20.1	202.6	19.21
A25	130	15	1.6	153	18.1	157.1	17.34
A26	145	15	1.6	173	19.0	172.9	17.85
A27	175	15	1.6	202	20.0	200.0	19.12
A28	140	18	0.8	167	18.7	165.4	17.79
A29	155	18	0.8	178	19.4	177.3	18.36
A30	175	18	0.8	193	21.3	193.3	19.11
A31	140	18	1.2	164	18.6	168.0	17.72
A32	155	18	1.2	177	19.2	172.22	18.35
A33	175	18	1.2	188	20.9	190.9	19.13
A34	155	18	1.6	182	28.2	178.2	18.33
A35	165	18	1.6	188	20.1	188.3	18.77
A36	175	18	1.6	189	20.0	193.1	19.21

Table 5.2 (contd)

RN	T	Sp	Bp	Ls	Lb
A10	2.02	0.533	0	3.55	2.325
A11	2.495	1.245	0.545	3.585	3.48
A12	2.685	1.07	1.415	3.99	3.75
A14	2.30	0.33	0	3.735	2.795
A15	2.425	0.455	0.68	3.17	3.53
A16	1.72	0.26	0.04	2.42	2.54
A17	1.685	0	0	3.27	1.945
A18	2.08	0.345	0.43	2.81	2.995
A20	2.45	0.87	0	4.05	3.015
A21	2.925	0	0	4.835	3.6
A22	1.69	0.40	0	4.08	1.875
A23	1.81	0.535	0	3.755	2.14
A24	2.375	0.22	0.13	3.865	2.95
A26	1.78	0.27		3.39	2.07
A27	1.815	0.30	0.12	3.705	2.22
A28	2.42	1.07	0.105	3.835	3.01
A29	2.63	0.97	0.685	3.96	3.535
A30	2.77	1.53	0.39	4.615	3.385
A31	1.845	0.55	0	2.81	2.62
A32	2.145	0.365	0.285	3.51	2.70
A33	2.425	0.235	0.095	3.625	3.135
A34	1.84	0.21	0.05	3.50	2.115
A35	1.95	0.34	0.255	3.13	2.605
A36	1.99	0	0	3.11	2.535

Note: A13,A19 and A25 are all poor quality welds

where

Ips	BDH 320 Average Current, Amps	Imean	Arcwatch Average Current, Amps
Vps	BDH 320 Average Voltage, Volts	Vmean	Arcwatch Average Voltage, Volts
Lb	Bottom Leg Length, mm	Ls	Side Leg Length, mm
Bp	Bottom Plate Penetration, mm	Sp	Side Plate Penetration, mm
T	Throat Thickness, mm		

The Models - Synergic Mode

Regression analysis is commonly used to develop empirical models for welding processes. However, there is no standard structure for the models. Arbitrary functions are normally fitted to the experimental data obtained over a limited working range; for example Shepherd[72] and Street et al.[211] used first-order polynomial(Equation 2.7) while, conscious of the process non-linear behaviour Dubovetskii[187] and Chandel et al.[184] used second-order polynomial(Equation 2.8) and multiplicity form(Equation 2.10) respectively.

The power source synergic welding programme used in this work was limited to dip transfer. It was envisaged that the synergic current will not be set outside the experimental range hence a model of any form could be fitted. The model must however be able to capture the non-linear characteristics of the process. Linear regression models although linear in parameters can account for non-linearity in a process by the inclusion of interacting and power terms in the models.

Hence, the model structure adopted here for the process models (with the exception of undercut) was the intermediate model type. That is,

$$QP = \alpha_0 + \alpha_1 CUR + \alpha_2 SO + \alpha_3 S + \alpha_4 CUR*SO + \alpha_5 CUR*S + \alpha_6 SO*S \qquad (5.1)$$

where

$$QP = T;\ Lmin;\ Lavg;\ Sp;\ Bp;\ Pr(Sp);\ Pr(Bp)$$

$$Lmin = \min(Ls, Lb);\quad Lavg = \frac{Ls+Lb}{2}$$

The model structure adopted for undercut was:

$$Pr(und) = \alpha_1 SO + \alpha_2 S + \alpha_3 \frac{CUR^2}{S} \qquad (5.2)$$

The intermediate structure does not provide a satisfactory model for undercut hence physical logic was used to identify the parameters in the model. With reference to section 2.1.4, it was established that undercut occur when the interval between the melting of a groove in the parent metal and filling of the groove with molten metal increases. This interval increases with welding speed and is also dependent on the arc pressure that creates the groove. This phenomena is therefore a function of the arc pressure divided by the welding speed; to capture the influence of the pressure, the square of the synergic current was used. The influence of standoff and speed was also incorporated in to the model.

Table 5.3 shows the regression coefficients. Note that all the models were developed to obtain the best fit for the experimental data by removing all insignificant parameters. This allow the interaction between the input parameters to be evaluated for their significant on the process response. The significant level used in developing the models was 95%.

Table 5.3 Synergic Mode Regression Coefficients

	T	Lavg	Lmin
α0	3.61	4.92	4.867
α1	*	*	*
α2	-0.204	-0.2438	-0.303
α4	0.0012	0.00148	0.0017
α5	-0.00625	-0.008	-0.0085
R2	0.897887	0.940589	0.789393
SE	0.128159	0.12019	0.273233

	Sp	Bp	Pr(Sp)	Pr(Bp)	Pr(und)
α0	*	*	1.8112	-1.481	*
α1	0.012009	0.009199	-0.01122	-0.0082	-0.1119
α2	*	-0.047378	*	0.111	1.5802
α3	*	-0.385393	*	0.833	4.629E-6
α5	-0.00935	*	*	*	*
R2	0.904429	0.620101	0.617347	0.993197	0.831784
SE	0.218307	0.274539	0.33065	0.052164	0.290014

* insignificant parameters

Testing the Models - Synergic Mode

Testing of the models in this project presents a unique problem since they are intended to be integrated and used for optimum procedure prediction. This will be illustrated later in the thesis. Another point that is unresolved however is how to define the prediction error. The question is, should it be based on percentage error or nominal deviation from actual measure.

The percentage error (ε) is defined as,

$$\varepsilon = \frac{abs(Actual - Predicted)}{Actual} x100\% \qquad (5.3)$$

The nominal deviation (dev) is defined as,

$$dev = Actual - Predicted \qquad (5.4)$$

From an industrial perspective, the prediction error might look big while the actual nominal deviation is acceptable. The author is of the opinion that it is better to express prediction error in terms of nominal deviation which is more logical. It is better to state that a model would predict to say 0.5mm accuracy rather than it has 30% prediction error as is shown by the simulation in Figure 5.2. Therefore most of the figures showing the correlation between predicted and actual values in this thesis would include a line chart of the prediction error nominal deviation.

A series of welds were done with arbitrarily set welding conditions to get a feel of the prediction accuracy. A satisfactory result was obtained as is shown in Figures 5.3 -5.6. The full test data is shown in Appendix A.

The maximum prediction error for average leg length for the data set was was -0.75mm; while for side and bottom plate penetration, the nominal error was -0.72mm and 0.96mm respectively. The modelling errors in the penetration models are large, this was expected because most of the penetration value used were less than 1 mm and actual response data ranges were very limited. The penetration model would however be supported with the possibility models Pr(Bp) and Pr(Sp). The test result shows high possibilities of inadequate penetration at synergic current value of 95 and 120 amps for side plate (see Table 4 in Appendix A). This is a good physical response as low current can lead to fusion problem. However, the possibility value for all bottom plate are all zero.
The undercut model returns the risks of undercut of 0, 0.34, 0 and 0.58 for welds with

the depth of undercut of 0.179, 0.3937, 0.157 and 0.25mm respectively.

It is important to stress that the "possibility" models for penetration and undercut should be considered as a measure of risk of the defects occurring. High possibility means the defect is very likely, while low possibility does not mean it is unlikely.

5.2.2 Manual Mode Models

Experimental Data

The range of the synergic mode welding and response parameters were limited. With the aim of extending the welding range and bead size, further welding trials were made using the power source in manual mode.

The use of synergic mode has the advantage of automatic selection of voltage and wire feed speed. However, in manual mode the user is required to specify both the wire feed speed and voltage. This obviously makes voltage a very difficult parameter to control systematically. This is further complicated by the fact that voltage is a very critical parameter, that influences most defects such as ignition problem, spatter and undercut.

An unplanned experiment approach was used. The setup voltage was treated loosely but controlled only by the condition that the arc be established and good weld appearance obtained. 18 weld runs corresponding to the combination shown in Table 5.4 were made on 3.2mm plate.

Table 5.4 Experimental and Response Data for Manual Welding

RN	WFS	S	V	SO	Ips	Vps	Imean	Vmean
C1	4	0.3	20	12	119	20.0	117.20	19.66
C2*	4	0.6	17	12	116	17.0	114.73	16.65
C3	8	1.2	24	12	208	23.9	201.95	23.51
C4	8	0.6	19	12	200	18.8	189.88	18.74
C5	6	0.4	20	16	151	19.9	147.23	19.55
C6	8	0.9	22	16	185	21.9	180.16	21.52
C7	12	1.4	28	16	245	28.5	243.00	27.40
C8	12	1.0	25	16	232	25.0	229.85	24.46
C9	12	0.4	26	16	232	25.9	228.96	25.58
C10	16	1.4	32	16	305	32.2	303.90	31.31
C11	16	0.6	28	16	268	28.0	264.70	27.36
C12	14	0.6	22	16	252	22.0	248.15	21.36
C13	8	1.0	24	20	174	23.9	171.56	23.56
C14	9	0.6	26	20	187	25.9	183.61	25.56
C15	12	1.0	28	20	232	28.0	227.94	27.43
C16	10	0.6	24	20	201	24.3	198.05	23.51
C17	16	1.0	30	20	275	30.0	271.53	29.37
C18	16	1.6	32	20	295	32.0	293.16	31.34

where:

WFS	Wire Feed Speed, m/min	V	Voltage, volts
S	Welding Speed, m/min	SO	Standoff,mm

Table 5.4 (contd)

RN	Ls	Lb	T	Sp	Bp	Spatter	Undercut
C1	4.575	5.06	3.44	*	*	present	none
C2	**	**	**	**	**	none	none
C3	3.35	4.00	2.71	0.60	0.40	present	none
C4	3.67	4.68	2.92	0.80	0.65	none	none
C5	5.03	4.16	3.26	0.41	0	present	present
C6	3.11	4.01	2.56	0.31	0.58	present	none
C7	3.87	3.67	2.56	0.93	1.21	none	none
C8	3.94	4.39	2.99	1.10	0.95	present	none
C9	7.15	7.36	5.21	1.215	1.32	present	none
C10	3.55	4.46	2.75	0.48	1.30	none	present
C11	6.43	6.29	4.56	0.86	1.69	present	none
C12	4.81	5.78	3.64	1.14	0.84	present	none
C13	3.33	3.93	2.57	0.56	0.22	present	present
C14	4.93	6.32	4.05	*	*	none	none
C15	3.99	4.59	3.05	0.88	1.28	none	present
C16	5.13	4.53	3.41	1.52	0.38	present	none
C17	4.62	4.66	3.20	1.69	*	none	present
C18	3.46	3.56	2.54	1.31	0.26	none	present

* cannot be accurately measured

** lack of fusion of the upper plate

The Models - Manual Mode

It is well established that bead geometry is dependent on the deposition rate but the final quality depends mainly on using optimum voltage subject to having a stable arc. The difficulty in selecting voltage indicates the need for a standard approach to welding process parameter selection and modelling.

The bead geometry is defined by joint configuration. In fillet joint the molten pool is constrained and supported, hence a filling action occurs. The main control parameter is therefore the rate at which the joint is filled. This is represented by the deposition rate, that is, wire feed speed to welding speed ratio. The bead geometry model structure could be made simpler by using this ratio and excluding voltage. That is,

$$BEAD\,DIMENSION = f\left(\frac{WFS}{S}\right) \tag{5.5a}$$

This model and assumption should hold for all kinds of joints that restrain the pool. The voltage could then be synergically selected. However, the models defining penetration and undercut should include voltage.

If the weld pool is not constrained as in close-fit butt-welds, then the model should include voltage, that is,

$$BEAD\,DIMENSION = f\left(\frac{WFS}{S}, V\right) \tag{5.5b}$$

Otherwise different models would need to be developed for different modes of metal transfer and voltage would then be an important factor. To support the physical hypothesis above, correlation analysis was carried out on the experimental data; the result show that the hypothesis is valid. The coefficient of correlation between deposition rate and side leg length, bottom leg length, average leg length and throat thickness are 0.9292, 0.8778, 0.9412 and 0.9237 respectively; the correlation with voltage was -0.0162, -0.0402, -0.0278 and -0.0273 respectively and therefore insignificant. The bead dimension correlation with standoff was also insignificant.

This means that the bead dimensions can be estimated from the deposition rate by models calibrating the dimensions to the deposition rate. The structure of this calibration model is important and its output must be logical physically.

For example, if a simple linear model is used:

$$BEAD\,DIMENSION = \alpha + \beta \frac{WFS}{S} \qquad (5.6a)$$

when deposition rate is zero, the bead size will be equal to α ie. the intercept of the model. While this model structure will be valid when used within the experimental range, its output is not logical physically.

However if the same model was used but based on natural log of the input and output parameters, that is:

$$\log_e BEAD\,DIMENSION = \alpha^* + \beta \log_e \frac{WFS}{S} \qquad (5.6b)$$

The resulting model can also be expressed as shown in Equation 5.7; if the deposition rate is zero, the bead size will also be equal to zero. It is proposed that Equation 5.5b should also use this structure.

Therefore the model structure adopted for the fillet weld was

$$[Lavg,\ T] = \alpha \left(\frac{WFS}{S}\right)^{\beta} \qquad (5.7)$$

However, no physical logic can be developed for penetration and undercut. Therefore, the models for penetration and undercut were developed using the "intermediate" model structure (Equation 2.9). The models were developed to get the best fit for the experimental data.
That is,

$$QP = \alpha_1 WFS + \alpha_2 SO + \alpha_3 V + \alpha_4 WFSSO + \alpha_5 WFSV + \alpha_6 WFSS + \alpha_7 VS \qquad (5.8)$$

where

$$QP = Sp;\ Bp;\ Pr\,(und)$$

The coefficients for the models are giving in Table 5.5 below. The significant level used in developing the models was 95%.

Table 5.5 Manual Process Models Coefficients

DIMENSION	α	β	R^2 %	SE
T	1	0.4478	99.45	0.08985
Ls	1	0.561068	99.58	0.0980
Lb	1	0.5926	99.35	0.12928
Lavg	1	0.577994	99.66	0.09187

	Sp	Bp	Pr(und)
α_1	*	0.0943	-0.0982
α_2	-0.2259	-0.1046	*
α_3	0.1588	0.0823	*
α_4	0.0279	*	0.0044
α_5	-0.0158	*	*
α_6	*	-0.056	*
α_7	*	*	0.0265
R^2 %	0.9524	0.9038	0.6933
SE	0.2568	0.3390	0.3502

* insignificant parameters

Testing the Models - Manual Mode

The test data was very limited as voltage cannot be selected optimally. The main concern was to check the accuracy of the penetration models. Three weld runs were made, the result (see Appendix B) suggests a better prediction accuracy than the synergic models. The response of the undercut model to a series of welding conditions leads to the conclusion that if its output is greater than 0.3, then there is the possibility of undercut being present (see Figure 5.7 and Table 4 in Appendix B).

It should be noted the undercut model gives a fuzzy response which is interpreted as possibility or risk of undercut occurring. Figure 5.7 suggest that the threshold should has been set at 0.14 however in setting the threshold at 0.3, the standard error of the regression model was considered; the standard error for the undercut model was 0.3502.

5.2.3 Arc Ignition Model

Once the welding procedure has been established, it is important to ensure that good arc ignition occurs. Bad ignition is usually caused by excessive wire feed for a set voltage, which results in defective welds, usually in the form of unwelded portion at the start of weld. A common approach for improving arc ignition process is dwelling and/or delayed wire feed. Dwelling involves holding the welding head stationary for a fixed duration before moving.

The study of arc ignition is beyond the scope of this work however but it is aimed, to develop a model for assessing the posibility of having bad ignition given the welding procedure.

A series of trial runs were made and from the correlation analysis of the data collected, it can be concluded that it was the wire feed speed and voltage combination that influence the success of arc ignition (see Table 5.6).

Table 5.6 Correlation Analysis of Arc Ignition Data

	Wire Feed Speed	Voltage	Speed	Dwell
ARC ON ? [Yes=1/No=0]	0.5471 (0.0001)	0.6144 (0.000)	0.1221 (0.4244)	0.1134 (0.4581)

Coefficient (Sample size = 45) significance level

A model for assessing the ease of ignition and sustaining an arc at procedural stage was developed. To do this a simple linear model was developed using the wire feed speed and voltage good ignition data only. That is,

$$V_{set} = 13.519345 + 0.97619\,WFS_{ign} \tag{5.9}$$

where

V_{set}	*is the setup voltage;*
WFS_{ign}	*is the ideal wire feed speed required to give good arc ignition.*

The ease of arc initiation depends on the initial wire feed speed set for a fixed voltage. Therefore, a measure of excess wire feed in relation to the voltage has to be established. To do this the regression model was rearranged to give

$$WFS_{ign} = \frac{V_{set} - 13.519345}{0.97619} \tag{5.10}$$

Trial runs of the ideal wire feed speed predicted for a set voltage values, all give good arc ignition and fusion at the start of the weld.

A new factor, Pr(arc) was used to define the possibility of bad ignition:

$$Pr(\text{arc}) = 1 - \frac{WFS_{ign}}{WFS_{set}} \tag{5.11}$$

where

WFS_{set} *is the setup wire feed speed.*

subject to if Pr(arc)<0 then Pr(arc)=0
if Pr(arc)>1 then Pr(arc)=1
else Pr(arc)=Pr(arc)

Validation trial runs, show that Pr(arc) greater than 0.4 suggest possible ignition problem with deteriorating weld appearance as the value increases.

5.3 Modelling Welding Transient Parameters

5.3.1 Introduction

The welding transient signals were captured using Arcwatch™, which also calculates some of the basic statistical features of the waveform. These features were then correlated with arc welding transient behaviour.
The following features were found to be important:

Mean	**arithmetic average of all samples;**
Background	**arithmetic average of all samples less than or equal to the mean;**
Maximum	**absolute highest value in a sample;**
Minimum	**absolute lowest value in a sample.**

5.3.2 Metal Transfer Mode and Stability Assessment

In consumable electrode welding, although the metal transfer occurs in three stages as described in section 2.1.1, for simplicity, the process can be reduced to two stages namely the "melting and detachment" stage.

During the melting stage, a droplet forms at the tip of wire and moves towards the pool. During detachment, the bridge between the droplet and electrode breaks to complete the transfer. The actual mode of metal transfer will depend on the time period of each stage, current and voltage amplitude.

During the melting stage, the current increases and voltage drops due to the reduction in arc length as the droplet forms at wire end. The maximum current reached influences the ease of the detachment. If its too low, the droplet may not transfer ie. detached, and if it is too high spatter may be produced.

The level of maximum current required for detaching the metal depends on the average current, which in turn influences wire fusion. It should be noted that an upper current limit exists above which the process becomes unstable and irregular bead shapes are produced.

As soon as transfer occurs the voltage will increase and current drop. If the current drops to too low a level, the arc will become unstable. This transient behaviour of the arc is also a reflection of the metal transfer mode.

Spatter is the main physical result of arc instability. The risk of spatter increases with current level. Spatter is however a transient occurrence depending on the dynamic stability of the process. The main indicator is therefore maximum current reached.

The studies of welding signal traces from the three main transfer modes dip, globular and spray (see Figures 5.8-5.10) show that as the transfer tends towards spray the minimum current approaches the mean welding current.

The metal transfer was therefore classified by a ratio called the transfer index (TI)

$$TI = \frac{I_{mean} - I_{\min}}{I_{mean}} \tag{5.12}$$

where

I_{mean} *is the arithmetic average of welding current transient samples;*
I_{min} *is the absolute lowest value in the samples.*

The voltage transient welding signal was also used to predict and confirm the mode of transfer. There is a relationship between the welding voltage, background voltage and the tendency for a dip mode transfer. The ratio derived, called **dip consistency index** (DCI) was

$$DCI = \frac{V_{mean} - V_{bk}}{V_{mean}} \tag{5.13}$$

where

V_{mean} *is the arithmetic average of welding voltage transient samples;*
V_{bk} *is the arithmetic average of all voltage transient samples less than or equal to* V_{mean}.

It is well established that the maximum (short circuiting) current amplitude gives an indication of process stability and spatter generation. With reference to section 2.1.3, **transfer stability index** (TSI) was defined as:

$$TSI = \frac{I_{\max}}{I_{mean}} \tag{5.14}$$

where

I_{mean}	*is the arithmetic average of welding current transient samples;*
I_{max}	*is the absolute maximum value in the samples.*

The initial classification of the indices based on video data and the subjective assessment of a skilled welder is shown in Figure 5.11. Initial validation trials showed that the indices developed using Migatronic BDH 320 power source, cannot be satisfactorily used independently because the current waveform can easily be distorted by inductance and slope settings on other power sources.

The indices were therefore combined together to develop monitoring rules using a pattern recognition approach. Table 5.7 shows the six rules developed to monitor process stability and detect instability. It should be noted that the rules are adaptable and more rules could be generated.

It is important to stress the need for appropriate monitoring hardware; the sensors being used must be able to follow the signals dynamics and any filtering carried out should not distort or suppress the waveform transient features, as this will affect the value of the indices. The monitoring hardware used for the work carried out has been optimised and used for data collection in various projects[106,219,220].

5.3.3 Qualitative Modelling of Spatter

The main indicator of instability is spatter. The presence of spatter can be confirmed by using a model based diagnosis approach. For every condition the ideal short circuit current (Imax) was estimated and compared with the actual maximum current (I_{maxi}). The size of the difference was found to correlate more with the amount of spatter generated. This difference was normalised and expressed as a ratio called **stability index** (SI). That is,

$$SI = abs\left(1 - \frac{I_{\max_i}}{I_{\max}}\right) \tag{5.15}$$

Table 5.7 Metal Transfer and Stability Assessment Rules

RULE 1

"PROCESS IS STABLE AND TRANSFER MODE IS SPRAY"

IF (TI > 0 AND TI < 0.1) AND
(DCI > 0 AND DCI < 0.1) AND
(TSI < 1.2)

RULE 2

"PROCESS IS STABLE AND TRANSFER MODE IS DIP/GLOBULAR"

IF (TI ≥ 0.3 AND TI < 0.5) AND
(DCI > 0.3 AND DCI < 0.8) AND
(TSI < 2)

if (DCI > 0.5) then *TRANSFER MODE IS "DIP"* else *"GLOBULAR"*

RULE 3

"PROCESS IN MIX MODE..GLOBULAR/SPRAY/DIP TRANSFER"

IF (TI < 0.3) AND
(TSI < 1.6)

RULE 4

"PROCESS IN MIX MODE ..GLOBULAR/DIP TRANSFER"

IF (TI < 0.3) AND
(TSI > 1.6)

RULE 5

"PROCESS IN DIP TRANSFER MODE, INCREASING DIFFICULTY IN MAINTAINING ARC,BAD WELD APPEARANCE AND POSSIBLY STUBBING"

IF (TI > 0.5) AND
(TSI > 2)

RULE 6

"ARC BREAK OCCURRENCE"

IF (TI ≥ 1)

Testing the Models

The monitoring rules in Table 5.7 appear to be independent of gas and power source characteristics. They have been satisfactorily used to predict the mode of transfer and presence of spatter for a range of shielding gases (see Appendix C). However, it must be pointed out that the ideal range of the indeces depends on the inductance and gas tolerance to process disturbances. A typical example of response to the indeces (TSI, TI and DCI) and applicable rule for the manual mode experimental data (see Table 5.4) is shown in Table 5.8.

Table 5.8 The Monitoring Rules Response

RN	TI	SI	TSI	DCI	Applicable Rule	Transfer Mode	Spatter
C1	0.41	0.50	2.18	0.34	2	dip	present
C2	0.39	0.04	1.76	0.75	2	dip	none
C3	0.12	0.05	1.23	0.03	3	mix mode	present
C5	0.35	0.14	1.73	0.63	2	dip	present
C6	0.29	0.29	1.80	0.38	2	dip	present
C7	0.07	0.04	1.09	0.03	1	spray	none
C8	0.18	0.22	1.57	0.19	3	mix mode	present
C9	0.20	0.30	1.59	0.24	3	mix mode	present
C10	0.06	0.02	1.05	0.04	1	spray	none
C11	0.14	0.17	1.39	0.11	3	mix mode	present
C12	0.30	0.01	1.48	0.54	3	mix mode	present
C13	0.18	0.52	1.85	0.10	4	mix mode	present
C14	0.08	0.03	1.11	0.04	1	spray	none
C15	0.07	0.01	1.10	0.03	1	spray	none
C16	0.21	0.36	1.74	0.17	4	mix mode	present
C17	0.06	0.01	1.07	0.04	1	spray	none
C18	0.04	0.01	1.05	0.04	1	spray	none

Mix mode usually contains mixture of dip and/or spray and/or globular transfer.

5.3.4 Ideal Process Transient Models

The objective was to develop models that will be used to predict the transient characteristics of the welding arc off-line. It has been established in section 5.3.2 that the features of the welding current and voltage waveforms such as minimum and maximum transient current can be used to develop monitoring indices. The indices TSI, TI and DCI describe the welding arc transient properties and offers the scope to control the stability of the process.

It was assumed that under a stable welding condition, the process transient features are relatively constant; therefore regression models can be used to correlate process transient parameters. The models for estimating the level of ideal process features and indices under stable condition were developed using the historical data (see Appendix D) from the previous experiments that span the process range and produce spatter free welds.

The welding current depends on the setup wire feed speed and standoff hence can be estimated off line by using the procedure. The welding current has a proportional relationship with wire feed speed however interaction was perceived between standoff and wire feed speed. It is well established that standoff influences the welding current (section 2.6.3) but its influence is dependent on the wire feed speed hence an intermediate model was developed (Equation 5.18). The welding voltage is assumed to be equal to the setup voltage. The estimated welding current and voltage can then be used to get an off-line estimate of the transient features.

The expected minimum and maximum transient current, background voltage and current depends on the welding current and voltage; the relationship was expressed as a first order model(Equations 5.16,5.17,5.22.5.23).

It was established in section 5.3.2 that transfer stability index (TSI) can used to identify the mode of transfer; the index depends on the welding current but standoff is included due to its inductive effect on the maximum current (Equation 5.19). Also for a stable arc the welding current can be estimated using the maximum and minimum current; regression analysis was used to determine the weighting (Equation 5.20).

The dip consistency index represent the tendency of the arc to short-circuit, this will however depend on the minimum current used to sustain the welding arc and the standoff due to its influence on the wire melting (Equation 5.21).

The Models

The following models for estimating the level of ideal process features under stable condition were developed.

1. Expected minimum transient current value

$$I_{\min} = \alpha_1 + \beta_1 I_{mean} + \delta_1 V_{mean} \tag{5.16}$$

2. Expected maximum transient current value

$$I_{\max} = \alpha_2 + \beta_2 I_{mean} + \delta_2 V_{mean} \tag{5.17}$$

3. Expected mean current from procedure

$$I_{mean} = \alpha_3 + \beta_3 WFS + \delta_3 SO\,WFS \tag{5.18}$$

4. Expected maximum to mean current ratio (ie. TSI)

$$\frac{I_{\max}}{I_{mean}} = \alpha_4 + \beta_4 I_{mean} + \delta_4 SO \tag{5.19}$$

5. Expected mean current from transient values

$$I_{mean} = \alpha_5 I_{\max} + \beta_5 I_{\min} \tag{5.20}$$

6. Expected background to average voltage ratio

$$\frac{V_{bk}}{V_{mean}} = \alpha_6 + \beta_6 I_{\min} + \delta_6 SO \tag{5.21}$$

7. Expected background voltage

$$V_{bk} = \alpha_7 + \beta_7 I_{mean} + \delta_7 V_{mean} \tag{5.22}$$

8. Expected background current

$$I_{bk} = \alpha_8 + \beta_8 I_{mean} + \delta_8 V_{mean} \tag{5.23}$$

where

WFS	*is the wire feed speed;*
SO	*is the standoff;*
V	*is the setup voltage;*
I_{mean}	*is the average welding current;*
I_{min}	*is the minimum current value in a sample;*
I_{max}	*is the maximum current value in a sample;*
I_{bk}	*is the background current;*
V_{mean}	*is the average welding voltage;*
V_{bk}	*is the background voltage;*
$\alpha_{1,..8}$, $\beta_{1,..8}$, $\delta_{1,..8}$	*are the regression constants.*

All these models were then combined to develop a new synergic welding algorithm. Table 5.9 gives the parameters for the models for the consumable used.

Table 5.9 Ideal Process Model Parameters

	α	ß	δ	
1	-131.83	0.446	8.912599	Imin
2	251.7677	1.715335	-14.3601	Imax
3	61.318	24.053	-0.4611	Imean
4	2.875834	-0.002549	-0.060936	TSI
5	0.363842	0.642844		Imean
6	-0.473176	0.002481	0.044959	Vbk/Vmean
7	-27.3364	-0.039555	2.2558	Vbk
8	-60.6953	0.73963	4.279697	Ibk
9	-0.9785	-7.00943E-6	0.083019	PR

Note: PR is a function that will presented later in this chapter.

5.3.5 Synergic and Metal Transfer Control Algorithm

In robotic welding applications, welding can be carried out in different positions which suggest the building of new process models for each position under conventional modelling approach. This is however not necessary if there is control over metal transfer mode.

The models of the process transient features (section 5.3.4) give the scope to actually specify and control metal transfer and process stability. Two synergic algorithm routines were developed. The control logic involves the following three steps:

1. Estimation of average welding current;
2. Determination of mode of transfer;
3. Calculation of appropriate voltage level.

Algorithm 1

The mode of transfer is mainly influenced by the welding voltage. The welding voltage was found to be positively correlated with minimum current. The minimum current model was therefore combined with the transfer index and used to estimate the voltage.

The transfer index was rearranged to give the minimum current

$$I_{\min} = I_{mean}(1-TI) \tag{5.24}$$

dividing through by Imean gives

$$\frac{I_{\min}}{I_{mean}} = (1-TI) \tag{5.25}$$

The minimum current model is

$$I_{\min} = \alpha_1+\beta_1 I_{mean}+\delta_1 V_{mean} \tag{5.26}$$

dividing through by Imean gives

$$\frac{I_{\min}}{I_{mean}} = \frac{\alpha_1}{I_{mean}}+\delta_1\frac{V_{mean}}{I_{mean}}+\beta_1 \tag{5.27}$$

put 5.25 into 5.26

$$(1-TI) = \frac{\alpha_1}{I_{mean}} + \delta_1 \frac{V_{mean}}{I_{mean}} + \beta_1 \qquad (5.28)$$

rearranged 5.28 to give the welding voltage as

$$V = V_{mean} = \frac{1}{\delta_1}\left(I_{mean}(1-TI) - (\alpha_1 + \beta_1 I_{mean})\right) \qquad (5.29)$$

The algorithm is specified below:

1. Estimate welding current

The welding current is estimated from the specified wire feed speed and standoff using Equation 5.18.

2. Determine mode of transfer

The mode of transfer would be specified initially (prior to welding) by the user. It could be assumed that if the welding current is less than 220 amps assume dip transfer else spray transfer. The transfer mode is selected by presetting the value for the transfer index.

That is,

IF dip transfer THEN TI=0.4 ELSE TI=0

3. Calculate appropriate voltage using Equation 5.29.

Algorithm 2

The next algorithm proposed for voltage selection is more suited for robotic application because it takes into consideration the effect of standoff, workpiece geometry and welding position.

The algorithm is specified below:

1. Estimate welding current using Equation 5.18

2. Determine mode of transfer

The mode of transfer is automatically selected by using the established monitoring rules (see Table 5.7 and Figure 5.11) as constrain in the algorithm. It should be noted that the algorithm will also constrain the mode of transfer to dip for positional welds and joints with gap.

2.1 Estimate Transfer Stability Index (TSI) using Equation 5.19 subject to the following constraints :

IF TSI<1 THEN TSI=1
IF 1≤TSI≤1.1 THEN TSI=TSI
IF 1.1<TSI<1.25 THEN TSI=1.1
IF 1.25≤TSI<1.60 THEN TSI=1.60
IF 1.6≤TSI≤ 1.8 THEN TSI=TSI
IF TSI>1.80 THEN TSI=1.80
IF GAP PRESENT AND TSI<1.6 THEN TSI=1.6 ELSE TSI=TSI
IF POSITIONAL AND TSI<1.6 THEN TSI=1.6 ELSE TSI=TSI

2.2 Estimate Transfer Index (TI)

dividing 5.20 through by Imean

$$1 = \alpha_5 TSI + \beta_5 \frac{I_{\min}}{I_{mean}} \qquad (5.30)$$

put 5.25 into 5.30

$$1 = \alpha_5 TSI + \beta_5 (1 - TI) \qquad (5.31)$$

therefore

$$TI = -\frac{1}{\beta_5}(1 - \alpha_5 TSI - \beta_5) \qquad (5.32)$$

2.3 Estimate DCI

put 5.24 into 5.21

$$\frac{V_{bk}}{V_{mean}} = \alpha_6 - \beta_6 I_{mean}(TI-1) + \delta_6 SO \tag{5.33}$$

rearrange 5.13 to give

$$\frac{V_{bk}}{V_{mean}} = 1 - DCI \tag{5.34}$$

put 5.34 into 5.33

$$DCI = 1 - \alpha_6 + \beta_6 I_{mean}(TI-1) - \delta_6 SO \tag{5.35}$$

The estimated DCI level is subject to the following constraints:

IF DCI<0.3 THEN DCI=0
IF 0.3≤DCI≤0.75 THEN DCI=DCI
IF DCI>0.75 THEN DCI=0.75
IF GAP PRESENT AND DCI<0.65 THEN DCI=0.65 ELSE DCI=DCI
IF POSITIONAL AND DCI<0.65 THEN DCI=0.65 ELSE DCI=DCI

8. Estimate voltage

divide 5.22 through by voltage

$$\frac{V_{bk}}{V_{mean}} = \frac{\alpha_7 + \beta_7 I_{mean}}{V_{mean}} + \delta_7 \tag{5.36}$$

put 5.34 into 5.36

$$1 - DCI - \delta_7 = \frac{\alpha_7 + \beta_7 I_{mean}}{V_{mean}} \tag{5.37}$$

therefore

$$V = V_{mean} = \frac{\alpha_7 + \beta_7 I_{mean}}{1 - DCI - \delta_7} \tag{5.38}$$

Testing the Algorithm

It was decided that the second algorithm was more suited to the objective of this project due to the more flexible control scope it offers. The algorithm was programmed using BASIC language and the voltage predicted tested as follows:

Bead-on-plate welds were made on a 6mm mild steel plate. The length of weld was approximately 40mm, welded at 0.5 m/min travel speed. The welding current and voltage waveforms were logged at 5kHz per channel. The welds produced were virtually spatter free. The standard deviations of the maximum current, arcing and short-circuiting times shown in Table 5.10 illustrate the consistency of the algorithm prediction.

The effectiveness of the algorithm however depends on the accurate prediction of welding current. The error of prediction of current could be as high as 23% but on the average it is about 10%. The over-estimation of current could however lead to overstating the voltage required. This is observed in dip welding especially when using long standoff and low wire feed speed.

An examination of the underlying physical concept suggests the arc power is also oscillating during metal transfer. The degree of fluctuation depends on the mode of transfer. A new factor was defined, which can be used for quick identification of transfer mode. The factor, called the power ratio (PR) is

$$PR = \frac{I_{bk}V_{bk}}{I_{mean}V_{mean}} \tag{5.39}$$

The index was found for stable welding conditions to be between 0.2 and 0.35 for dip transfer, up to 0.45 for globular and greater than 0.95 for spray. The region in between was found to be very unstable. The power ratio can also be estimated from the procedure and then be used to correct any over-estimation in voltage.

Table 5.10 Synergic Algorithm Validation Data

MEASURED RESPONSE

RN	WFS	SO	V	TI	TSI	DCI	SI
SD1	4	12	16.3	0.38	1.89	0.63	0.03
SD2	6		17.6	0.41	1.76	0.58	0.01
SD3	8		19.2	0.35	1.53	0.55	0.07
SD4	10		207	0.36	1.46	0.50	0.06
SD5	12		22.3	0.29	1.32	0.40	0.11
SD6	14		23.9	0.33	1.24	0.31	0.12
SD8	4	15	17.5	0.33	1.67	0.59	0.07
SD9	6		18.2	0.36	1.61	0.58	0.06
SD10	8		20.3	0.40	1.60	0.52	0.03
SD11	10		21.8	0.33	1.48	0.45	0.01
SD12	12		23.3	0.24	1.34	0.27	0.03
SD13	14		31.3	0.05	1.04	0.02	0.01
SD14	16		32.3	0.04	1.03	0.01	0.03
SD15	4	20	19.6	0.39	1.93	0.49	0.22
SD16	6		21	0.38	1.79	0.51	0.25
SD17	8		27.4	0.21	1.60	0.07	0.61
SD18	10		28.4	0.07	1.06	0.02	0.02
SD19	12		29.3	0.13	1.07	0.02	0.02
SD20	14		30.2	0.07	1.05	0.02	0.01
SD21	16		31.2	0.07	1.04	0.02	0.03

Table 5.10 (contd)

SD*	tarc	SD(tarc)	tsc	SD(tsc)
1	11.26	0.6	3.08	0.15
2	8.56	0.97	2.96	0.26
3	7.43	0.58	2.68	0.15
4	6.66	0.91	2.22	0.21
5	5.04	0.51	1.73	0.13
6	4.04	0.61	1.61	0.39
8	12.31	0.91	2.79	0.19
9	10.45	0.71	2.85	0.18
10	8.8	1.10	2.71	0.32
11	6.46	0.74	2.04	0.16
12	4.17	0.70	1.47	0.17
13	0.98	0.10	1.27	0.16
14	0.93	0.09	1.01	0.11
15	10.23	3.10	2.03	0.41
16	12.34	2.37	2.75	0.42
17	2.32	0.6	1.34	0.16
18	1.16	0.09	1.13	0.11
19	1	0.1	1.55	0.19
20	1.04	0.1	1.49	0.15
21	1.09	0.29	1.20	0.16

where

tarc	is the arcing time, msec;
tsc	is the short-circuiting time, msec;
SD(tarc), SD(tsc)	is the standard deviation of "tarc" and "tsc" respectively.

Table 5.10 (contd)

SD*	Ipred	Iactual	% Error	Imax	SD(Imax)
1	135.4	105.38	22.17	199.59	24.45
2	172.4	154	10.67	259.45	27.85
3	209.5	189	9.79	288.45	9.95
4	246.5	209.42	15.04	306.36	6.07
5	283.6	235.94	16.80	311.00	2.83
6	320.6	253.63	20.89	314.9	3.57
8	129.9	108.15	16.74	180.36	5.19
9	164.1	145.26	11.48	233.56	10.78
10	198.4	181.24	8.65	289.19	11.81
11	232.7	207.06	11.02	305.58	6.05
12	267	232.83	12.80	312.22	1.8
13	301.2	271.41	9.89	281.5	3.44
14	335.5	303.71	9.48	313.31	2.54
15	120.6	106.04	12.07	204.78	8.45
16	150.3	143.92	4.24	256.93	6.49
17	180	183.06	1.70	292.64	35.17
18	209.6	215.17	2.66	228.34	2.77
19	239.3	234.3	2.09	249.81	8.66
20	269	260.07	3.08	273.85	6.08
21	298.6	286.34	4.10	298.21	4.88

where

Ipred and Iactual is the predicted and measured average current respectively;

Imax is the maximum transient current;

SD(Imax) is the standard deviation of Imax.

The algorithm for voltage correction is as follows

Estimate the power ratio

$$PR = \alpha_9 + \beta_9 I_{mean}^2 + \delta_9 V_{mean} \tag{5.40}$$

The estimated PR level is subject to following constraints:

IF PR<0.2 THEN PR=0.2
IF 0.2≤PR≤0.45 THEN PR=PR
IF 0.6≥PR>0.45 THEN PR=0.45
IF 0.6<PR<0.95 THEN PR=0.95
IF 0.95≤PR≤1 THEN PR=PR
IF PR>1 THEN PR=1

The corrected voltage (obtained by rearranging 5.40) is:

$$V = \frac{PR - \alpha_9 - \beta_9 I_{mean}^2}{\delta_9} \tag{5.41}$$

Figure 5.12 shows the comparison between algorithm 1 and 2, and the effect of power ratio voltage correction on the voltage prediction. It can be seen that it corrects for high voltage in spray mode and in dip transfer at long standoff. The overestimation of voltage can also be attributed to the fact that series of linear models are used; welding is a non-linear process.

5.4 Models Relating Transient Parameters to Disturbance Parameters

The main quality disturbances in thin sheet welding are joint geometrical variations (gap) and standoff variation. Standoff variation can be monitored and controlled. Gap can only be monitored but not controlled.

5.4.1 Estimation of Standoff Deviation

It should be noted that the welding current value is dependent mainly on the wire feed speed and standoff (Equation 5.18); but the influence of voltage can also be included in the regression model.
The resulting model would be:

$$I_{mean} = \alpha + \beta WFS + \delta SO V + \gamma SO WFS \qquad (5.42)$$

where

I_{mean}	*is the welding current;*
WFS	*is the wire feed speed;*
V	*is the setup voltage;*
SO	*is the standoff;*
α,β and δ	*are consumable dependent constants; the values of* α,β,δ *and* γ *in the work carried out are* 36.595, 26.506, 0.1223 *and* -0.7396 *respectively.*

It is however well established that changes in standoff can be estimated from the deviation of the welding current from a reference value obtained from trial runs.
That is,

$$\Delta SO_i = SO_i - SO_{ref} = \theta\,(I_{mean_i} - I_{ref}) \qquad (5.43)$$

where

ΔSO_i	*is the change in standoff at interval* i;
SO_i	*is the standoff at interval* i;
SO_{ref}	*is the reference standoff;*

I_{meani}	*is the welding current at interval* i;
I_{ref}	*is the reference welding current*;
Θ	*is a constant.*

The proportionality constant (Θ) can be estimated by rearranging Equation 5.42 in the form of Equation 5.43. This is motivated by the work carried out by Kim and Na[101] and it can be proven that the proportionality constant would be:

$$\theta = \frac{1}{\delta V + \gamma WFS} \tag{5.44}$$

However if the process is being controlled at regular intervals (ie. under adaptive control) then the constant needs to be recalculated and a new reference current value from trial runs obtained. This is not possible nor desirable in an automated environment. An approach was proposed to improve the model above (Equation 5.43).

The method is based on the assumption that if there was no standoff variation, then the welding current is expected to fluctuate around a steady state value. Therefore, the difference between successive representative welding current samples should fluctuate around zero. Any trend (increasing or decreasing) is therefore proportional to the sum of these differences.

That is, standoff variation is

$$\Delta SO_i = \theta \sum (I_{mean_i} - I_{mean_{i-1}}) \tag{5.45}$$

The new standoff is obtained by adding the estimated deviation to the reference standoff value. That is,

$$SO_i = SO_{ref} + \Delta SO_i \tag{5.46}$$

Testing the Models

Using the synergic algorithm developed as a guide to selecting stable welding condition a series of welds were made. The welding robot was programmed to simulate step and slope changes in standoff. The welds were bead on plate at 0.5m/min travel speed and the total welding run was 150mm in length. The transient signal was sampled at 8kHz across three channels; the sampling (averaging) time for each block of data (windows) was 192msec at an interval of 0.5sec in order to obtain data for the whole weld run.

The models were programmed into Arcwatch™ so that the standoff prediction at each sampling interval can be evaluated. It should be noted that it is difficult to measure standoff precisely in this experiment; the estimates given above were obtained using the cursor position of Arwatch™. The output figures show the mean current, the standoff estimation using equations 5.43 and 5.45 respectively together with the welding parameters used.

Figures 5.13 and 5.14 shows the welding current response to a sloping standoff change and the estimated standoff. Figures 5.15 and 5.16 shows the welding current response to a step change in standoff change and its estimation.

For sloping standoff change of 13 to 15mm, in Figure 5.13a the estimation at the simulated 15mm point was 19.06 and 14.73mm for equations 5.43 and 5.45 respectively. This was for Figure 5.13b, 14.41 and 16.97mm and for Figure 5.13c, 12.92 and 16.73mm respectively.

For sloping plate change ie. continous from 13 to 20mm, in Figure 5.14a the estimation for the 20mm position was 18.15 and 19.72mm for equations 5.43 and 5.45 respectively. This was for Figure 5.14b, 13.09 and 17.86mm and for Figure 5.14c, 18.05 and 17.05mm.

For a step change of 13 to 15 to 20mm, in Figure 5.15a the estimation for the 20mm position was 19.75 and 22.93mm for equations 5.43 and 5.45 respectively. This was for Figure 5.15b, 19.15 and 20.28mm and for Figure 5.15c, 18.94 and 18.24mm. This was also in Figure 5.16a, 18.25 and 19.65mm and for Figure 5.16b, 21.88 and 21.88mm.

The result shows that the ability to detect standoff variation increases with current. Also it can be seen that the use of the sum of the welding current differences improves standoff detection.

It should be noted, that arc welding process is very chaotic, if the averaging time was too small and/or sampling interval too large this could result in oscillatory behaviour of the standoff prediction. One way of preventing this is by using moving average techniques to filter out the oscillatory effect.

5.4.2 Gap Detection

Gap is a dimensional variation which often occurs in thin sheet welding. Experimental trials and limited published work (Section 2.4.2) on through arc gap detection show that gaps are hard to model or quantify precisely.

Satisfactory results have been obtained by using a threshold technique and monitoring look-up table to detect gap and estimate its size. The presence of gap and weld pool failure are reliably detected using the arc.

Gap Detection Hypothesis

A physical hypothesis of the pool behaviour in gap situations was built and used to develop the models. A weld pool consists of two surfaces, top and bottom. In joints with no gap and partially penetrated, the bottom surface of pool is fully supported. In joints with gap, the pool is unsupported, and the top surface of the pool would be depressed easily by the arc pressure. The depression depth would increase with the gap size, until the arc pressure is greater than the resisting force of the molten pool and the weld will be destroyed.

The depression of pool surface leads to increase in the arc length. With reference to Figure 5.17, the arc length will increase with gap size until pool fails and returns to the original arc length due to the arc self-adjustment property. The changes in arc length caused by the weld pool depression will result in detectable changes in arc voltage and current and may be used for gap sensing.

Testing the Hypothesis

The background voltage and current were found to have good correlation with gap presence due to their good correlation with arc length. The voltage signal is generally more sensitive to gap than current. The sensitivity of current to gap, however increases with current value. The sensitivity depends on the self-adjusting property of the weld pool and arc in relation to gap size and arc pressure.

Figures 5.18 and 5.19 show the signature of the background voltage and current signals with gaps using a dip transfer condition. With diverging gap the background voltage is expected to increase with the slope increasing with gap size with no significant arc instability. While in converging gap, the background voltage decreases with the gap but arc is expected to be more unstable.

The background voltage also shows sensitivity to burnthrough. The occurrence of burnthrough is usually preceded by period of over-penetration and this period could be observed on the voltage signal (see Figures 5.20 and 5.21). The trend in background voltage therefore suggests correlation with increasing penetration. The sudden change in direction is an indication of increasing penetration and burnthrough tendency.

It has to be stressed that it is essential to start with a procedure with "gap bridging" capacity[n] and a stable arc. The detection strategy essentially depends on process instability influenced by gap presence. Hence, an unstable arc can render the gap detection concept redundant.

It was found difficult to quantify gap in spray transfer but there is a noticeable drop in current with gap increases and decreases (see Figures 5.22 and 5.23). This might be due to the fact that in comparison with dip and globular transfer, the pressure of arc is not fluctuating, and is hence subjecting the pool surface to continuous pressure.

In dip transfer and probably to some extent in globular transfer, the pool is depressed during the melting period. The depression decreases with the reduction of arc length during melting and the surface tension forces act on the pool. This fluctuation allows the weld pool depression to partially or fully recover, hence resulting in detectable changes in the arc characteristics.

Gap Detection Models

A model based approach was adopted to detect the presence of gap due to the fact that converging or diverging gap leads to a continuously changing dynamic property of the pool and arc. The strategy adopted is to predict reference values for background voltage and current dynamically from a new steady state welding current and voltage.

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n The Bridging Effect is a weld bead instability defined by Scotti[35]. It is defined as the ability of the molten metal to attach to both walls of a joint.

The measured and predicted values are compared using the equations:

$$GV_{bk} = \frac{V_{bk}}{V_{bk_{ref}}} - 1 \tag{5.47}$$

where

GV_{bk}	*is a factor for normalising actual and predicted background voltage;*
V_{bk}	*is the actual background voltage;*
V_{bkref}	*is the reference background voltage (estimated from Equation 5.22).*

$$GI_{bk} = 1 - \frac{I_{bk}}{I_{bk_{ref}}} \tag{5.48}$$

where

GI_{bk}	*is a factor for normalising actual and predicted background current;*
I_{bk}	*is the actual background current;*
I_{bkref}	*is the reference background current (estimated from Equation 5.23).*

A moving average filter was used on the model output to reduce their sensitivity to process noise. It was assumed that for joints with no gap, the model outputs should be (expected to be) zero and the value should increase with gap size. This however does not take into account the complex interaction due to metal transfer and pool oscillation. Therefore, there is need for thresholding as some error is expected.

The selection of thresholds is very subjective; some characteristic behaviour of the models was established by experimental trials made on 1.6 and 3.2mm plate thickness for fillet welds in the horizontal vertical position. These were used to established the thresholds.

Table 5.11 shows the monitoring look-up table established from trial runs. It was found adequate to set the initial thresholds at the standard error (SE)° of the regression models (Equations 5.22 and 5.23) divided by a standard predicted value estimated from the procedure.

° **standard error** of the regression model is a measure of the amount of error in the prediction model.

That is,

$$GV_{bkmin} = \frac{SE}{V_{bk_{ref}}} \tag{5.49}$$

where

GV_{bkmin} *is a the threshold value for the factor for normalising actual and predicted background voltage;*

$$GI_{bkmin} = \frac{SE}{I_{bk_{ref}}} \tag{5.50}$$

where

GI_{bkmin} *is a the threshold value for the factor for normalising actual and predicted background current;*

Table 5.11 Gap Detection Monitoring Look-up Table

1. Dip transfer

$GV_{bk}<GV_{bkmin}$	$0<GI_{bk}<GI_{bkmin}$	gap=0
$GV_{bk}<GV_{bkmin}$	$GI_{bk}>GI_{bkmin}$	gap=0.50*pt
$GV_{bk}>GV_{bkmin}$	$GI_{bk}<GI_{bkmin}$	gap=0.75*pt
$GV_{bk}>GV_{bkmin}$	$GI_{bk}>GI_{bkmin}$	gap=pt
$GV_{bk}<0$		burnthrough (gap=10)

2. Spray transfer

$GV_{bk}>2*GV_{bkmin}$	$GI_{bk}<0$	gap present and filled (gap=1)
$GV_{bk}<2GV_{bkmin}$		burnthrough (gap=10)

Testing the Models

The response of the look-up table is "digital". While the table gives a satisfactory result, there was over estimation of gap at the thicker thickness of 3.2mm. It was found adequate to just use 1.6mm as the datum thickness. It was however, clear that it might be difficult to use the table in real time control situation.
To facilitate control, an estimation equation to quantify the gap continuously was developed. The equation involves trial-and-error setting of parameters.

$$gap = \alpha |gv| + \beta |gi| - \theta \qquad (5.51)$$

where

$$gv = \frac{GV_{bk}}{GV_{bkmin}}$$

and

$$gi = \frac{GI_{bk}}{GI_{bkmin}}$$

α and ß are the trial-and-error parameters set at 0.5 and 0.1 respectively so that the models response fits simulated gap variations. The model will however predict some value for gap when it is not present. The bias (Θ) is used to correct the prediction; it was found adequate to use 0.5. For joint with no gap, gap size of less than 1mm was normally predicted.

The estimation model performance was satisfactory. However, the presence of gap causes variation in current which could also suggest standoff variation. Figure 5.24 shows how the background voltage and current react to step changes in standoff. The estimation model however proved to be robust, it still predicts gap size less than 1mm for situation were standoff changes. The monitoring table does however have the tendency to predict risk of burnthrough. This illustrates the difficulty in setting up the necessary thresholds.

The response of the models to burnthrough, constant, diverging and converging gaps shows that both the monitoring table and estimation can be combined together for effective gap monitoring.

The test runs were limited to dip transfer since it is the most commonly used for thin sheet welding. Figures 5.25 and 5.26 show how the models responded to perfectly filled diverging and converging gaps. It is also important to establish how the models will respond to abnormalities such as gap not bridging and burnthrough. The model response to a discrete burnthrough (see Figure 5.21) in a good weld is shown in Figure 5.27. Figure 5.28 shows the response to intermittent burnthrough.

It was observed that for a welding procedure to produce a "bridging effect" the leg length must be about 2.5mm greater than the size of the gap. Figure 5.29 shows the response of the situation where the procedure was inadequate to fill part of the gap. Note that no burnthrough was predicted, however if there is any tendency towards bridging, burnthrough will be predicted (see Figure 5.30). Trial runs carried out in the spray mode also gave satisfactory results (Figures 5.31 and 5.32). It should also be noted that in all the figures GIbk and GVbk are amplified by multiplying by 100.

5.5 Models Relating Transients and Quality Parameters

The output quality cannot be measured directly but it can however be estimated on line by monitoring welding current and voltage; models were developed for estimating bead size, penetration and risk of undercut. The following structures were adopted for the models.

Bead dimension model

The bead size is determined by the wire feed speed to travel speed ratio, that is, deposition rate (see section 5.2.2) this could also be represented by the ratio of welding current to travel speed because the welding current is also dependent on the wire feed speed. To ensure that variations due to different metal transfer mode is accounted for the welding voltage is included in the model.

$$[T; Lavg] = \alpha \frac{I_{mean}}{S} + \beta V_{mean} \tag{5.52}$$

where

T	*is the throat thickness;*
L_{avg}	*is the average leg length;*
I_{mean}	*is the measured welding current;*
V_{mean}	*is the measured welding voltage;*
S	*is the welding speed.*

Penetration model

The model was an adaptation of Persson and Stenbacka[191] penetration model; the influence of welding speed was added.

$$[Sp; Bp] = \alpha (I_{mean} V_{mean})^{0.5} + \beta S \tag{5.53}$$

where

Sp	*is the side plate penetration;*
Bp	*is the bottom plate penetration.*

Undercut model

The undercut model was based on the knowledge that risk of undercut increases with the level of current, voltage and speed. However, the possibility of undercut occurrence increases with bead size (see section 2.5.2); leading to the use of the inverse of speed in the model.

$$Pr(und) = \alpha I_{mean} + \beta V_{mean} + \frac{\delta}{S} \quad (5.54)$$

where

Pr(und) *is the possibility measure of presence of undercut.*

and subject to

if Pr(und)<0 **then** Pr(und)=0
if Pr(und)>1 **then** Pr(und)=1
else Pr(und)=Pr(und)

Table 5.12 On-line Models Parameters

DIMENSION	α	ß	δ	R^2	SE
T	0.00651	0.054296		0.993916	0.277402
Lavg	0.009105	0.077603		0.995331	0.34258
Sp	0.01782	-0.449818		0.89074	0.356612
Bp	0.019058	-0.639698		0.829175	0.415507
Pr(und)	-0.003914	0.069165	-0.349646	0.659836	0.368979

Testing the Models

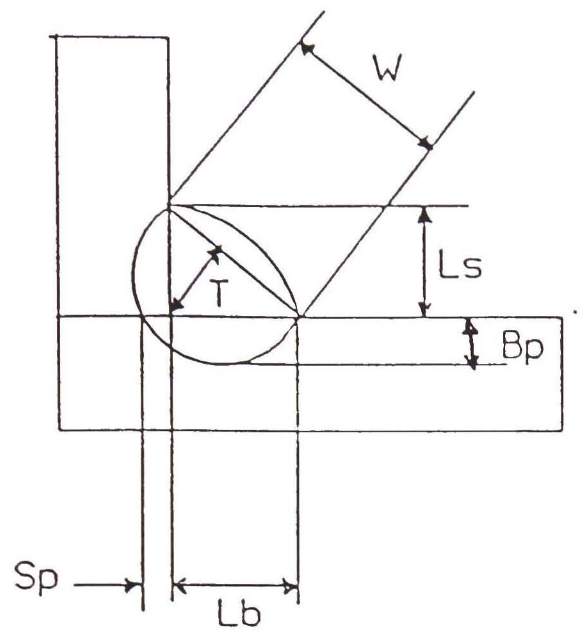
The bead dimension models were tested on the same data used to test synergic and manual models (see Appendix A and B). A good correlation exists between the predicted and the actual values (see Figures 5.33-5.36 and Appendix E).

The maximum prediction error was -0.38mm for the throat thickness; -0.64mm for the leg length. The prediction error for the penetration was 0.709mm and 0.588mm for side and bottom plate penetration respectively.

The response of the undercut model to a series of welding condition lead to the conclusion that if its output is greater than 0.3, then there is the possibility of undercut being present (see Table 2 in Appendix E).

The models developed in this work can be further classified as either off-line or on-line depending on the parameters used in developing them. The off-line models are developed using the welding setup and quality parameters; examples are models developed in section 5.2. While, the on-line models are based on process disturbance, transient response and quality parameters; examples are models in sections 5.3-5.5.

The prediction of the on-line models shows good correlation with the off-line models as shown in Figure 5.37. Therefore the structure adopted for the on-line models could provide a standard way of modelling penetration and undercut for example; the off-line models for undercut and penetration were developed to get the best fit to the experimental data. The predicted value of current and voltage from the synergic algorithm could be used as inputs into the models, however the prediction error associated with current must be accounted for.



Ls side leg length
Lb bottom leg length
Sp side plate penetration
T throat thickness
W bead width
Bp bottom plate penetration

Figure 5.1 Definition of Fillet Weld Geometry

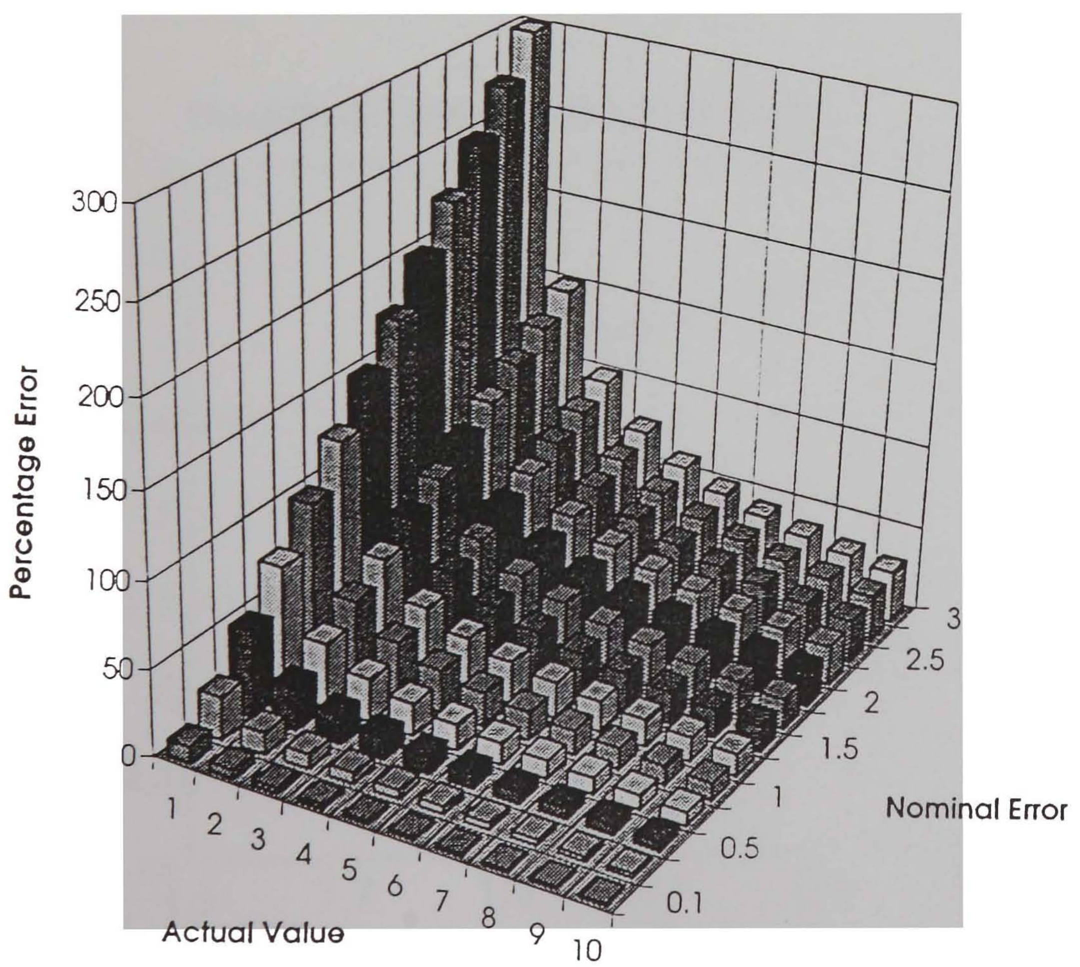


Figure 5.2 Simulated Relationship between Percentage Error and Nominal Error

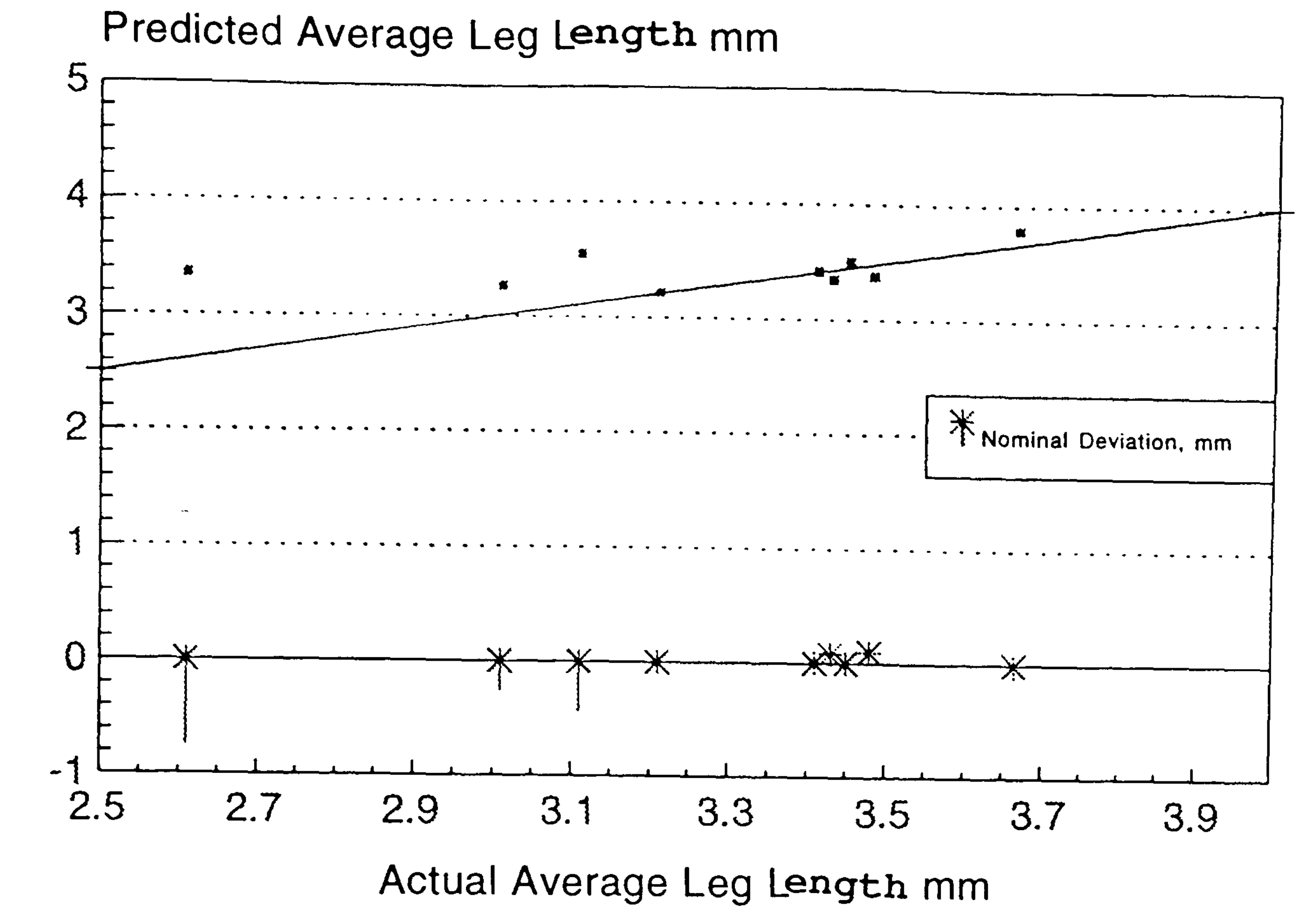


Figure 5.3 Testing Leg length Model

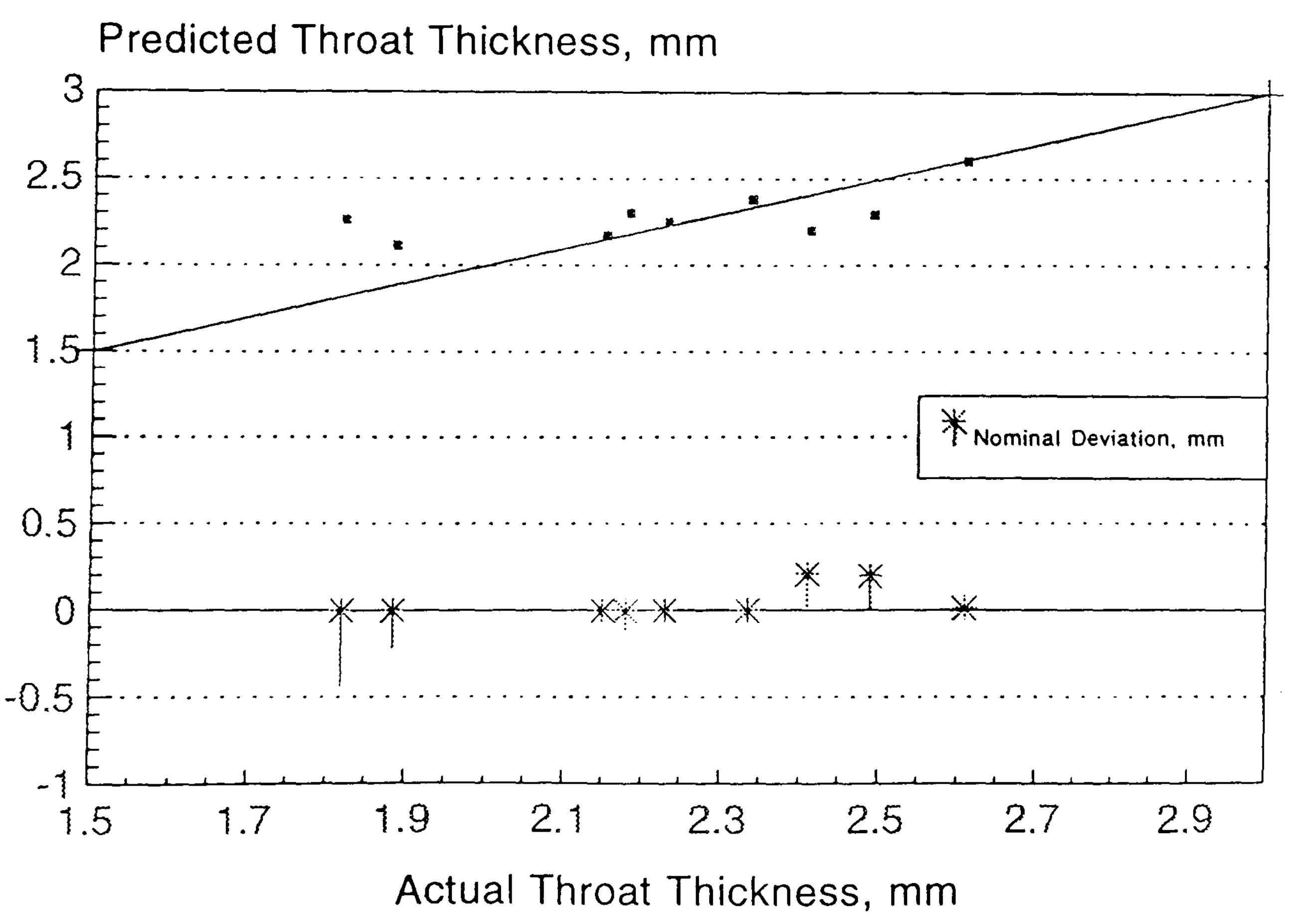


Figure 5.4 Testing Throat Thickness Model

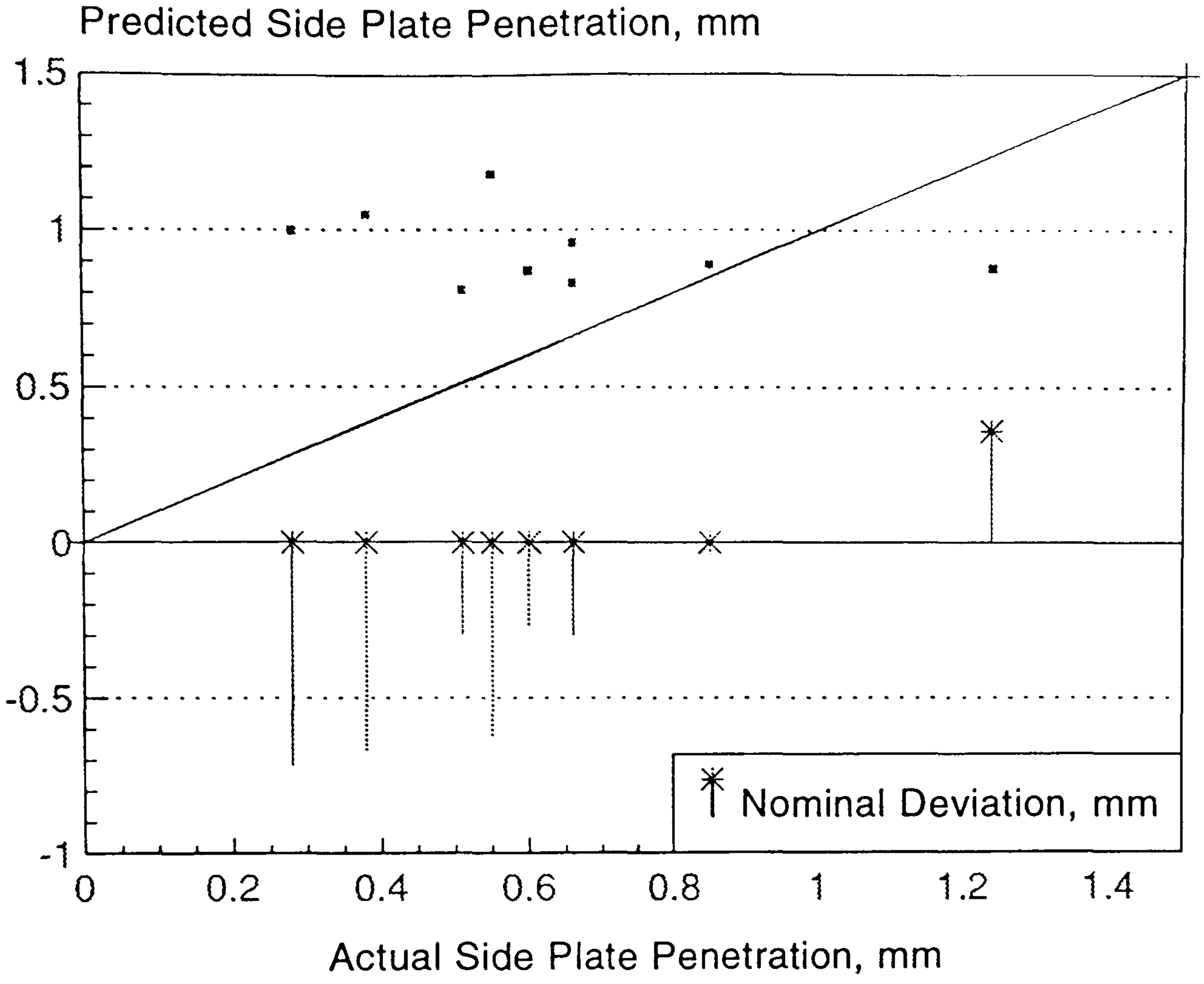


Figure 5.5 Testing Side Plate Penetration Model

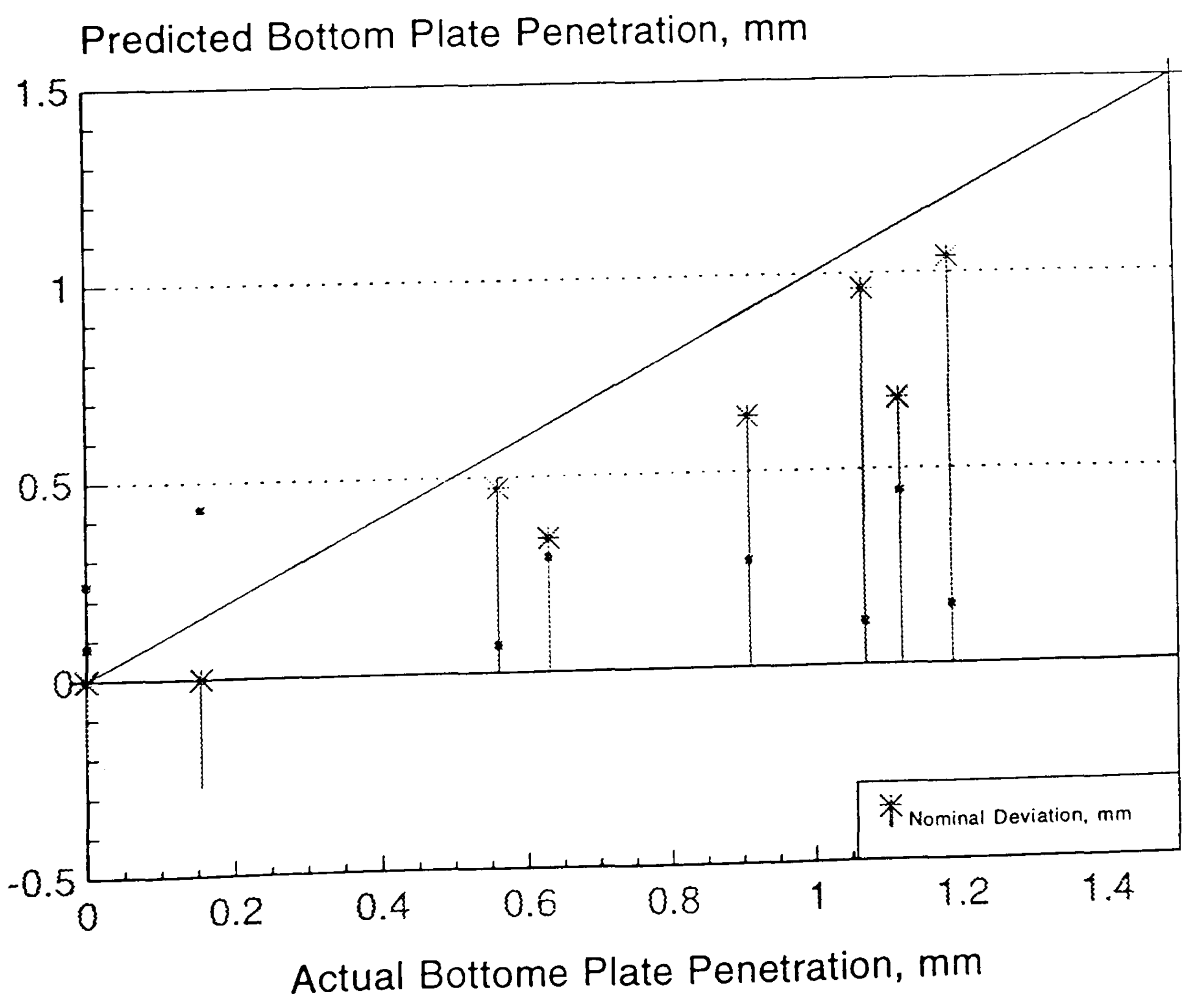


Figure 5.6 Testing Bottom Plate Penetration Model

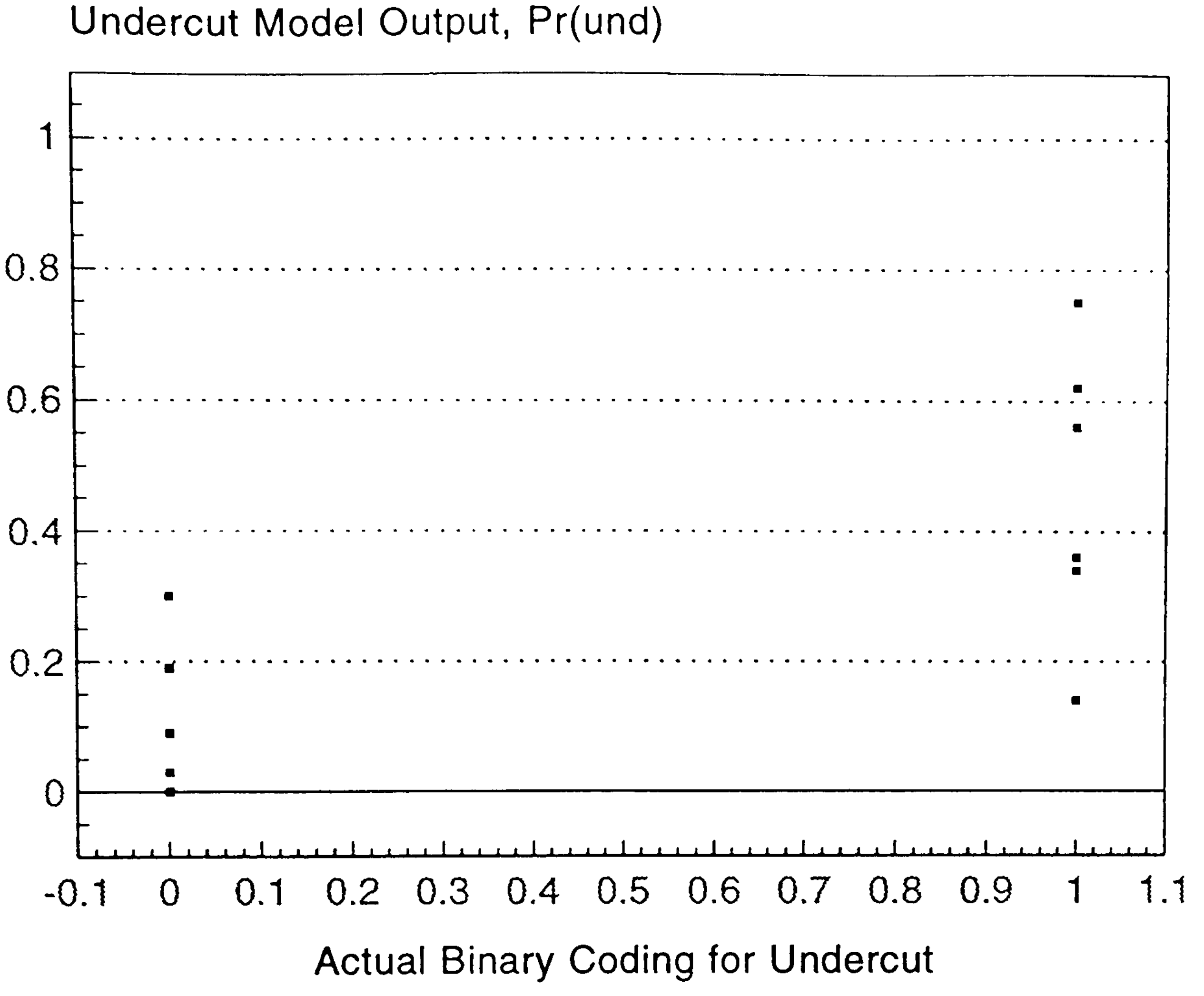


Figure 5.7 The Undercut Model Response: Manual Mode

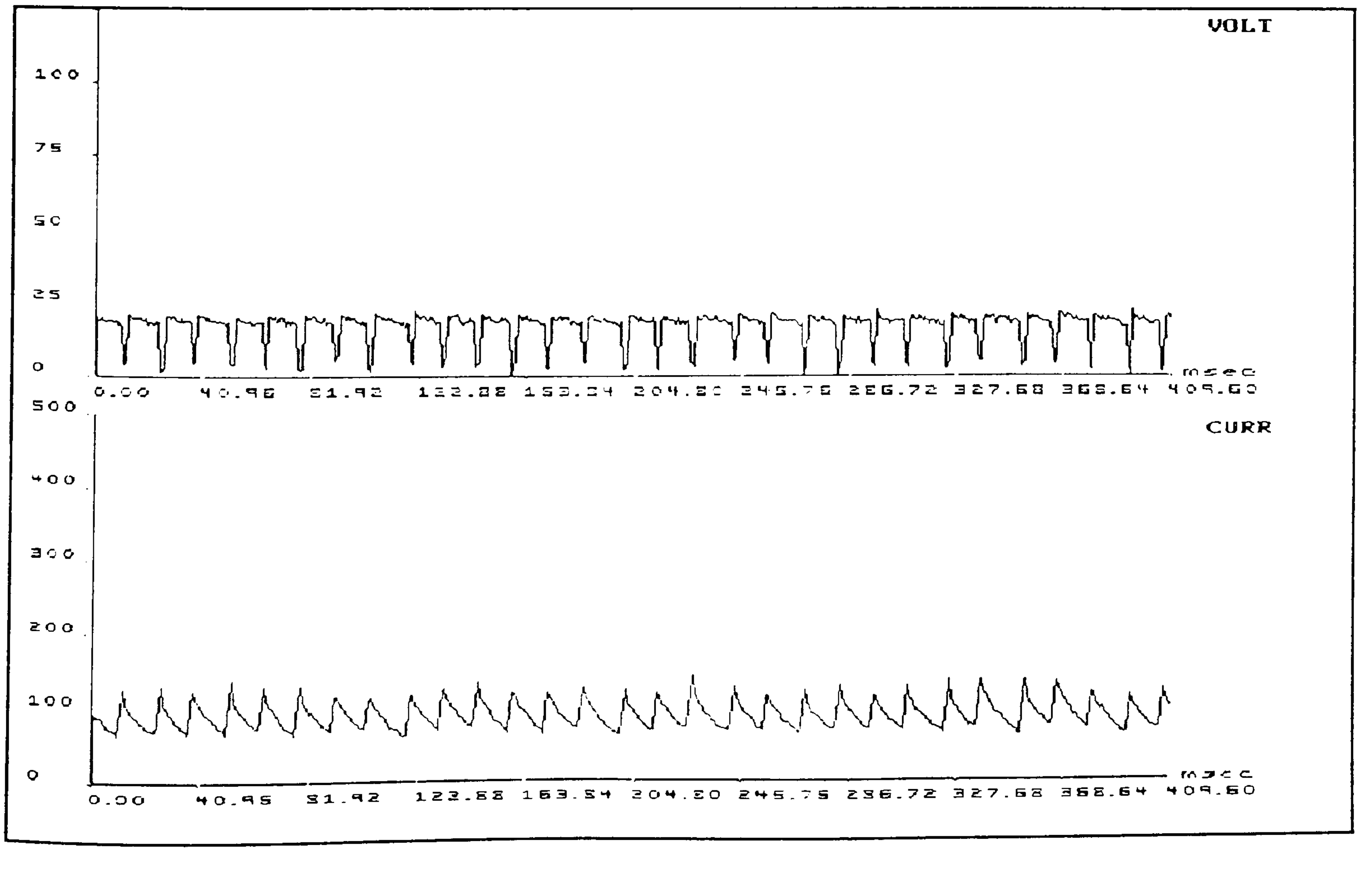


Figure 5.8 Dip Transfer Voltage and Current Waveform

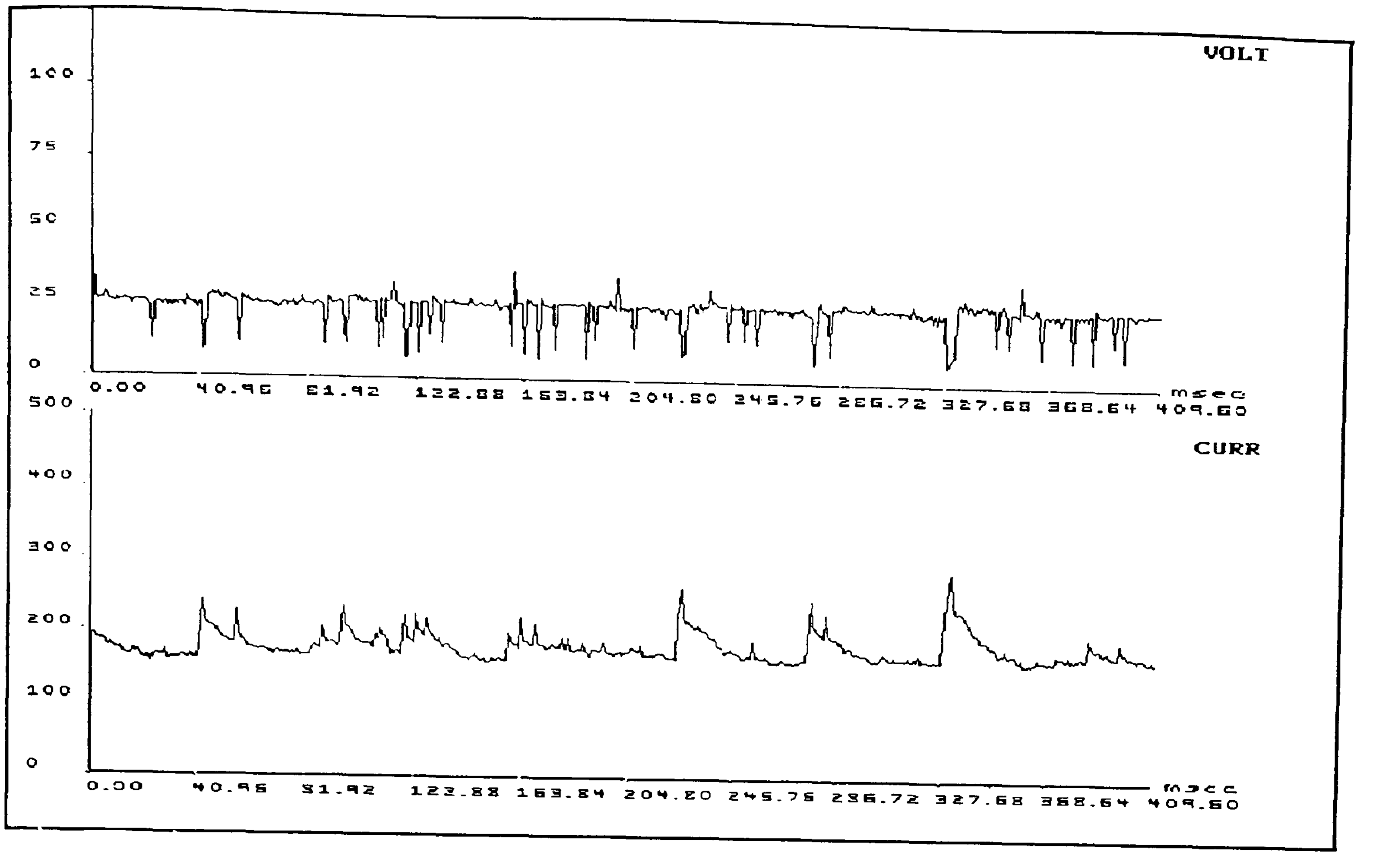


Figure 5.9 Globular Transfer Voltage and Current Waveform

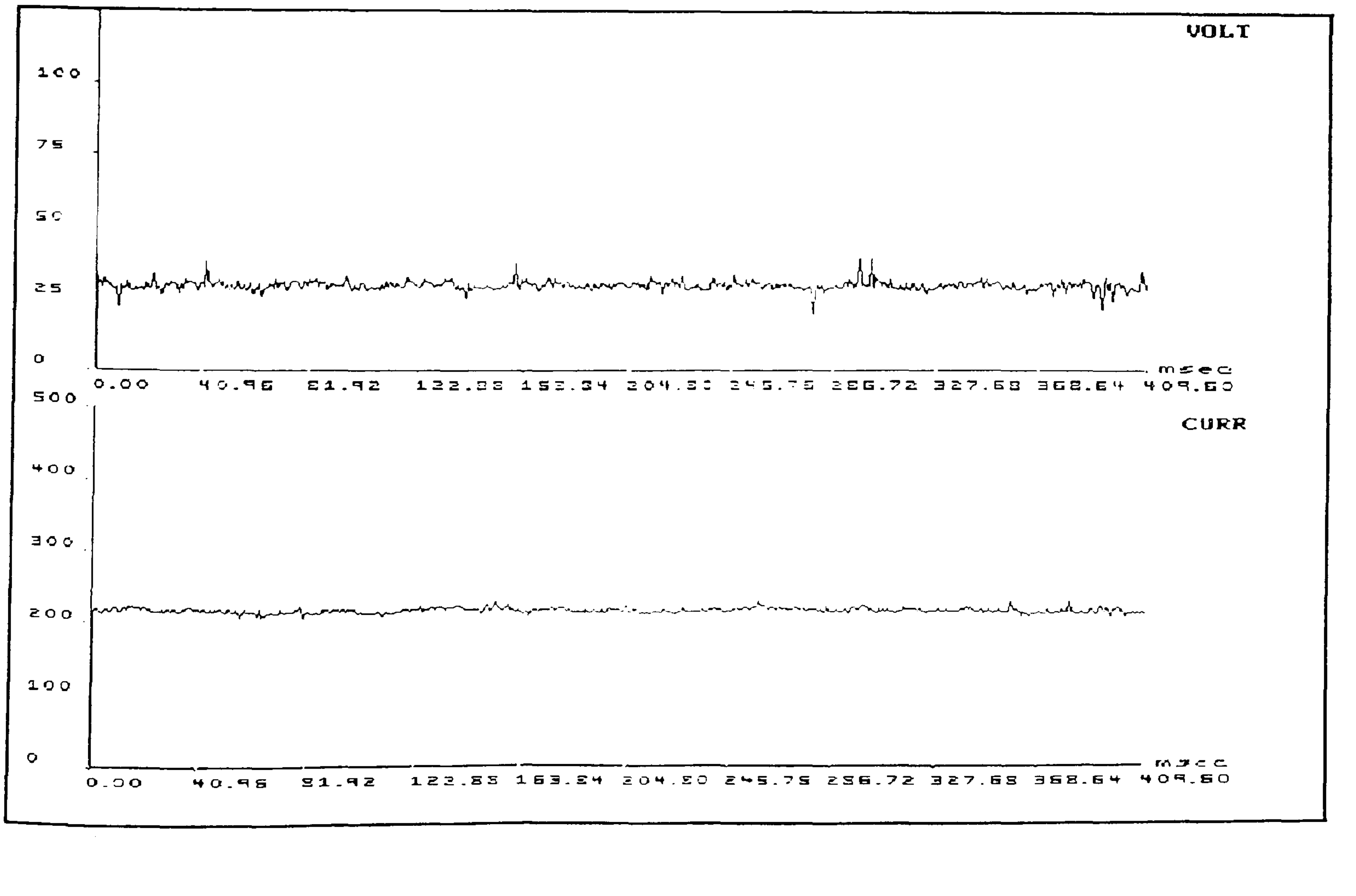


Figure 5.10 Spray Transfer Voltage and Current Waveform

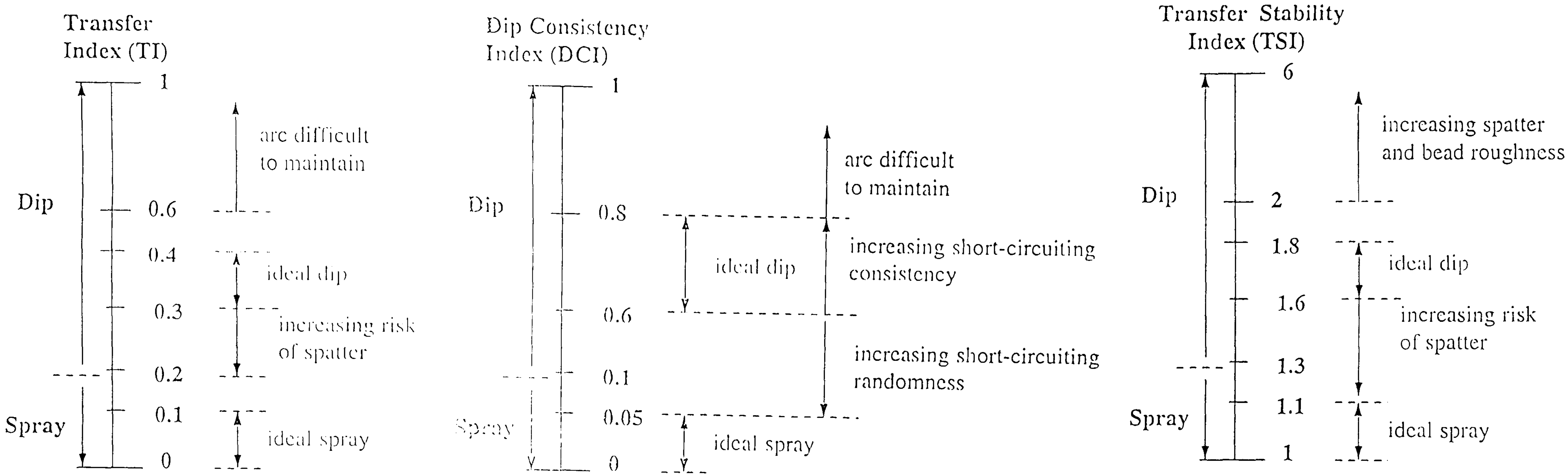


Figure 5.11 **Metal Transfer and Stability Assessment Chart**

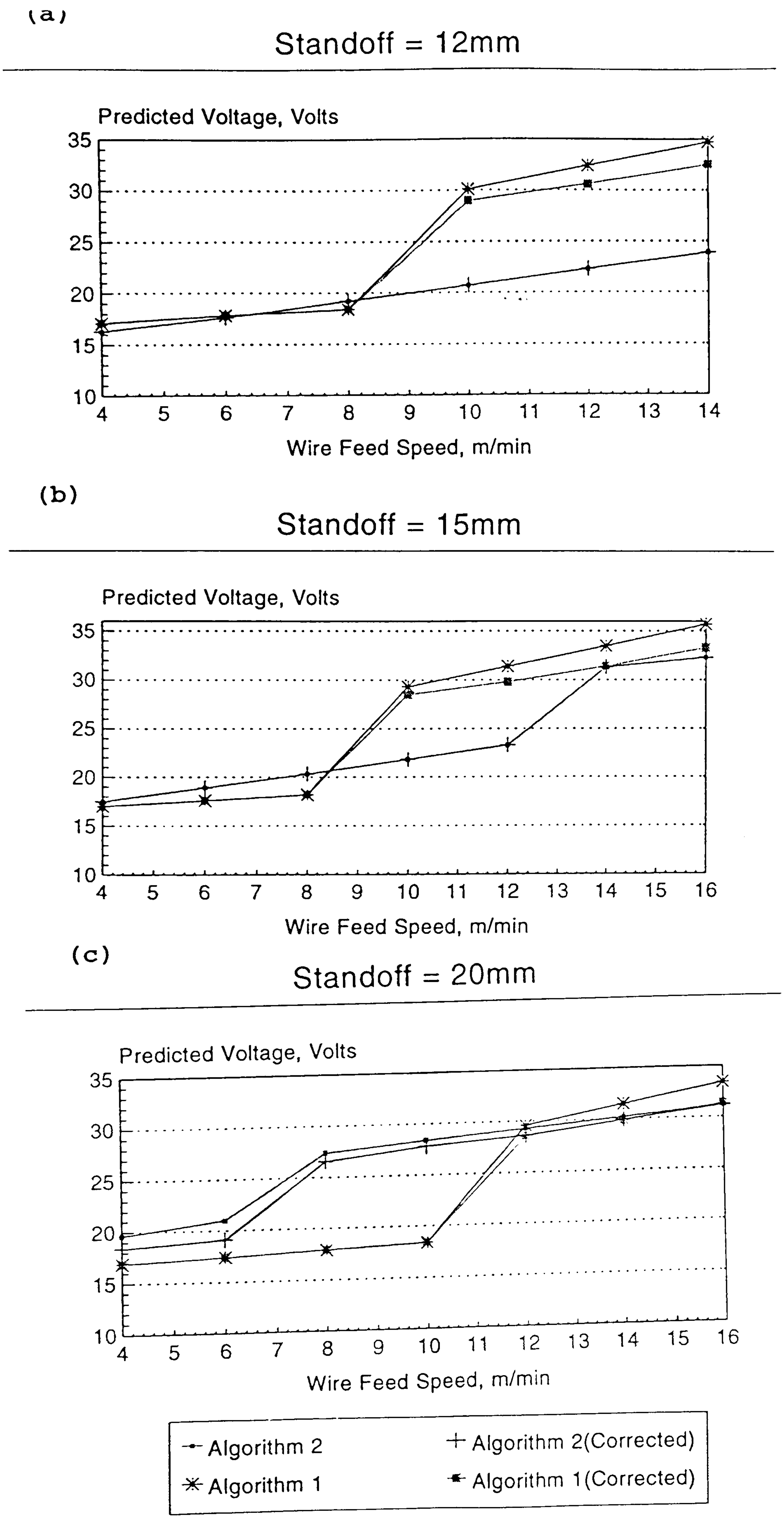
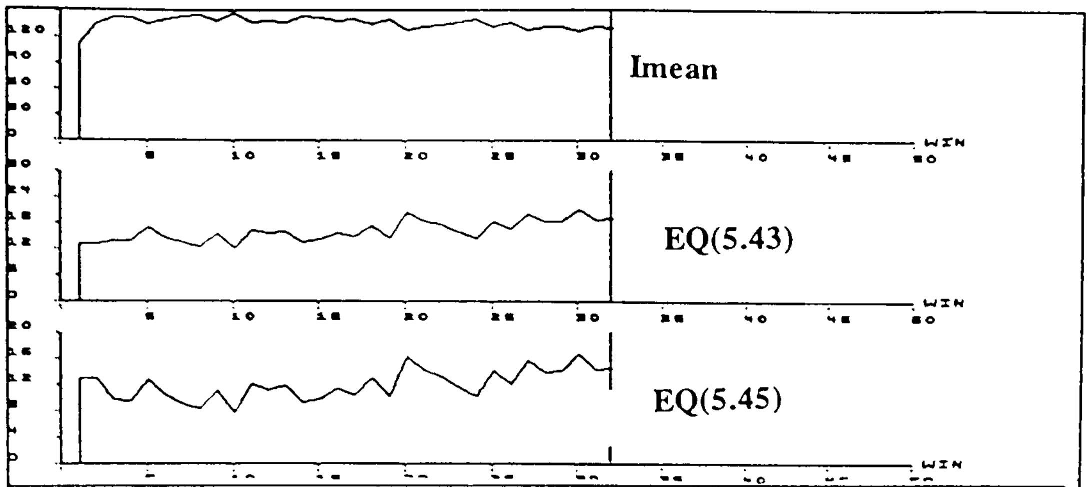


Figure 5.12 **Comparison of the Synergic Algorithms**

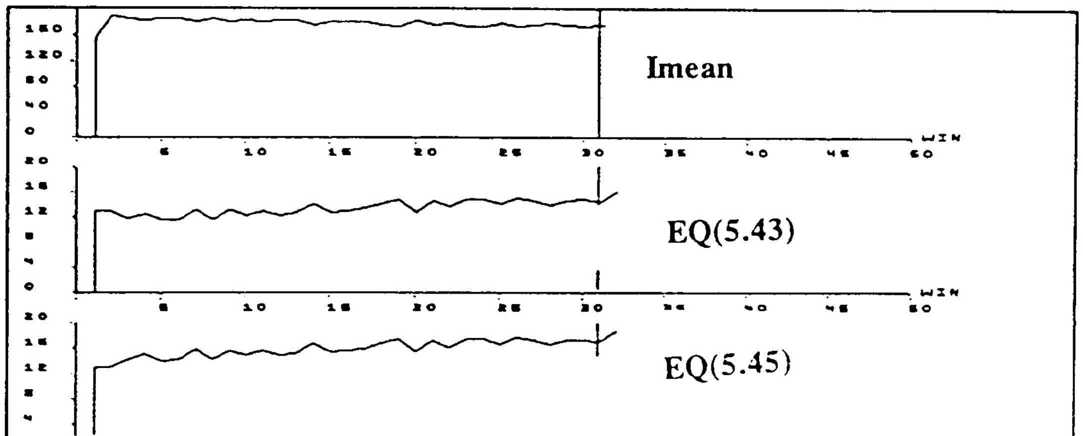
(a)



WFS	V	SOref	Iref
6	17.6	13	145.83

Simulated standoff change was sloping from 13 to 15

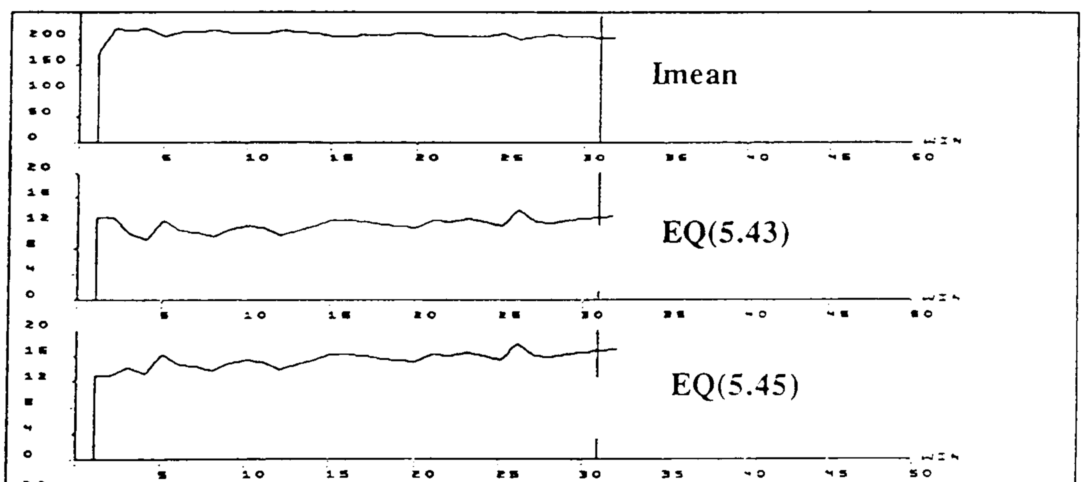
(b)



WFS	V	SOref	Iref
8	19.2	13	182.43

Simulated standoff change was sloping from 13 to 15

(c)

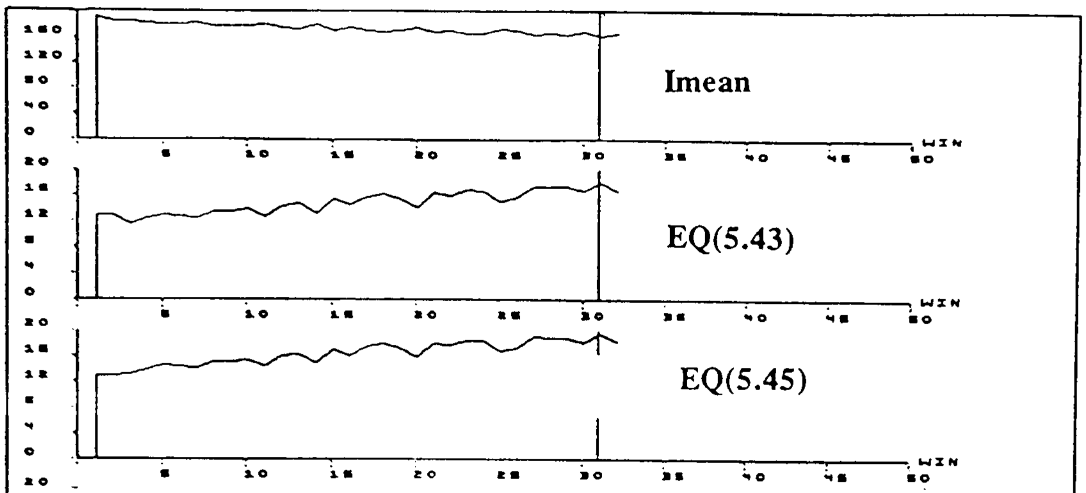


WFS	V	SOref	Iref
10	21	13	204.74

Simulated standoff change was sloping from 13 to 15

Figure 5.13 The Welding Current Response to Sloping Standoff Changes and Standoff Estimation

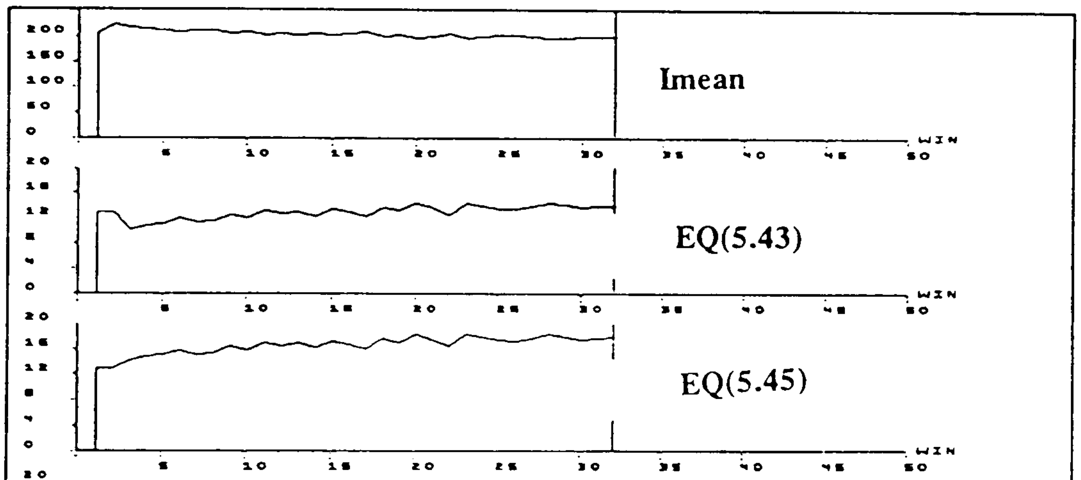
(a)



WFS	V	SOref	Iref
8	19.2	13	182.43

Simulated standoff change was sloping from 13 to 20

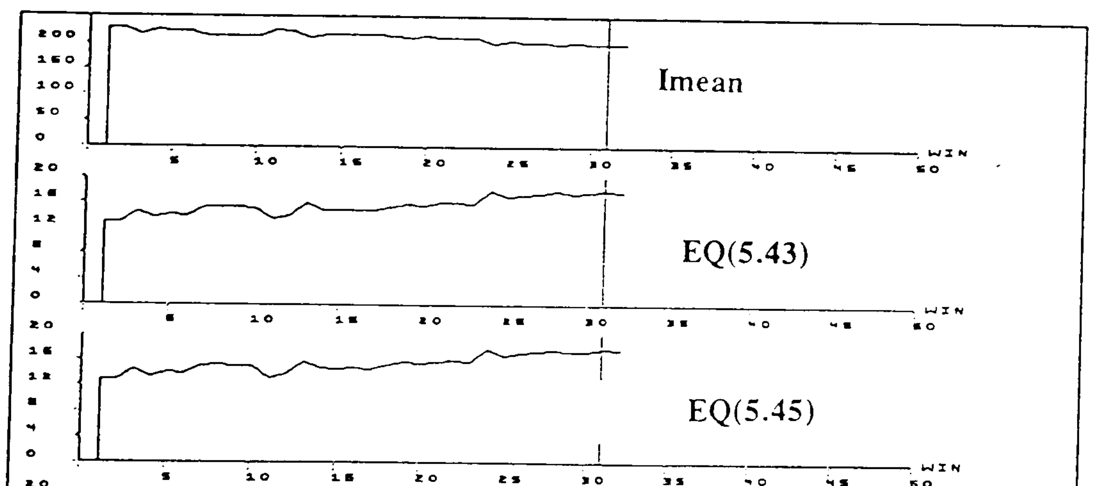
(b)



WFS	V	SOref	Iref
10	21	13	204.78

Simulated standoff change was sloping from 13 to 20

(c)

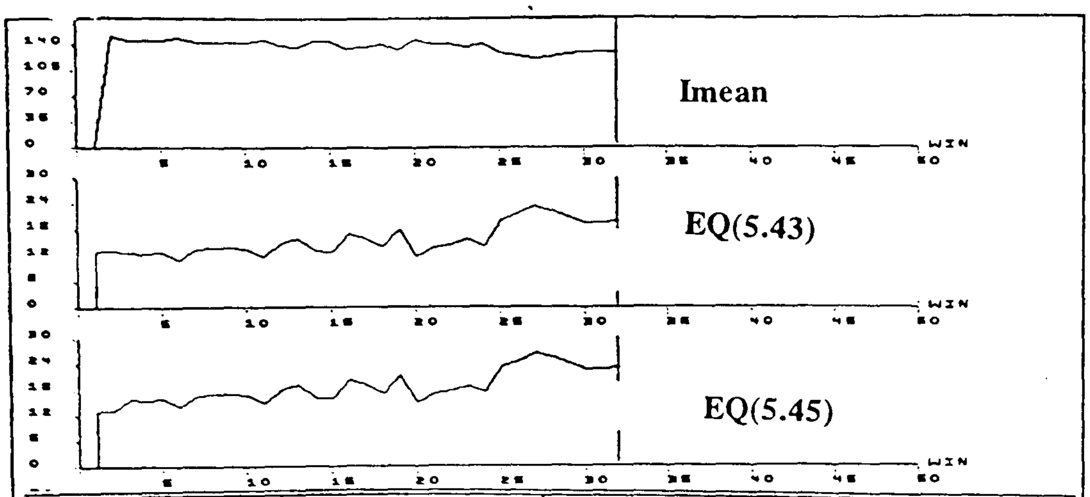


WFS	V	SOref	Iref
12	23.2	13	230.46

Simulated standoff change was sloping from 13 to 20

Figure 5.14 The Welding Current Response to Sloping Standoff Changes and Standoff Estimation

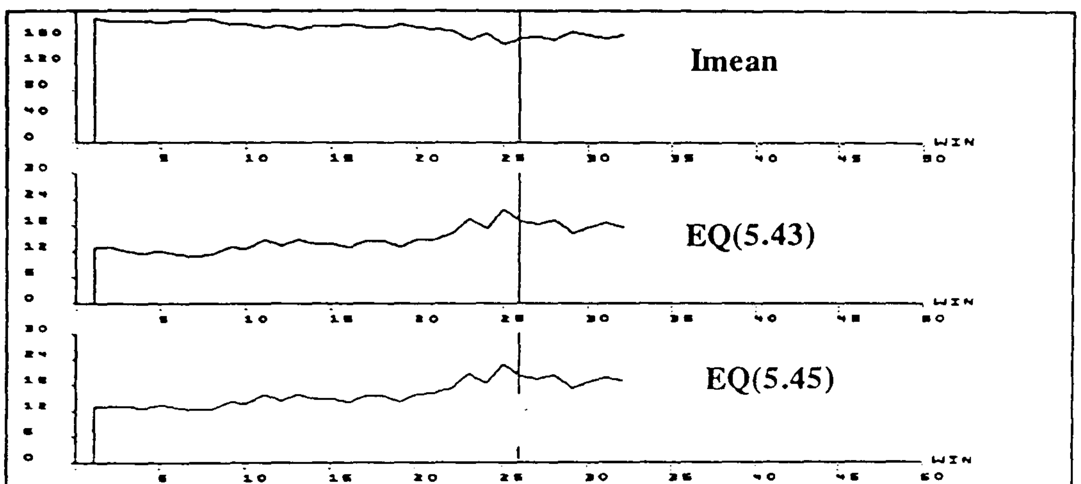
(a)



WFS	V	SOref	Iref
6	17.6	13	145.83

Simulated standoff change was stepping from 13 to 15 and then 20

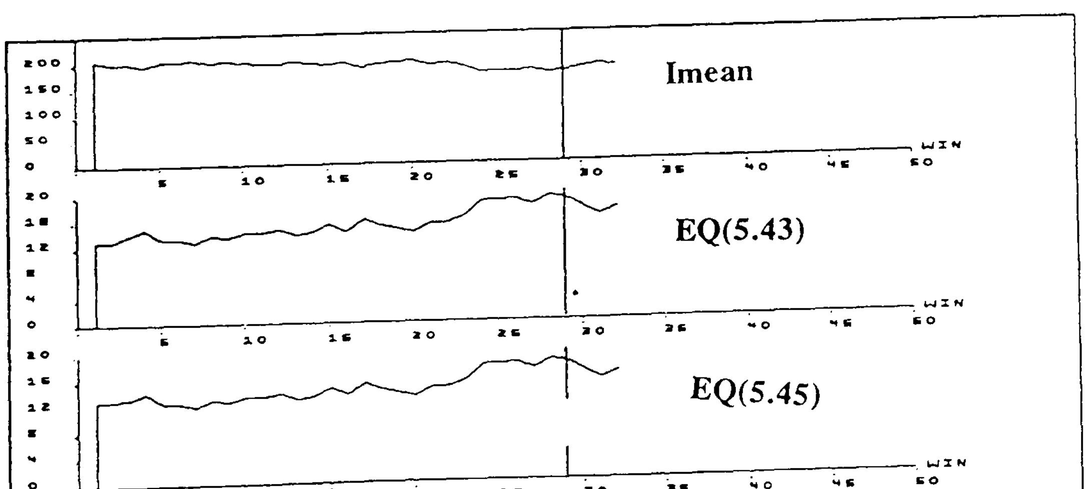
(b)



WFS	V	SOref	Iref
8	19.2	13	182.43

Simulated standoff change was stepping from 13 to 15 and then 20

(c)

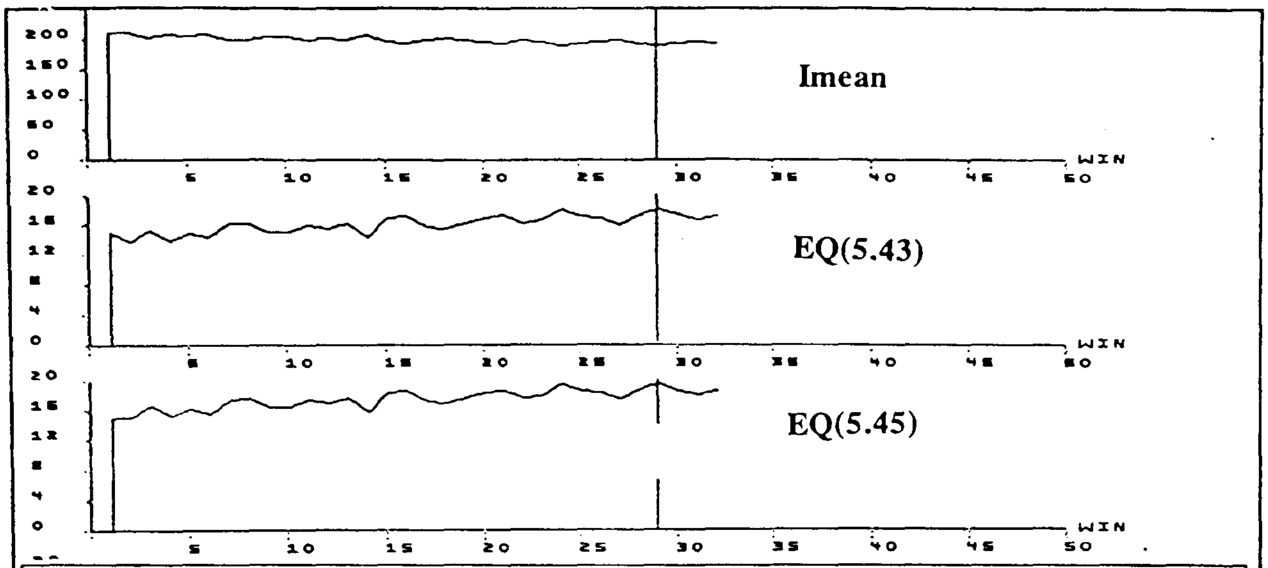


WFS	V	SOref	Iref
10	21	13	204.74

Simulated standoff change was stepping from 13 to 15 and then 20

Figure 5.15 The Welding Current Response to Step Standoff Changes and Standoff Estimation

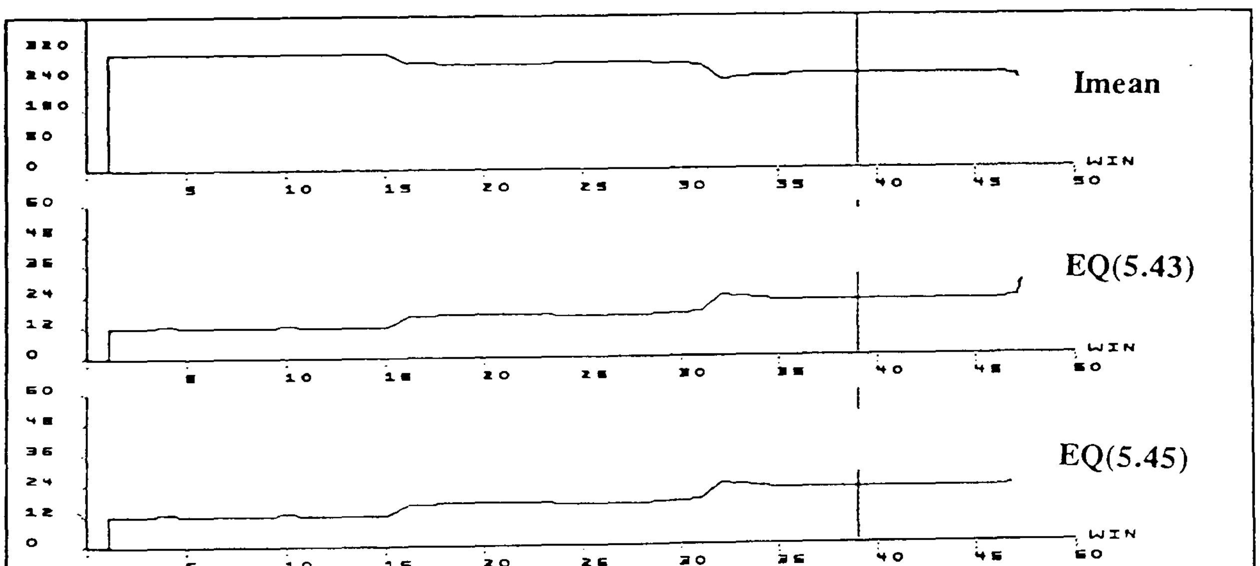
(a)



WFS	V	SOref	Iref
12	23.2	13	230.46

Simulated standoff change was stepping from 13 to 15 and then 20

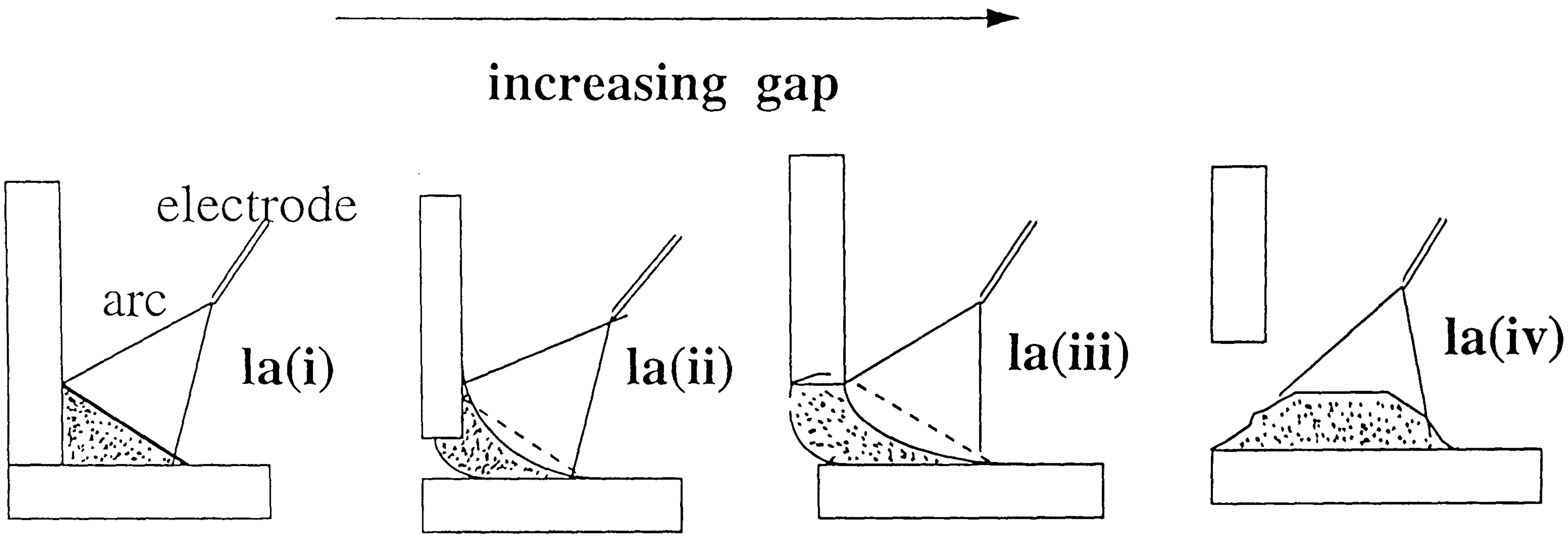
(b)



WFS	V	SOref	Iref
13	30.7	12	306.55

Simulated standoff change was stepping from 12 to 15 and then 20

Figure 5.16 The Welding Current Response to Step Standoff Changes and Standoff Estimation



$la(i) < la(ii) < la(iii)$ and $la(iv) \approx la(i)$

Where "la" is the arc length

Figure 5.17 Perceived Effect of Gap on Weld Pool and Arc Length

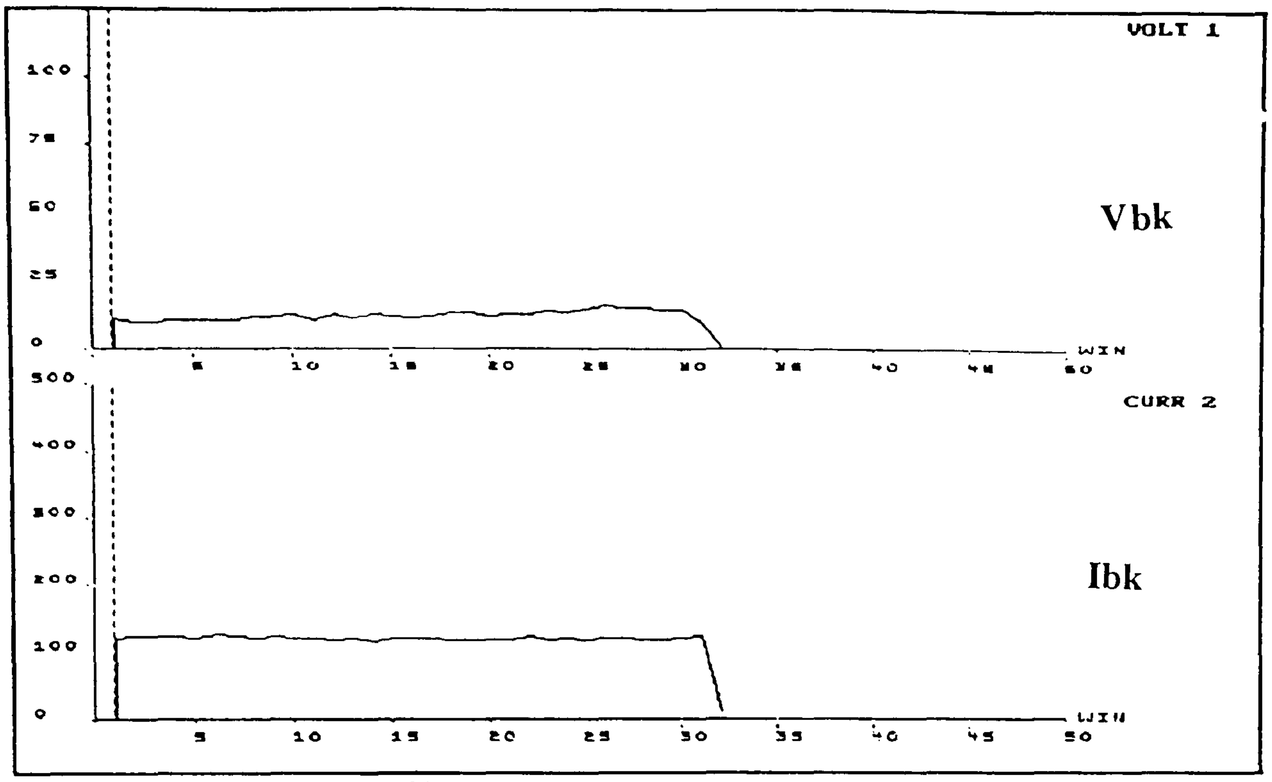


Figure 5.18 Typical Pattern of Background Signals with Diverging Gap

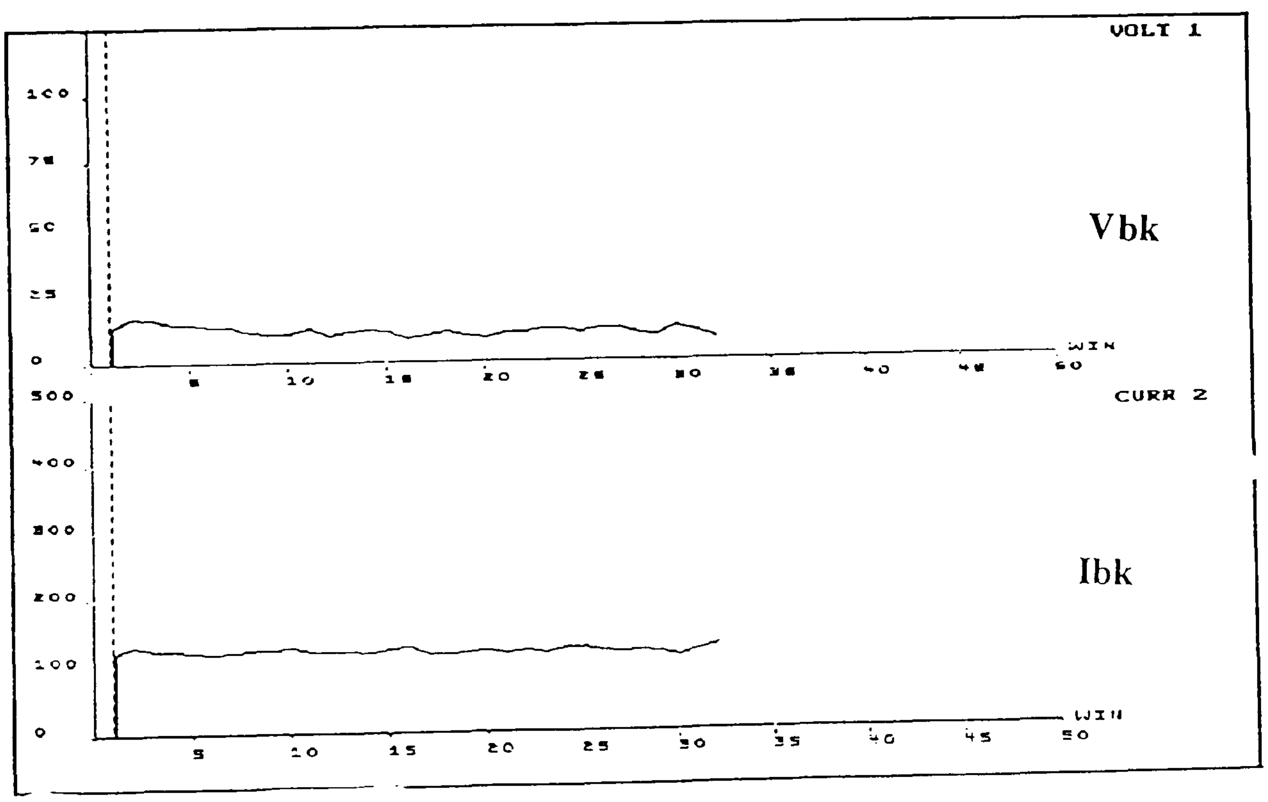


Figure 5.19 Typical Pattern of Background Signals with Converging Gap

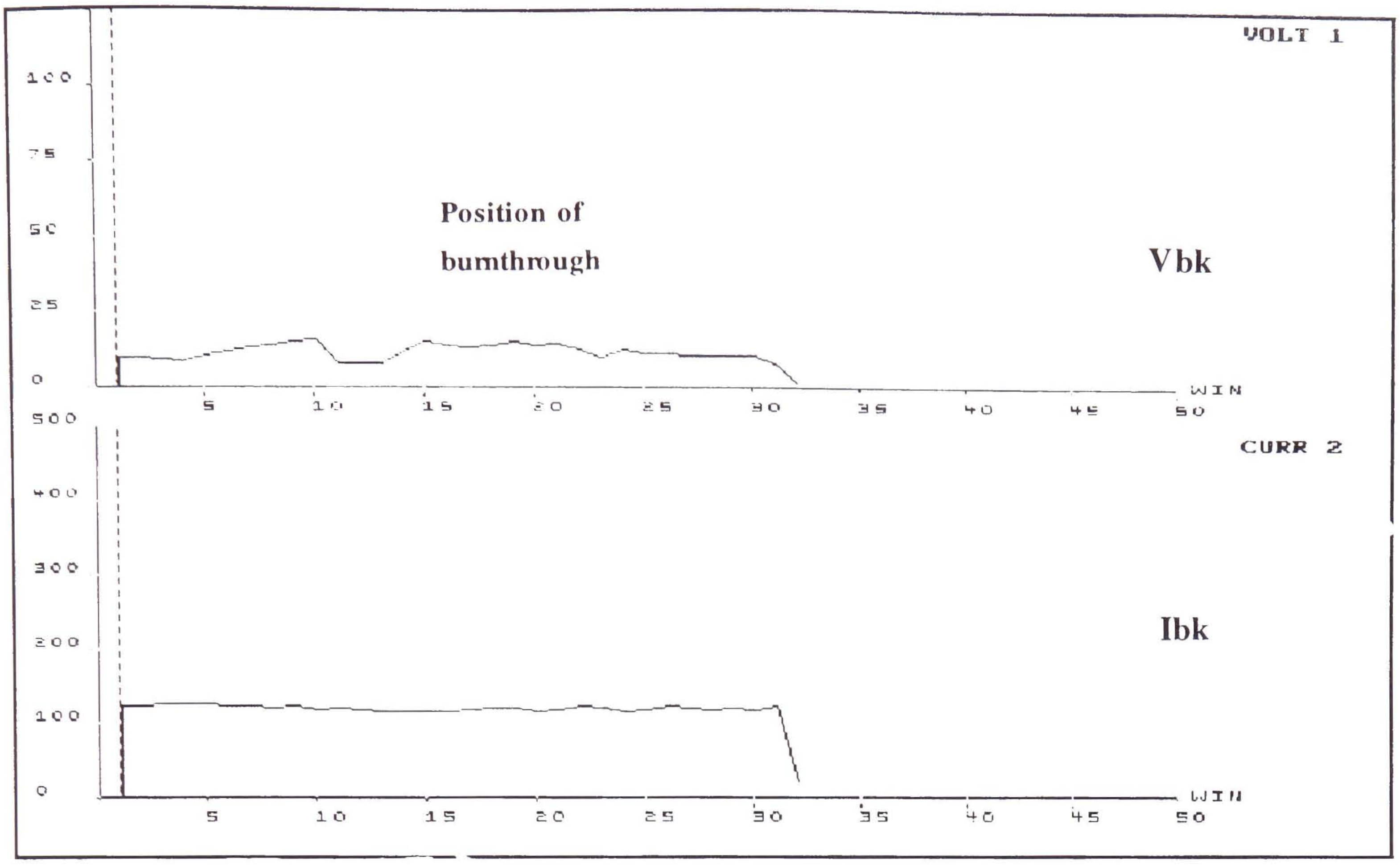
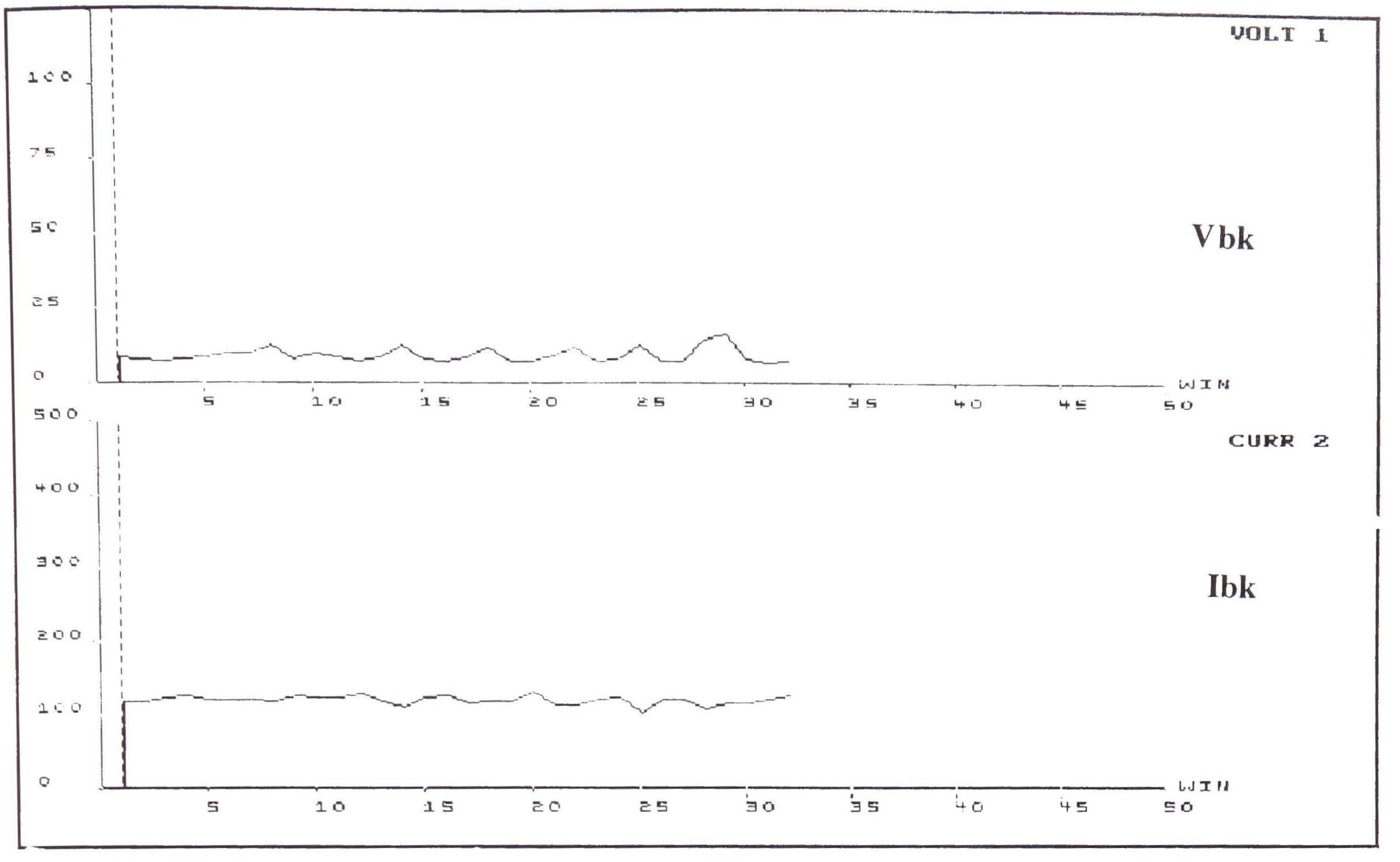


Figure 5.20 Typical Pattern of Background Signals with Discrete Burnthrough



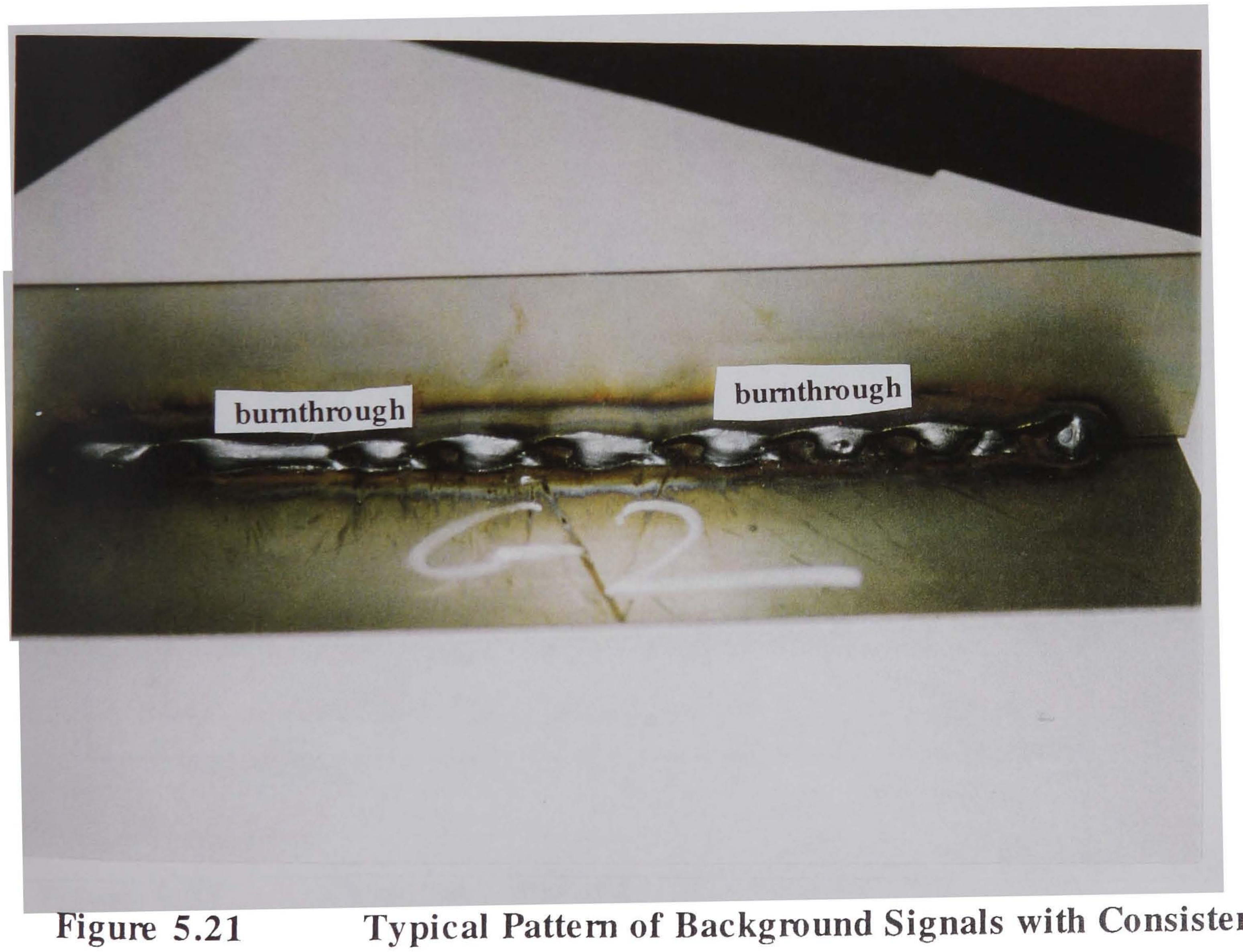


Figure 5.21 Typical Pattern of Background Signals with Consistent Burnthrough and Intermittent Fusion with Diverging Gap

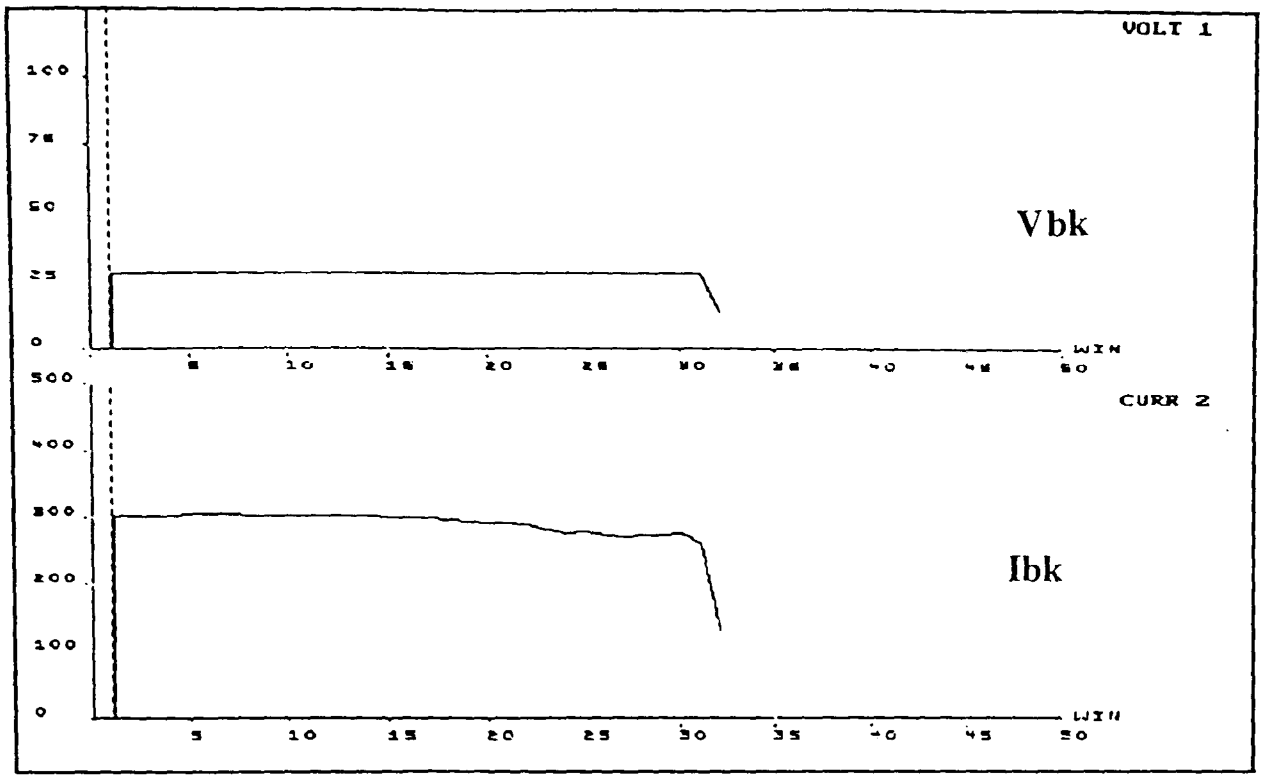


Figure 5.22 Typical Pattern of Background Signals with Diverging Gap in Spray Transfer

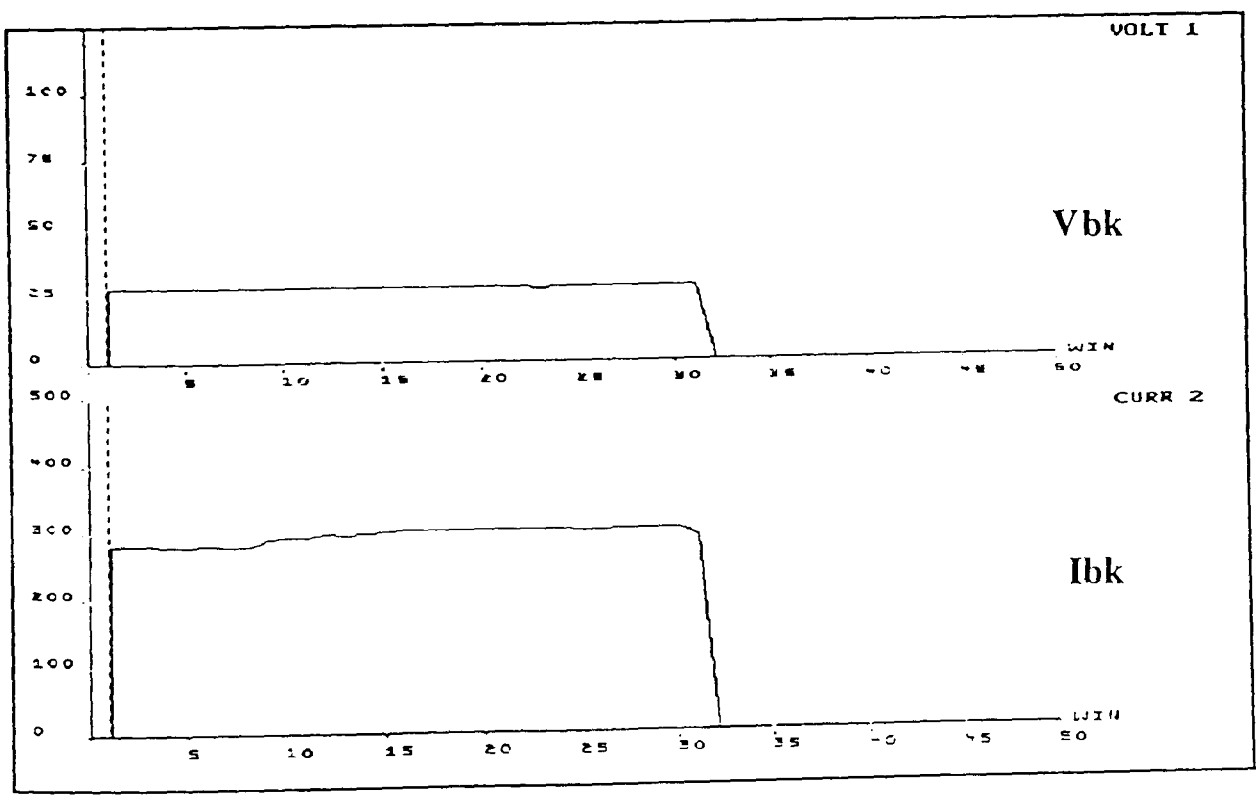
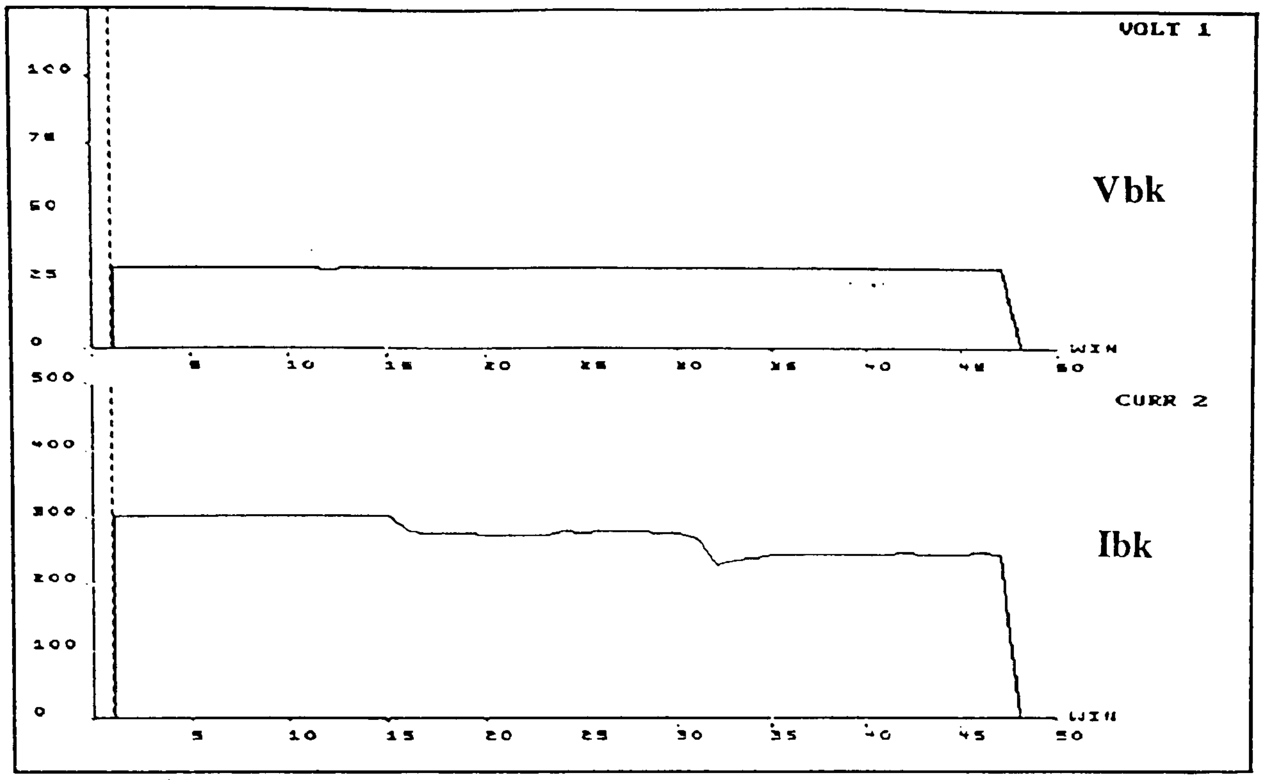


Figure 5.23 Typical Pattern of Background Signals with Converging Gap in Spray Transfer

(a)



Typical Pattern of Background Signals with Step Standoff

(b)

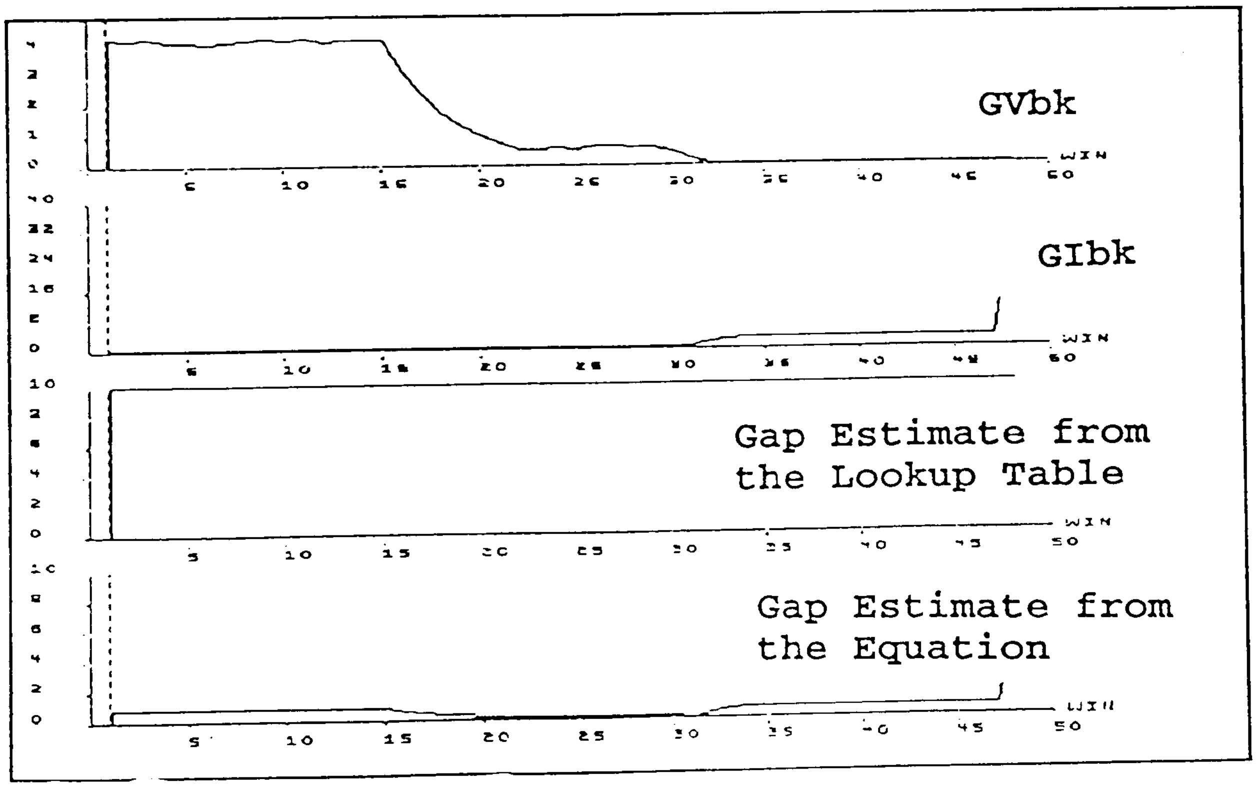
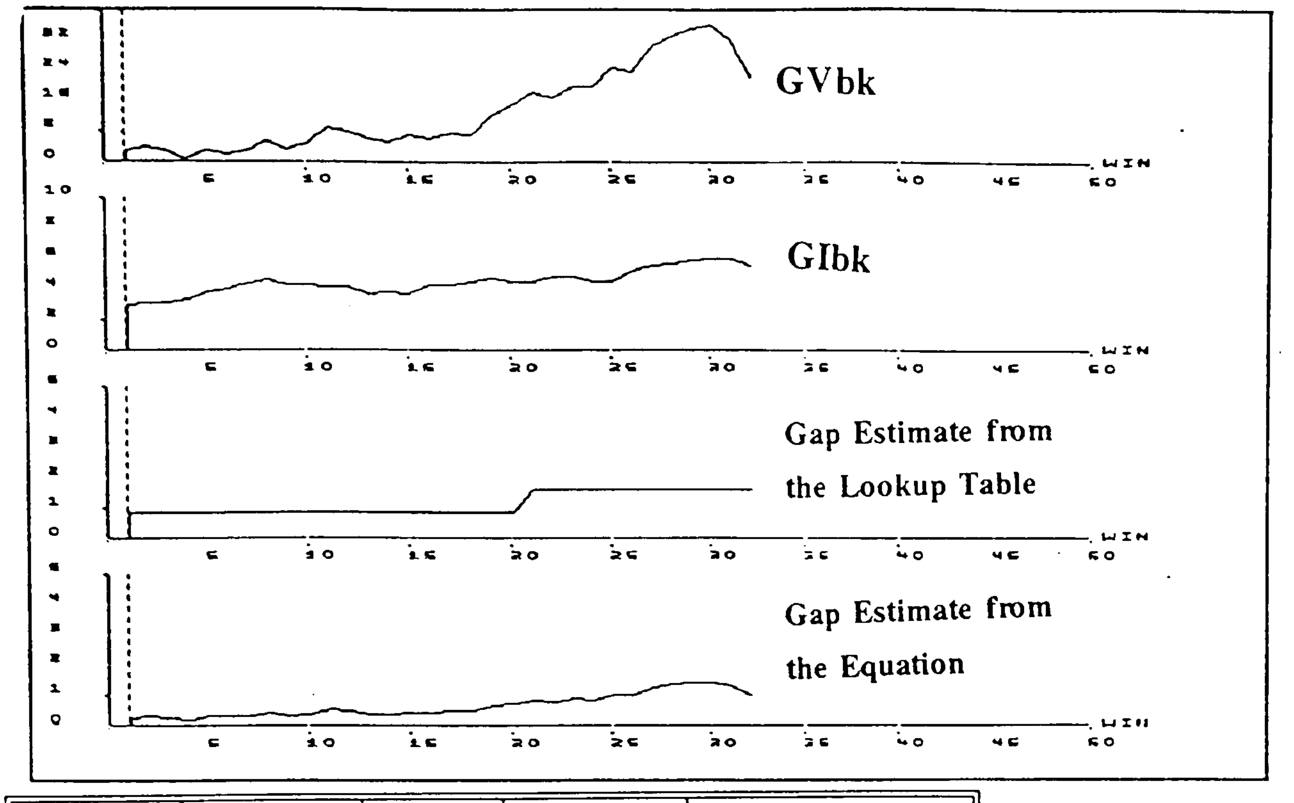


Figure 5.24 Gap Detection Model Responses for step standoff changes

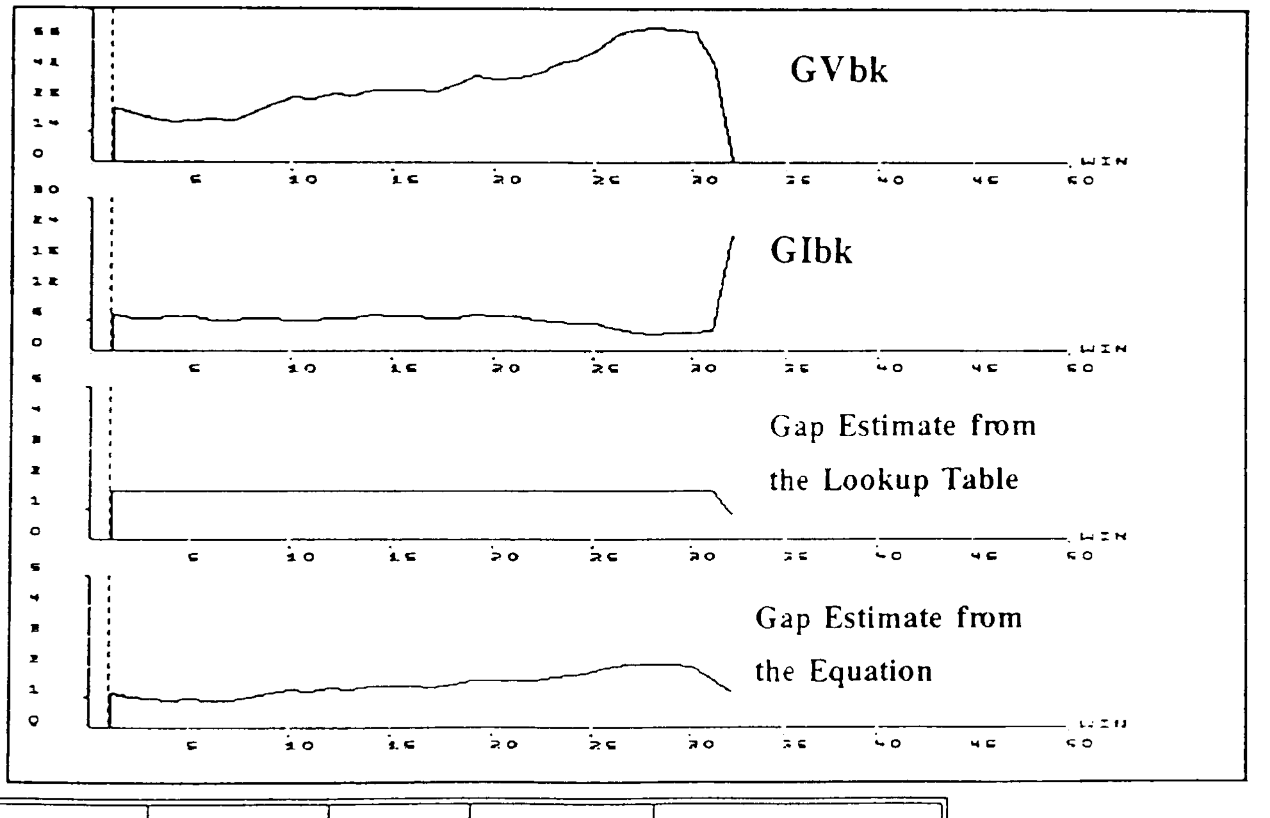
(a)



WFS	V	S	SOref	Comment
6	18.9	0.5	15	Good weld

Simulated gap variation was diverging from 0 to 2 mm. The plate thickness was 3.2mm.

(b)

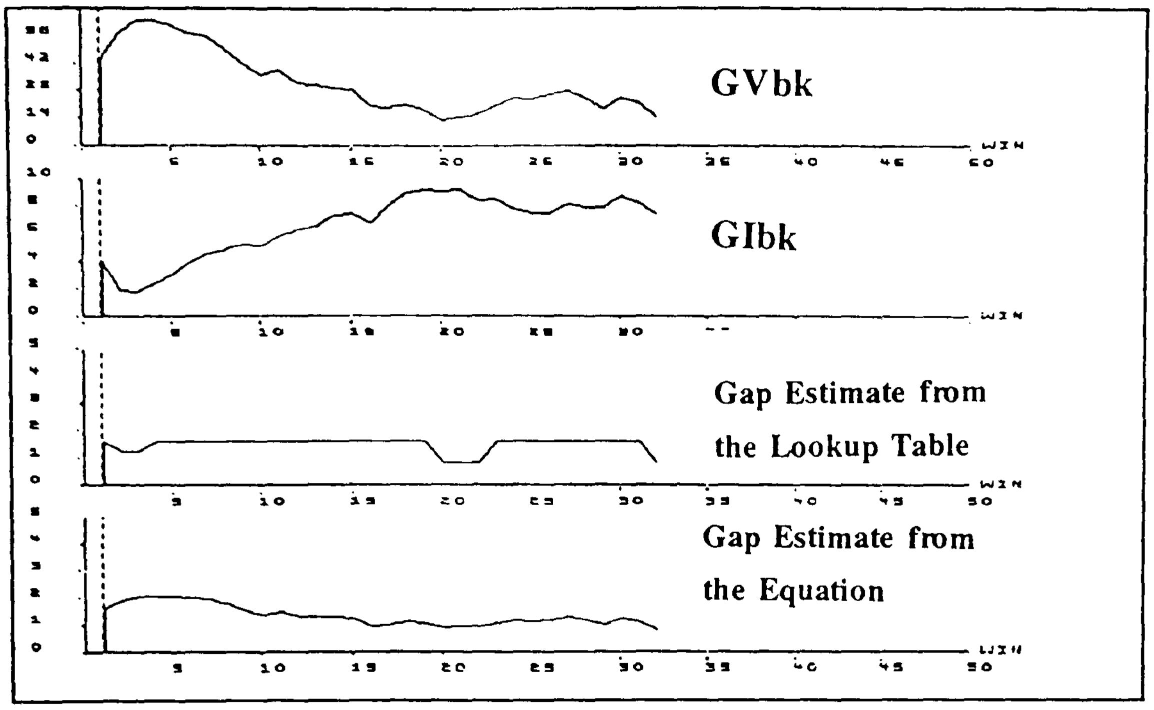


WFS	V	S	SOref	Comment
6	18.9	0.5	15	Good weld

Simulated gap variation was diverging from 0 to 1.6 mm. The plate thickness was 3.2mm.

Figure 5.25 **Gap Detection Model Responses for Diverging Gap**

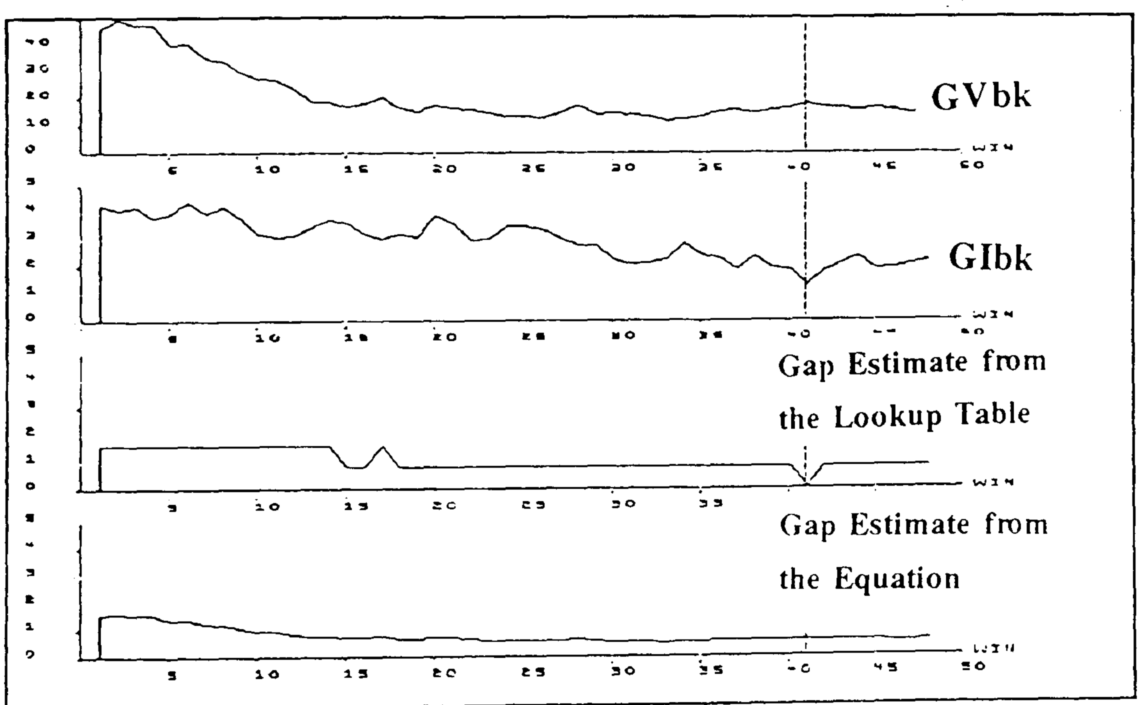
(a)



WFS	V	S	SOref	Comment
6	18.9	0.5	15	Good weld

Simulated gap variation was converging from 1.6 to 0 mm. The plate thickness was 3.2mm.

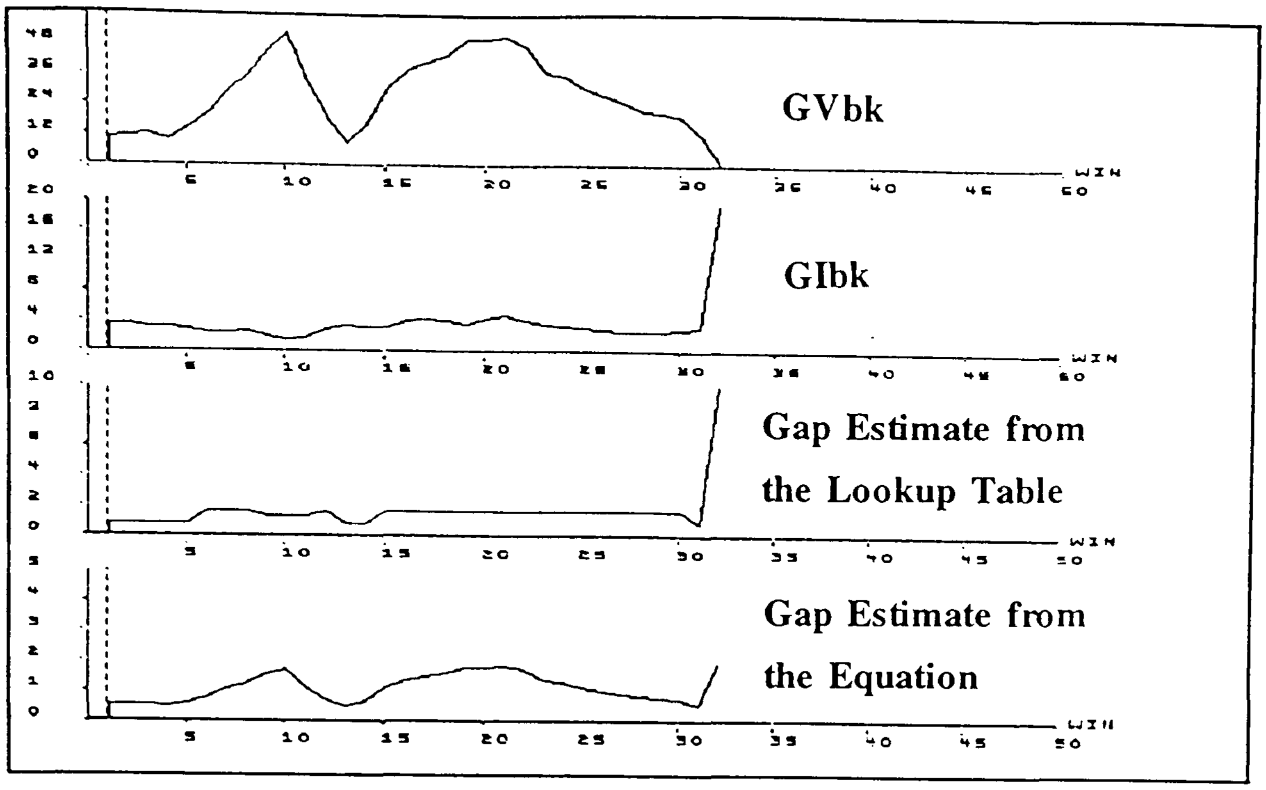
(b)



WFS	V	S	SOref	Comment
8	19.2	0.8	12	Good Weld

Simulated gap variation was converging from 1.6 to 0 mm. The plate thickness was 1.6mm.

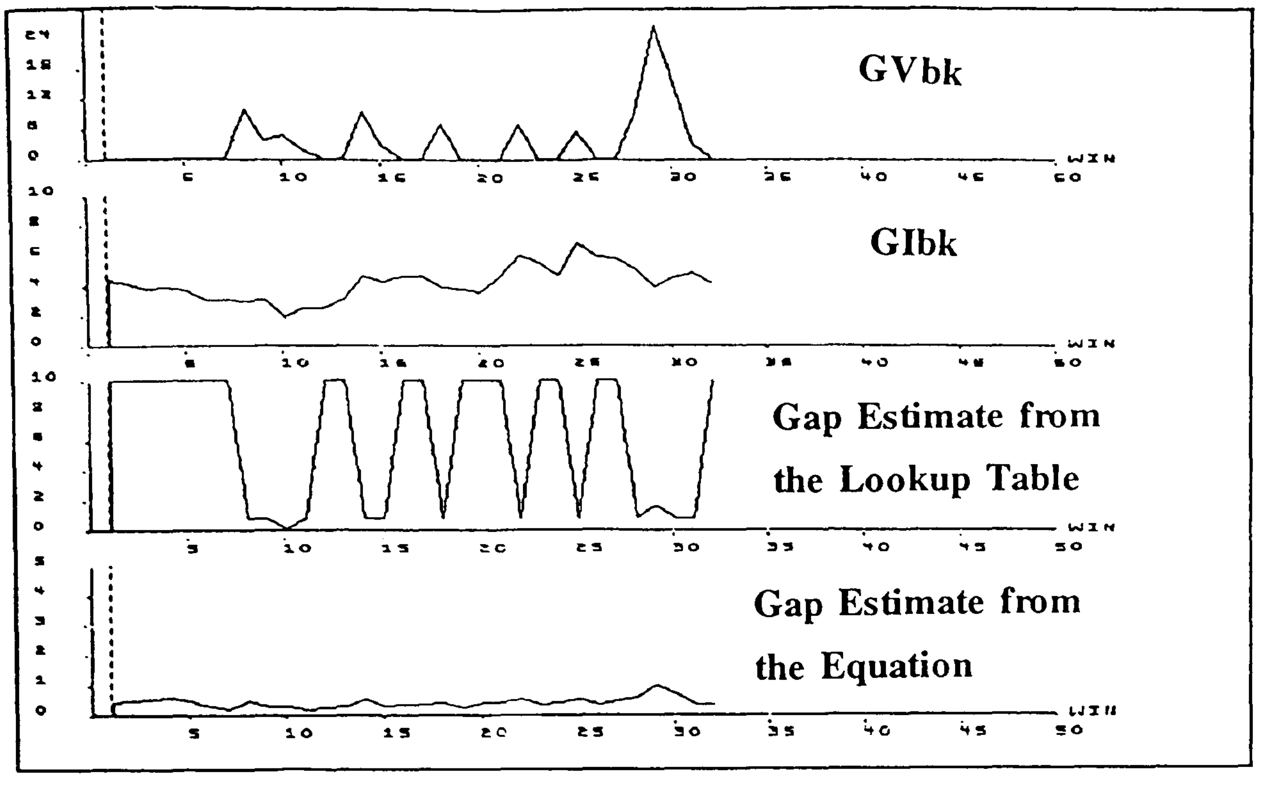
Figure 5.26 Gap Detection Model Responses for Converging Gap



WFS	V	S	SOref	Comment
6	18.9	0.75	15	Burnthrough present

Joint has no gap. The plate thickness was 1.6mm.

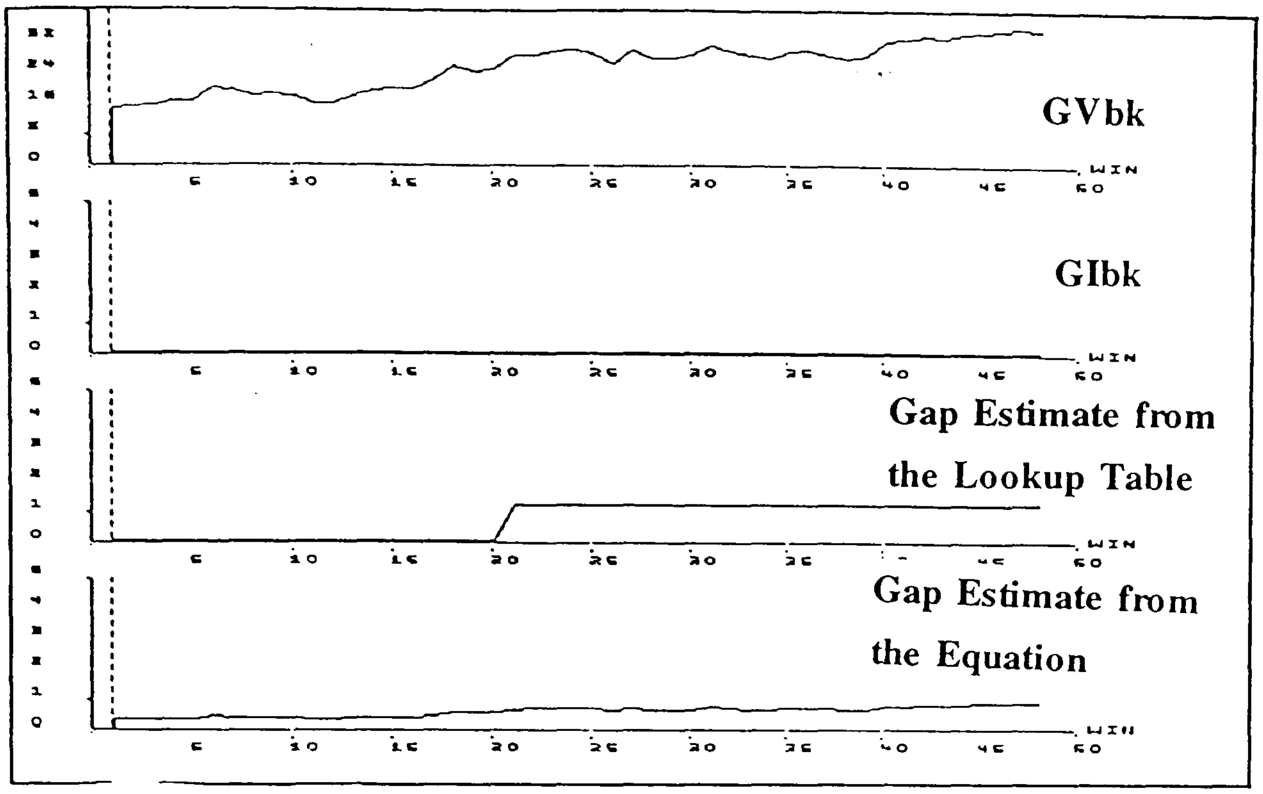
Figure 5.27 Gap Detection Model Responses for Discrete Burnthrough



WFS	V	S	SOref	Comment
6	18.9	0.75	15	Consistent intermittent burnthrough present

Simulated gap variation was diverging from 0 to 1.6 mm. The plate thickness was 1.6mm.

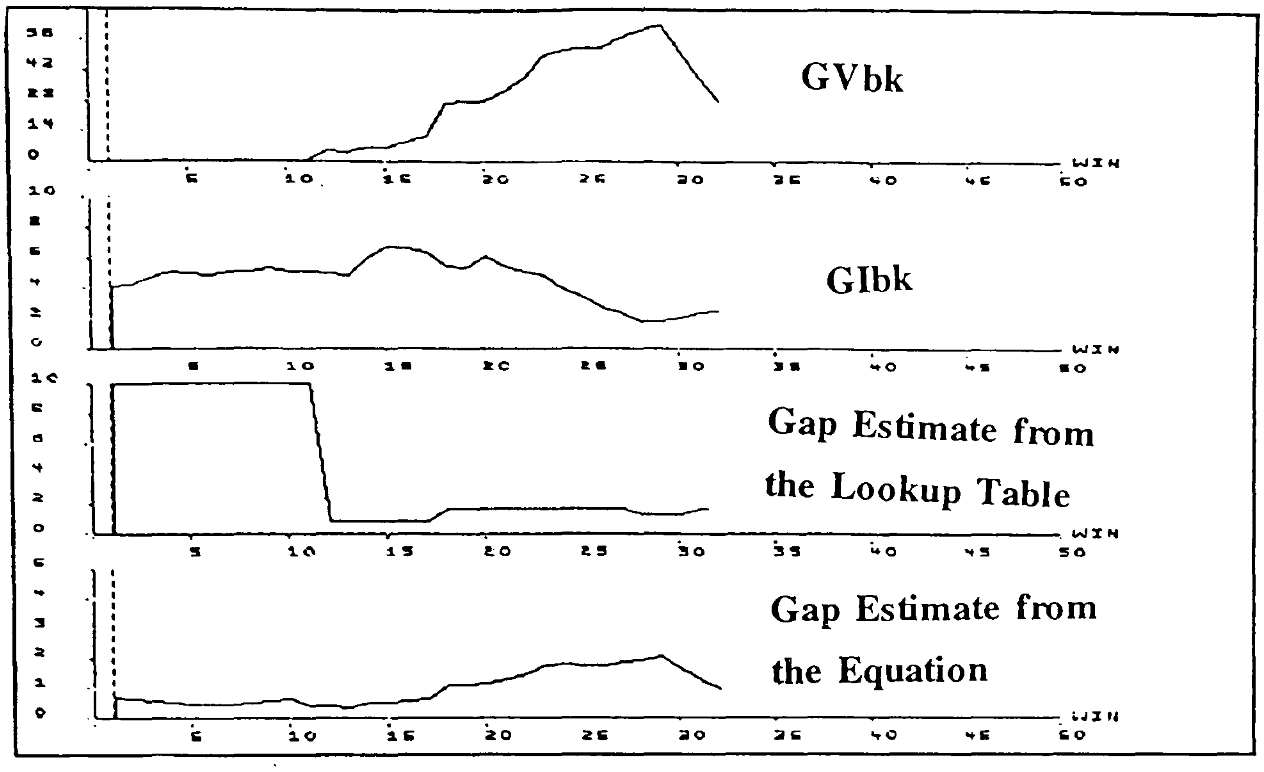
Figure 5.28 Gap Detection Model Responses for Intermittent Burnthrough



WFS	V	S	SOref	Comment
6	17.6	0.6	12	Gap not filled

Simulated gap variation was converging from 1.6 to 1 mm. The plate thickness was 1.6mm.

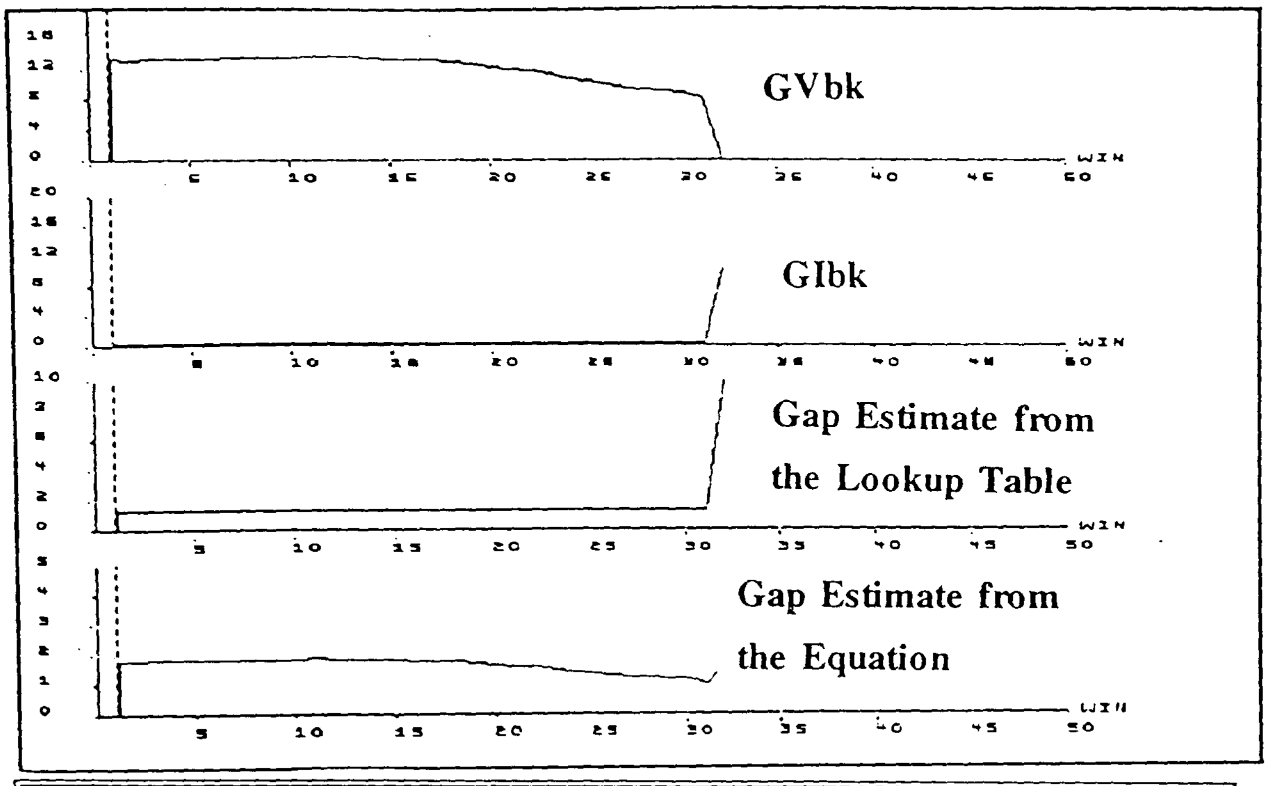
Figure 5.29 Gap Detection Model Responses when Procedure is not adequate for Gap in some part



WFS	V	S	SOref	Comment
6	18.9	0.75	15	Gap not filled

Simulated gap variation was converging from 3.2 to 1.6 mm. The plate thickness was 1.6mm.

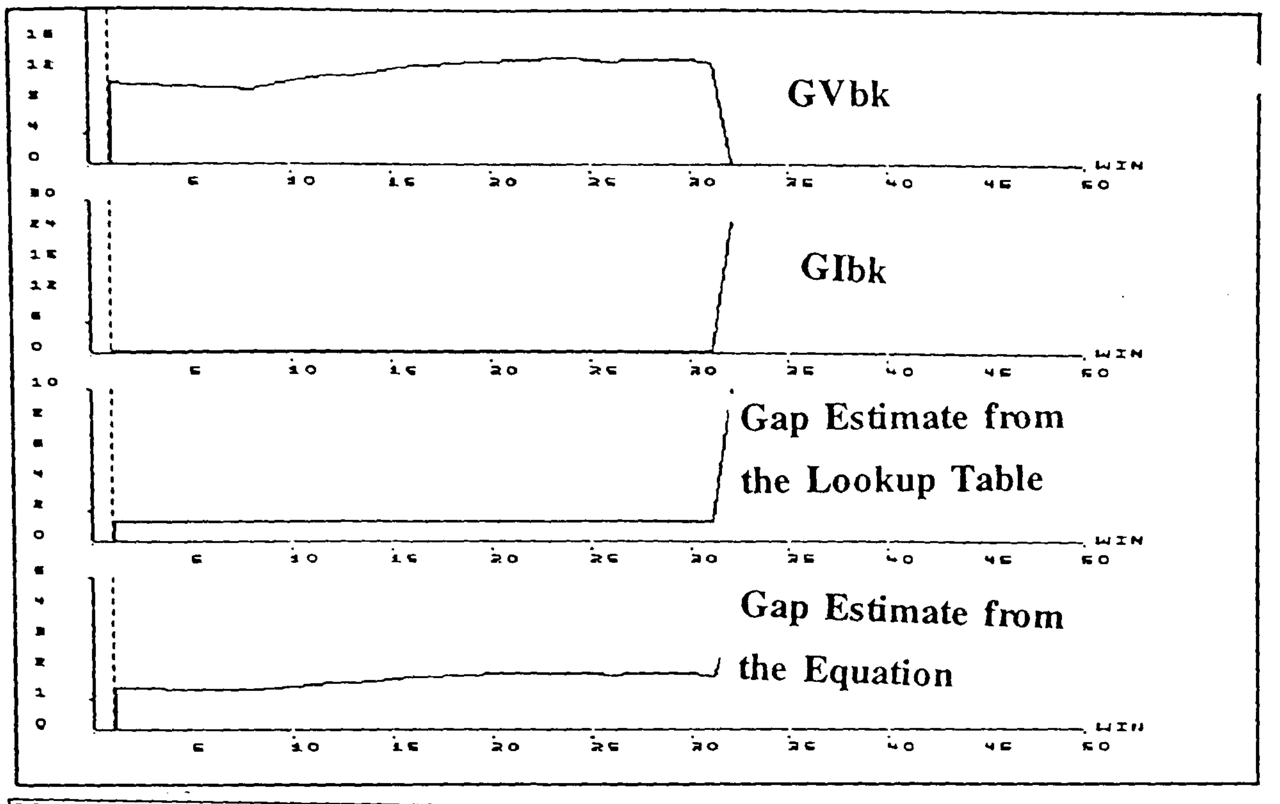
Figure 5.30 Gap Detection Model Responses when Procedure is burning through the Gap in some part



WFS	V	S	SOref	Comment
14	28.8	0.75	15	Good fill until 14cm into the weld

Simulated gap variation was diverging from 0 to 3.2 mm. The plate thickness was 3.2mm.

Figure 5.31 Gap Detection Model Responses for Diverging Gap with Spray Transfer



WFS	V	S	SOref	Comment
14	28.8	0.75	15	Gap not filled until 11cm into weld

Simulated gap variation was converging from 3.2 to 0 mm. The plate thickness was 3.2mm.

Figure 5.32 Gap Detection Model Responses for Converging Gap with Spray Transfer

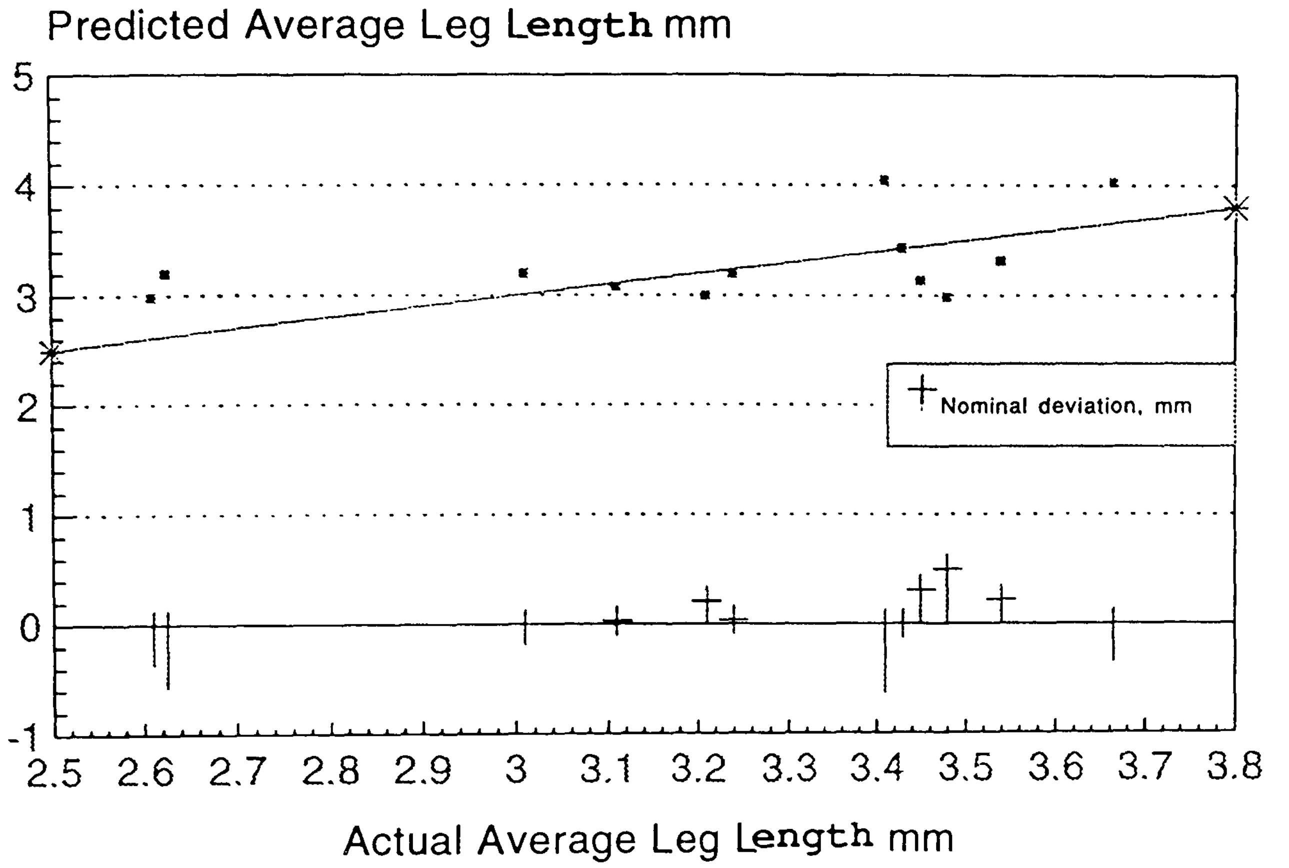


Figure 5.33 Testing Leg length Model: on-line

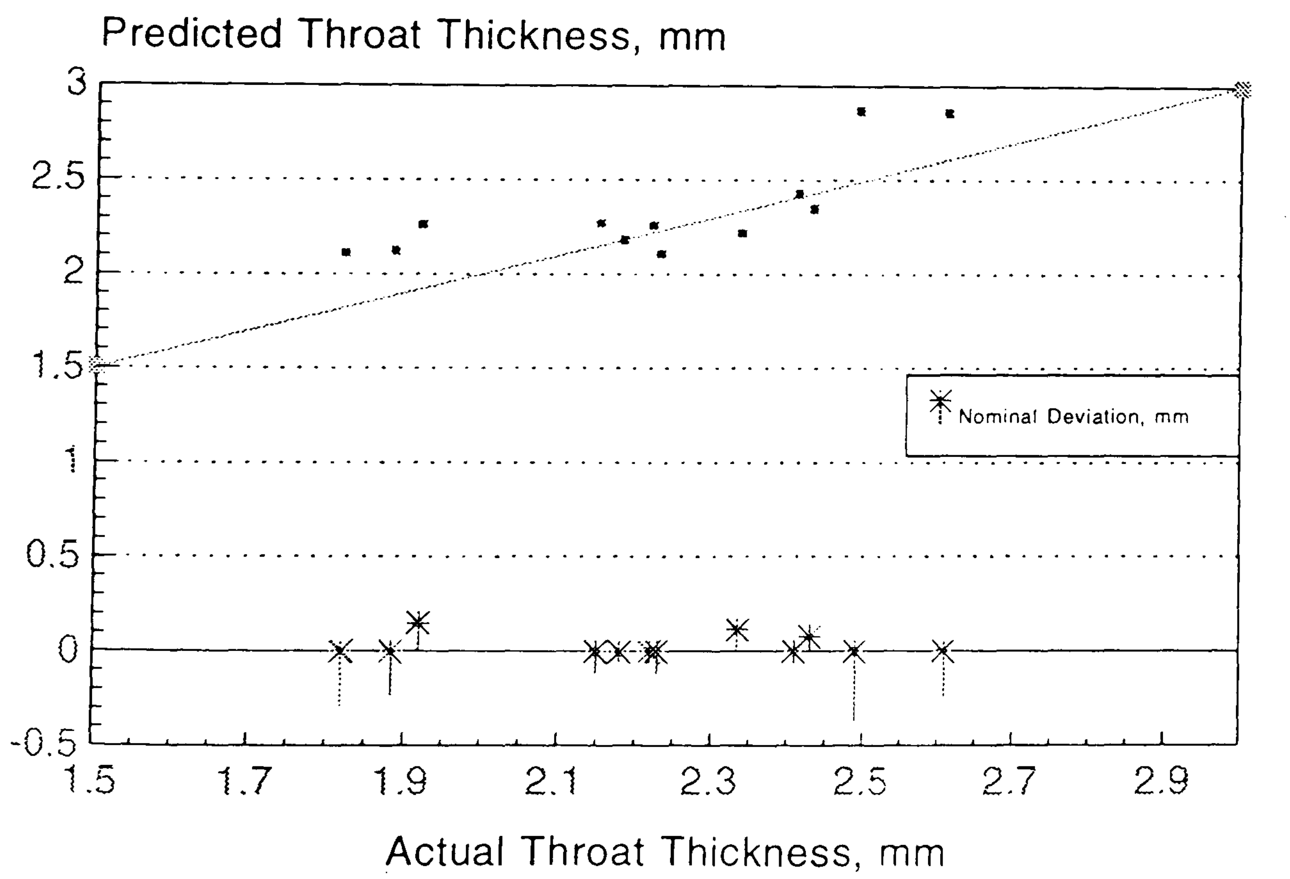


Figure 5.34 Testing Throat Thickness Model:on-line

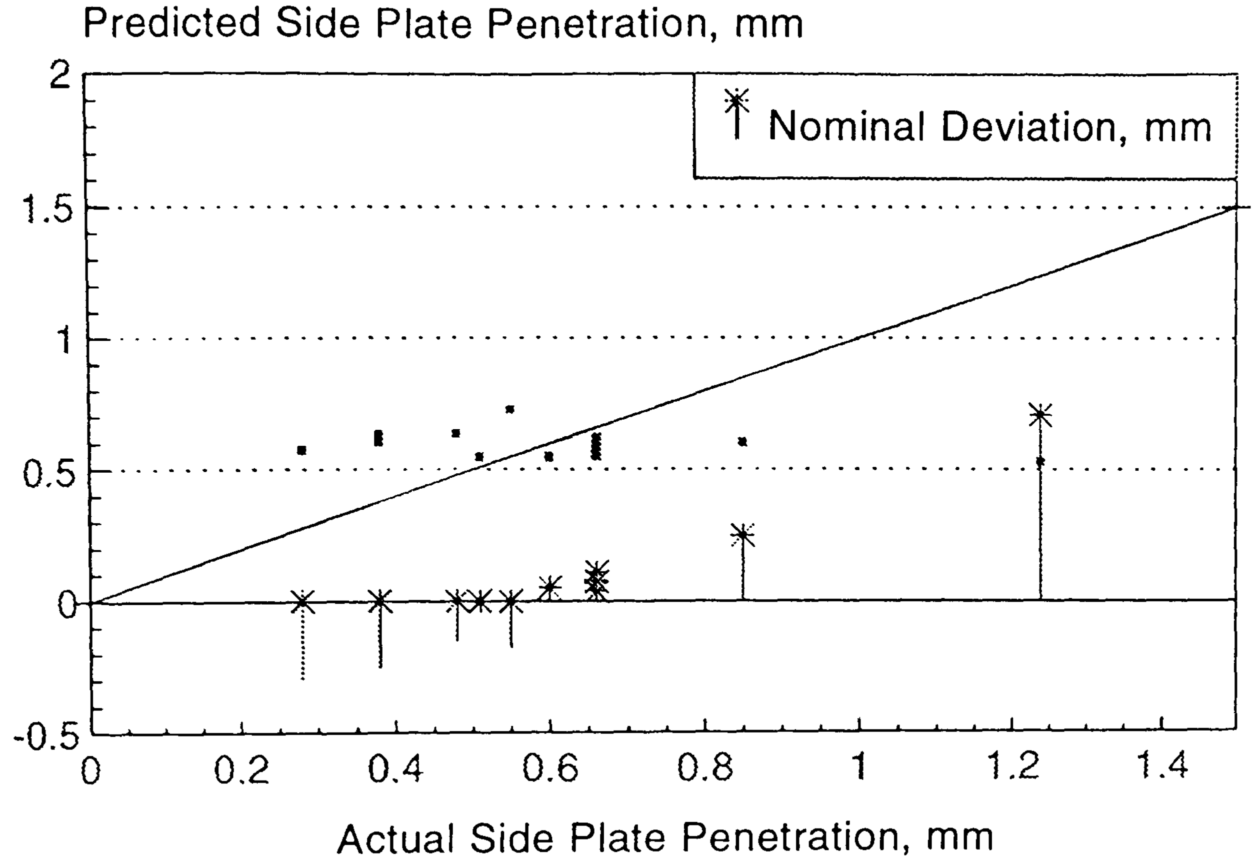


Figure 5.35 **Testing Side Plate Penetration Model:on-line**

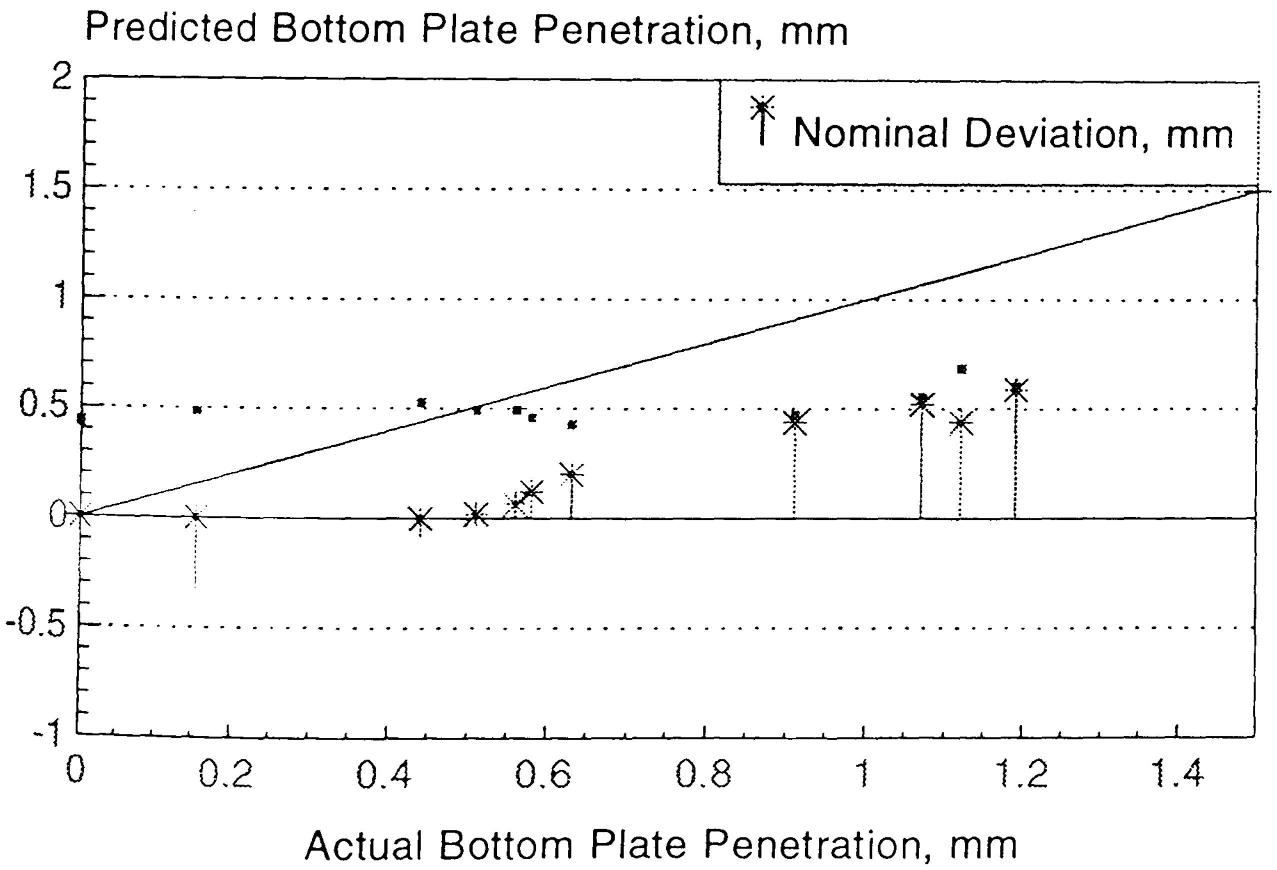


Figure 5.36 **Testing Bottom Plate Penetration Model:on-line**

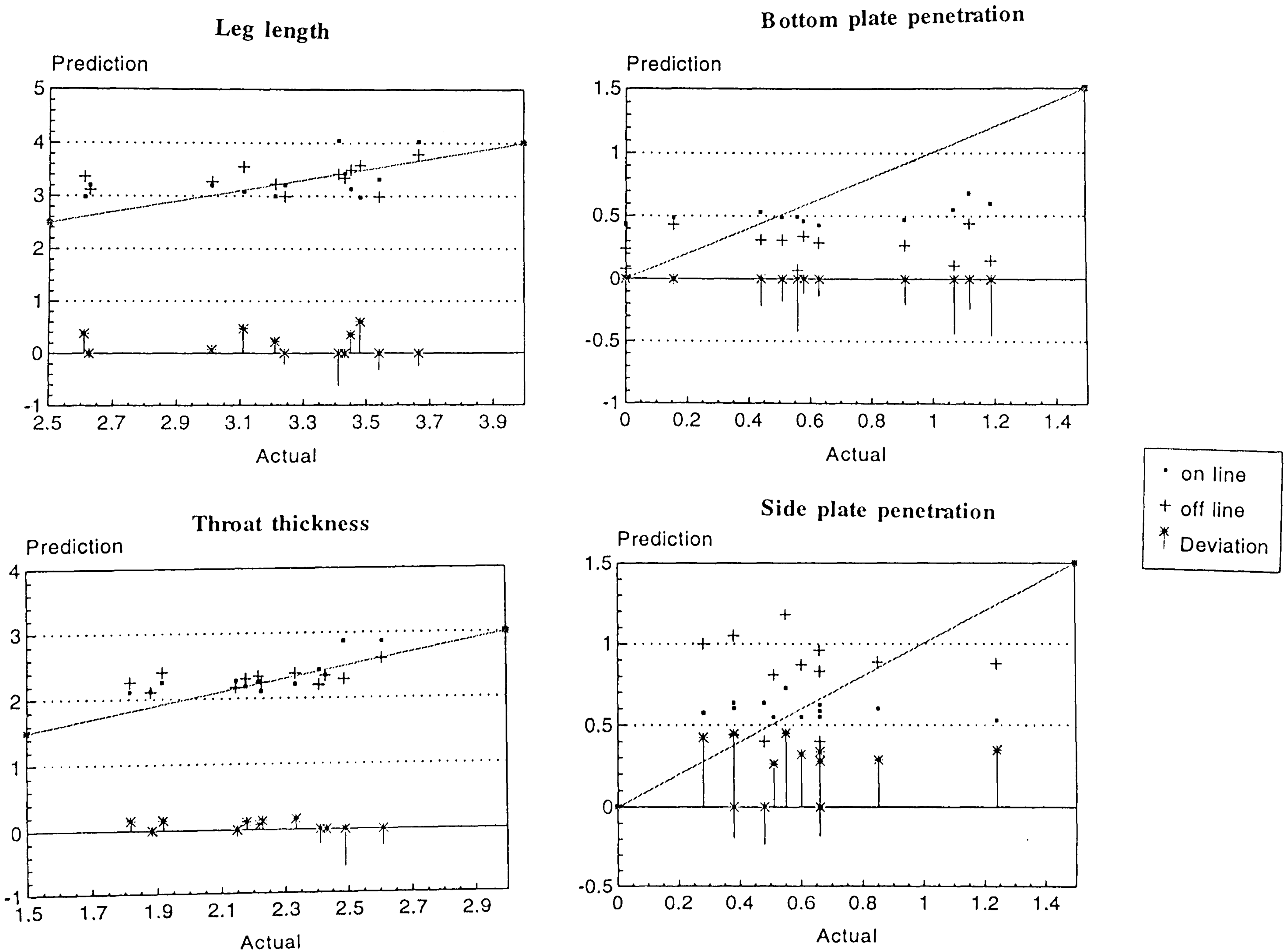


Figure 5.37 **Comparison between on-line and off-line predictions**

Chapter 6
Welding Procedure Optimisation Algorithm

The first line of defence against producing defective welds is to use optimum welding parameters. An optimisation algorithm was therefore developed. The optimisation algorithm presented makes it possible to meet different specifications and quality requirements.

The algorithm is used to identify welding parameter combinations that would satisfy the required multiple quality objectives. This involves the integration of some of the models taking into account specified quality requirement, joint geometry and welding position.

The optimisation strategy was based on an iterative strategy utilising a **bubble sort**[P] procedure to minimise an objective function. It involves running all possible combinations of input parameters in the developed models within the experimental parameters range and assigning an objective factor to them. The optimisation routine is supplemented with the developed synergic algorithm (section 5.3.5) in manual mode. This should minimise the occurrence of spatter. The optimisation concept is explained below in steps.

6.1 Specification of Quality Requirements

In sheet metal welding fabrication a major indicator of quality is bead dimension. The leg length or throat thickness is usually specified in the case of fillet welds. Also required are application specific information such as the welding position, plate thickness and the gap size (if any) in the joint.

P Samways and Byrne-Jones[221] defines bubble sort as follows: A bubble sort is a routine for sorting items into an order, for example from highest to lowest value. This involves starting at the top of a list and comparing each data item with the next and moves it up the list if appropriate (rising like a bubble). The process is reapeted over and over again until there is no movement during a complete pass through, and all the items have 'bubbled' into their place.

6.2 Establishing Process Constraints

Bead dimensional accuracy is very critical in most welds. An over-size weld is likely to imply higher cost and under size may result in inadequate joint strength. Hence, a maximum and minimum tolerance has to be established for bead size. It would be assumed in this work that the predicted bead size by the models should not deviate by more than 20% of the specified or 0.5mm which ever is smallest.

It is desirable to have a robust strategy that could be transferred easily. It was thought that the model although developed for 3.2mm plates can be extended to plate thickness ranging from 1.6 to 6mm. The main problem would be obtaining adequate fusion on the thicker plates and preventing overpenetration and burnthrough in thinner plates.

It was assumed based on data from Cary[122,] that there is a minimum acceptable voltage level related to a plate thickness, so that enough power is available to melt the plate, especially in dip welding subject to having a stable arc. The voltage ranges given for dip welding are 17-20, 18-20, 19-24 volts for 1.6, 2 and 3.2mm plate thickness respectively. The minimum voltage requirement was subsequently set as 15 plus the plate thickness (in mm). The manufacturers of welding wires also specify the working range for their wires; the maximum voltage specified for each wire would not be exceeded in this case.

The models developed were also used to predict welding conditions for positional welds and welds with gap; to accomplish this it was found necessary to constrain the maximum wire feed speed to 10m/min.

6.3 Process Parameter Range

The parameter range must be determined and fixed within the experimental range used to develop process models. The range for the synergic and manual mode must be determined and then put into an array or a database.

The optimisation technique involved full iteration of all possible parameter combinations within the experimental parameters' range. In the synergic mode, the iteration steps are 0.05m/min and 5amps for the welding speed and synergic current respectively, while in the manual mode, the steps are 0.5m/min and 0.05m/min for wire feed speed and travel speed respectively. However to make the iteration process faster standoff is required to be fixed at a value between 12 and 20mm.

6.4 Integrating Process Models

The various models developed here could be used to predict the characteristics defining the weld quality. For each parameter combination, expected leg length, penetration depth and risk of undercut would be calculated. The synergic algorithm developed could then be used to select the adequate voltage for each wire feed speed.

6.5 Establishing the Objective Function

The objective function is used to express the quality requirements in numerical form. Separate optimisation functions were designed for synergic and manual mode.

The basic quality requirements are summarised below:

1. Dimensional accuracy;
2. Minimise the risk of undercut;
3. Ensure adequate penetration;
4. Ensure good ignition;
5. Stable arc with low spatter.

It should also be noted that optimisation is used in this context to merely satisfy these requirements; hence there could be series of good working conditions rather than a unique welding condition. The advantage of this is that choices can be made amongst several possibilities. Therefore, the optimisation algorithm was designed to predict procedures that would produce welds with minimum possibility of defects.

It should be noted however, that the optimisation criteria in this work is focused only on the quality requirements and prevention of the main quality problems; productivity requirements (such as, required minimum number of components per shift or day) and cost considerations were not incorporated into the concept.

Synergic Mode Objective Function

The result of initial testing of synergic mode models shows that risk of undercut is not a problem within the experimental range. However, a logical approach is required in the use of penetration model. The apparent lack of a reliable model for penetration means that care is required. Although when the models predict adequate penetration, it is actually true but the accuracy of the prediction is usually very poor. Hence the optimisation was based only on obtaining dimensional accuracy and any combination that didn't give adequate penetration was rejected.

The objective function to be minimised was

$$F = \alpha F1 + \beta F2 \qquad (6.1)$$

where

F1= (Lmn-Lmin)/(L-Lmin)

F2=(Lavg-Lmax)/(L-Lmax)

α=0.15 and β=0.85

Lmin	*is the minimum leg length acceptable;*
Lmax	*is the maximum leg length acceptable;*
Lmn	*is the predicted minimum leg length;*
Lavg	*is the predicted average leg length;*
L	*is the required (specified) leg length.*

and subject to

IF F1<0 THEN F=999

IF F2<0 THEN F=999

IF Pr(Sp)>0.4 THEN F=999

IF Pr(Bp)>0.4 THEN F=999

The bubble sort approach was used to sort F and any value of F less than 999 then printed out. It should be noted that the values of the constants (α and β) in the synergic mode objective function could affect the efficiency of the optimisation.

Manual Mode Objective Function

It was desired to design an objective function structure that could be used in most welding situations. It should be noted that when welding in the downhand position and/or the joint is with no gap, the main concern is to produce welds with low risk of undercut and adequate fusion. While if welding is positional and/or joint with gap, the concern is to have the weld pool staying in place and gap well filled (see Section 2.1.4).

The arc power is the key optimisation parameter for quality control. It has to be minimised to ensure a good weld whatever the welding position. Arc power (PARC) is the product of the welding current and voltage.

The objective function was modular and designed to minimise the arc power while taking into account the quality requirements.

The objection function was:

$$F= F1+F2+F3+F4+(PARC*1E\text{-}4) \qquad (6.2)$$

A goal seeking approach was adopted with each sub-function making decision. F1 was used to decide whether the bead is within the required dimension range. F2 is used to ensure adequate penetration and F3 assess the ease of arc ignition. F4 is used to ensure low risk of undercut.

The decisions to be made are:

1. Is bead size within required tolerance ?

IF (Lmn>Lmin)AND(Lavg<Lmax) THEN F1=0 ELSE F1=999

2. Is penetration adequate ?

The modelling work by Kutenov et al.[192] was adopted. Penetration was expressed as a ratio of plate thickness. According to the specifications, at least 10 percent of the plate must be penetrated. The ratio was constrained within 0.1-0.6. The minimum voltage (Vmin) level checked to ensure adequate arc power to plate thickness.

That is,

```
IF (P>.1)AND(P<.6)AND(V>Vmin) THEN F2=0 ELSE F2=999
```

where P is the ratio of penetration depth to plate thickness.

3. Is the possibility of bad arc ignition low ?

```
IF Pr(arc)<0.4 THEN F3=0 ELSE F3=999
```

4. Is the possibility of undercut low ?

```
IF Pr(und)<0.35 THEN F4=0 ELSE F4=999
```

The bubble sort routine was used to sort F and any value of F less than 999 then printed out.

6.6 Testing the Optimisation Algorithm

The models and optimisation routine were computerised using BASIC programming language and some of its predictions were tested. The emphasis was on manual mode but the synergic mode was also tested. It was decided to make standoff a fixed parameter; to be specified by the user.

The synergic mode models were used only on 1.6mm plate; whilst, manual mode was used on both 1.6 and 3.2mm.

Synergic Mode

Test runs were made for predicted welding conditions expected to give 2.5-4mm leg length on a 1.6mm mild steel. The standoff was fixed at 12mm. The welding condition predicted gives good weld quality. Figure 6.1 and Table 1 in Appendix F shows the correlation between predicted quality and actual quality.

Manual Mode

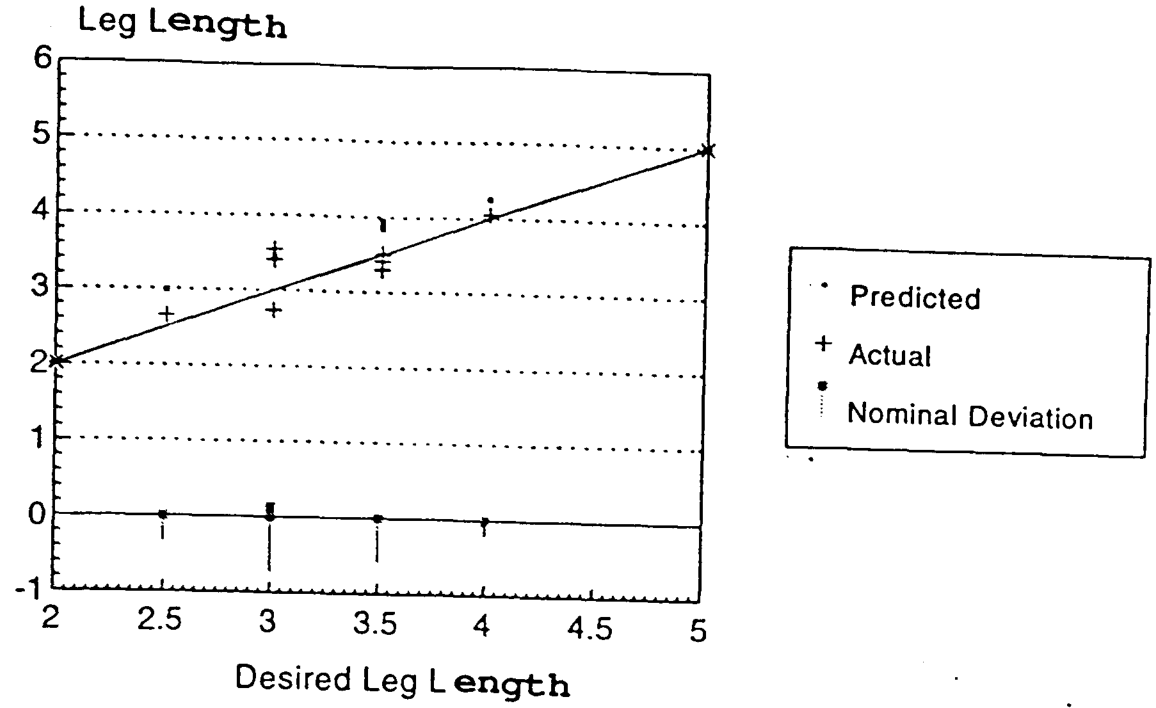
Test runs were made for predicted welding conditions expected to give 2.5-6mm leg length on both 1.6 and 3.2mm mild steel plate. The predicted condition gives good quality welds on both plates (see Figures 6.2 and 6.3).

Although the models are developed in horizontal vertical position for a fillet with no gap. It was proven that the models can be adapted to joints with gap and/or positional welds. The main requirement is that the welds be done using dip transfer and subject to the constraint identified in the synergic algorithm (see section 5.3.5). The synergic algorithm was critical to the adaptation of the models. It should be noted that some errors are expected. Satisfactory weld quality was obtained for joints with constant and diverging gap (see Table 3 in Appendix F).

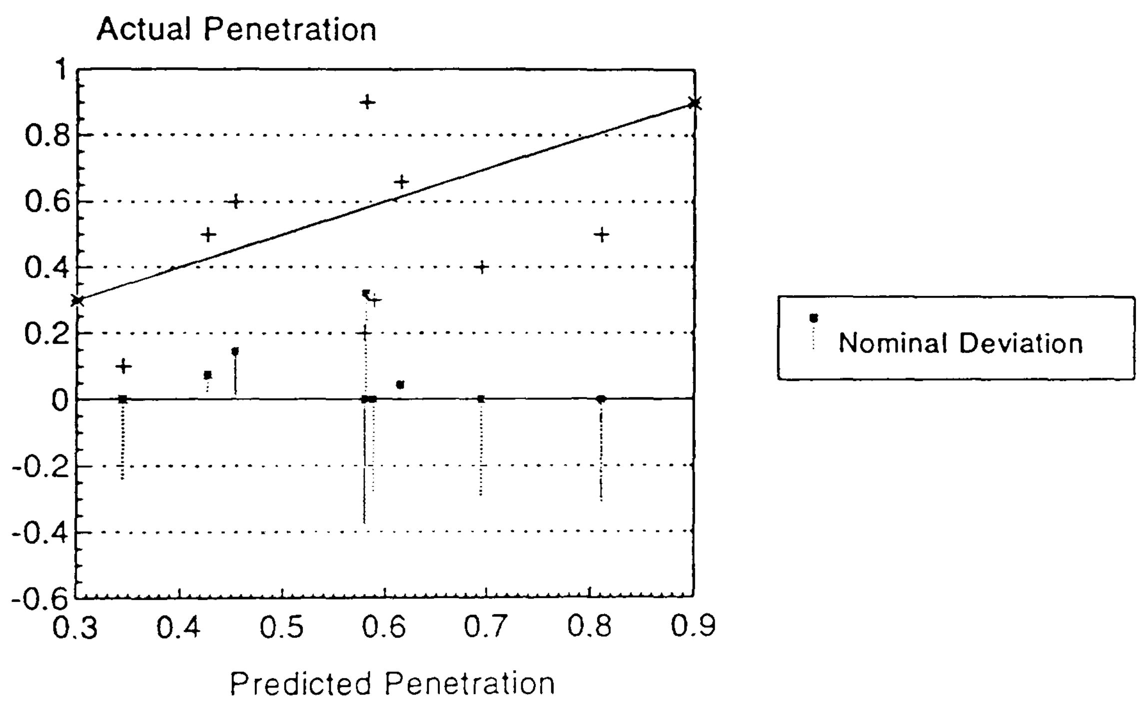
In generating the welding parameters for joint with gap; the amount of metal required to fill or that would be forced into the space created by the gap wasn't considered. It was assumed that this would be minimal due to the use of dip transfer; however approximately half millimetre drop in leg length dimension per millimetre gap size was observed.

Satisfactory weld quality was obtained for vertical down welds (see Figure 6.4). Vertical up welds of good quality were obtained but these were "peaky" leading to poor dimensional accuracy.

a) Leg Length



b) Bottom Plate Penetration



c) Side Plate Penetration

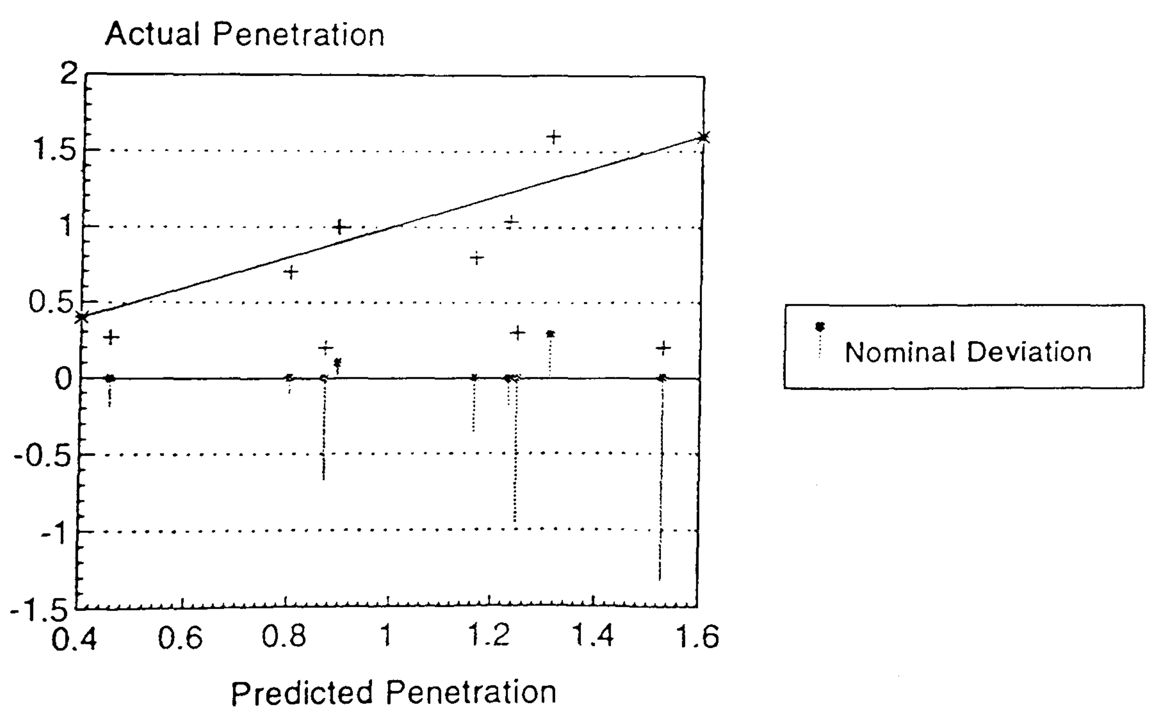
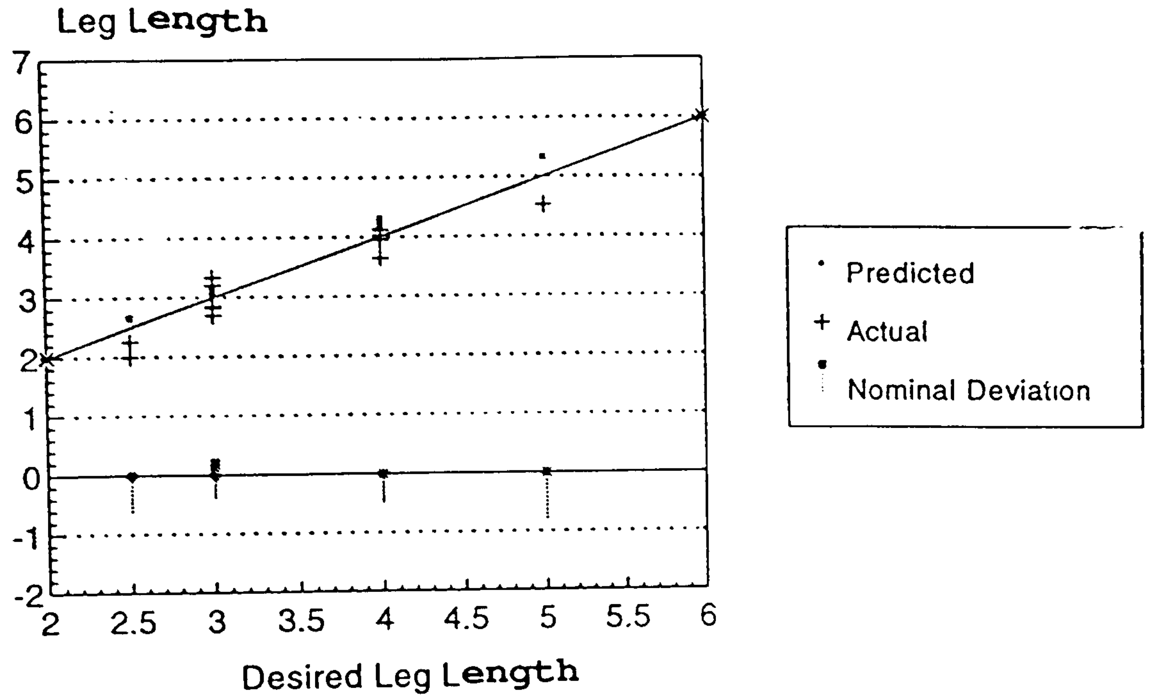
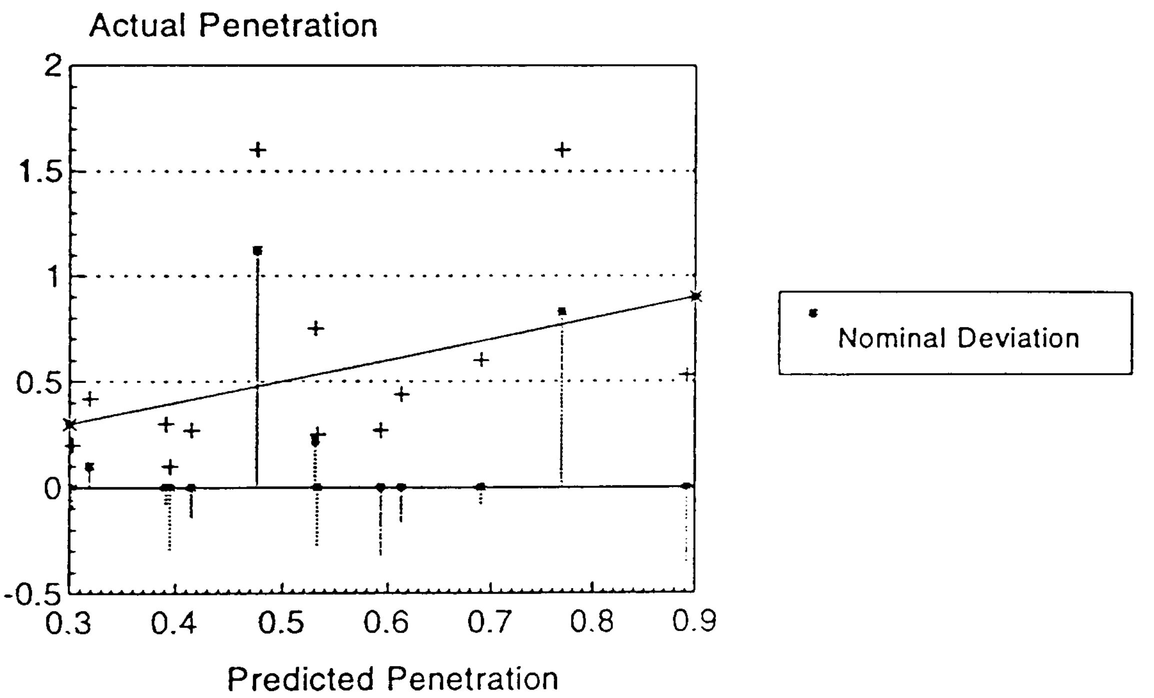


Figure 6.1: Testing Synergic Mode Optimisation Algorithm

a) Leg Length



b) Bottom Plate Penetration



c) Side Plate Penetration

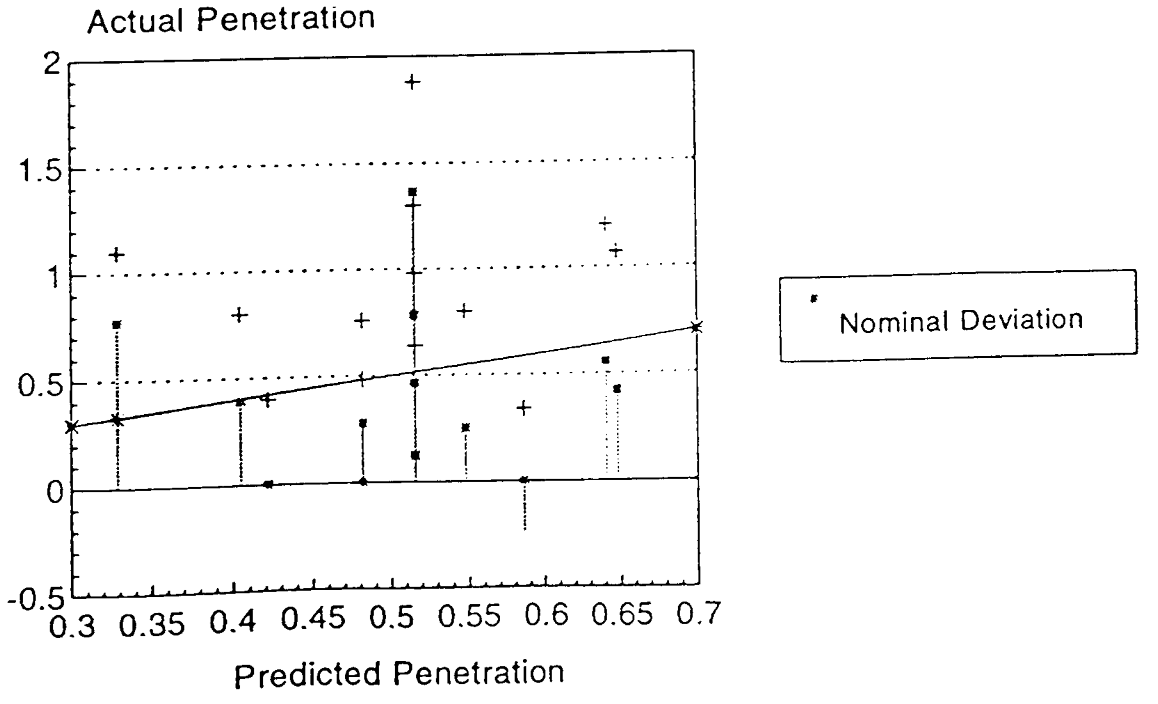
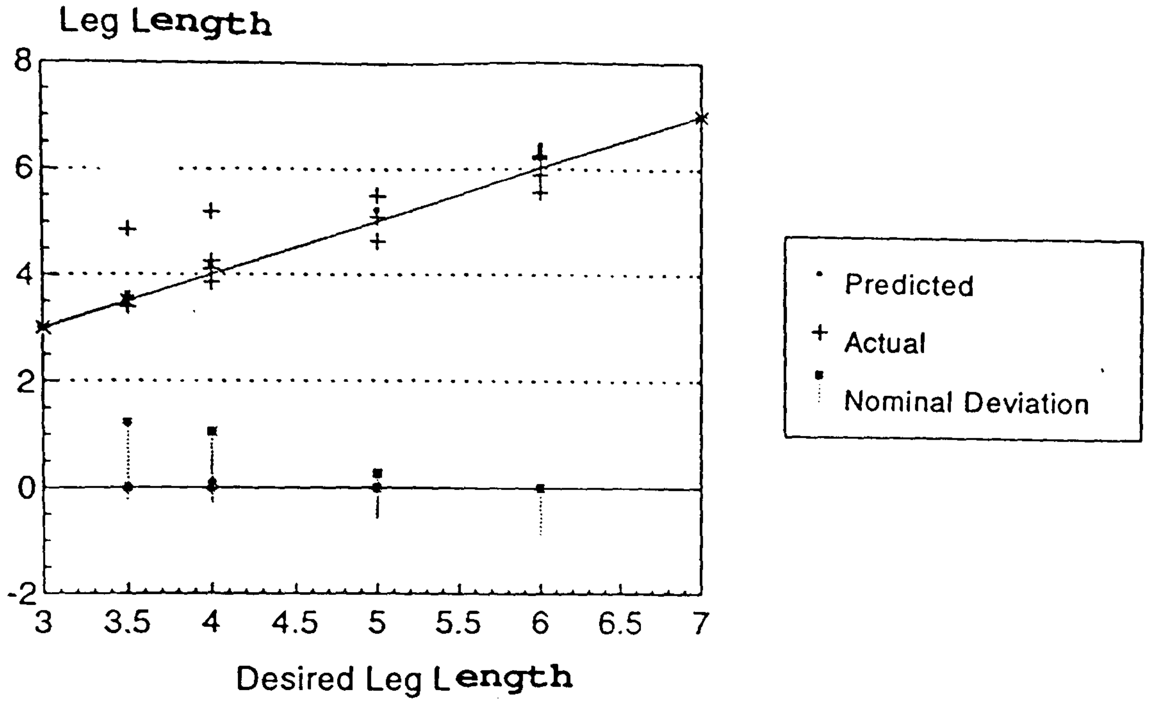
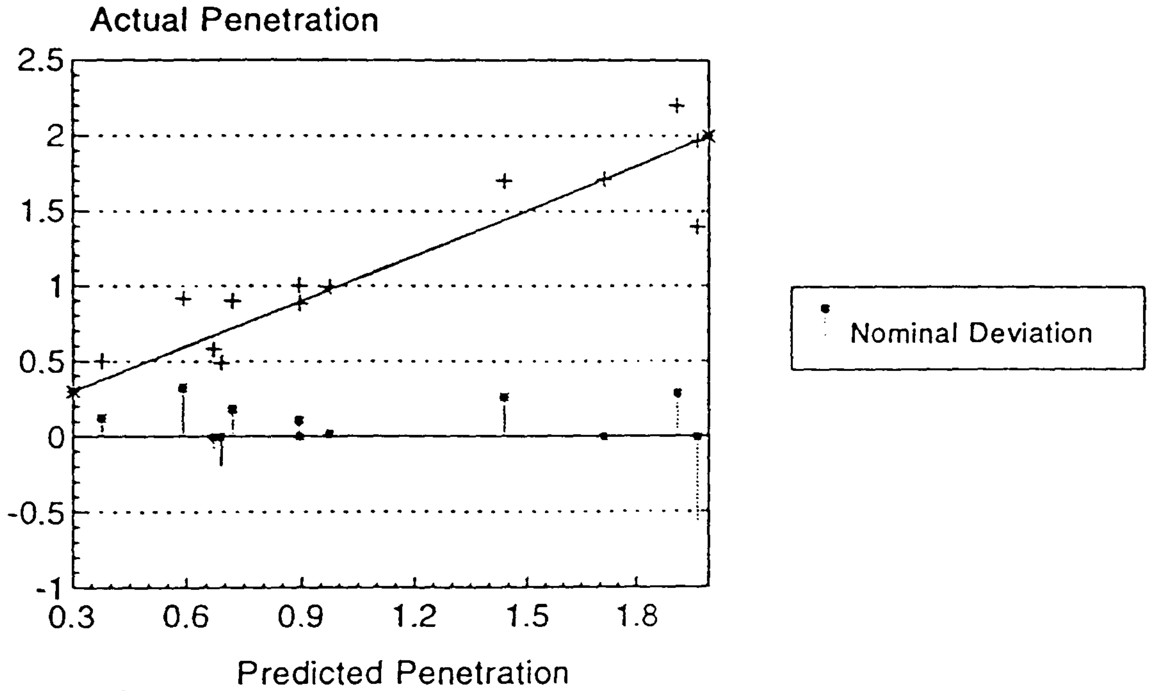


Figure 6.2: Testing Manual Mode Optimisation Algorithm: Plate Thickness=1.6mm

a) Leg Length



b) Bottom Plate Penetration



c) Side Plate Penetration

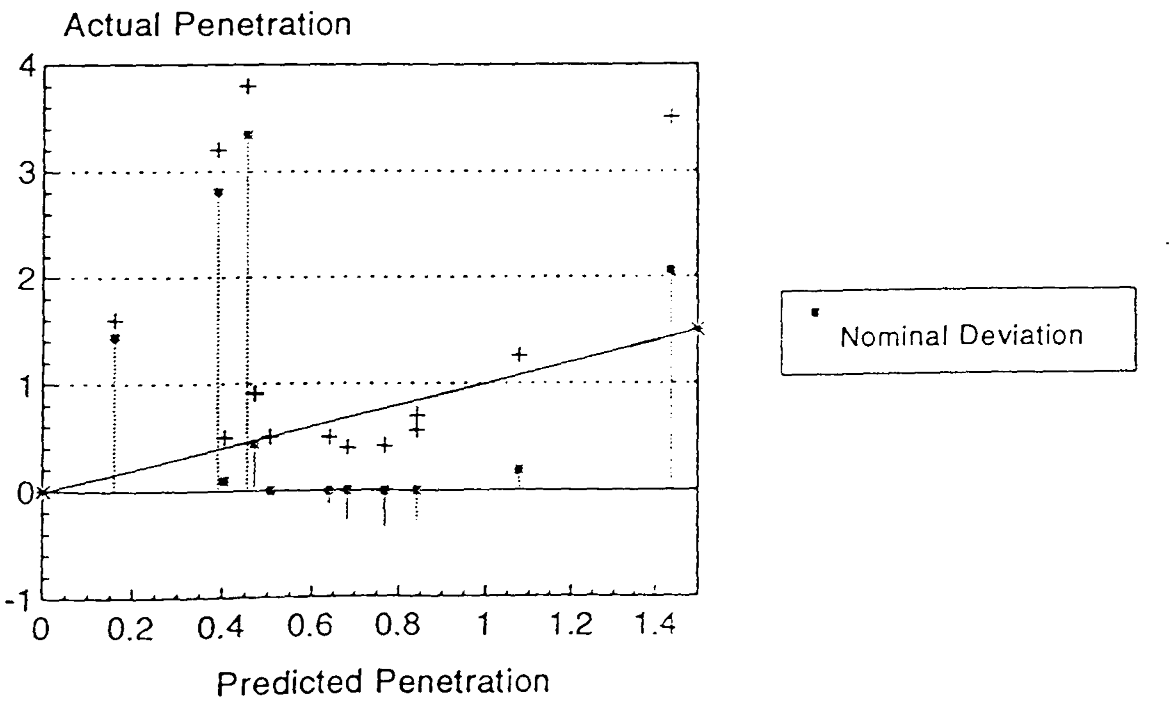
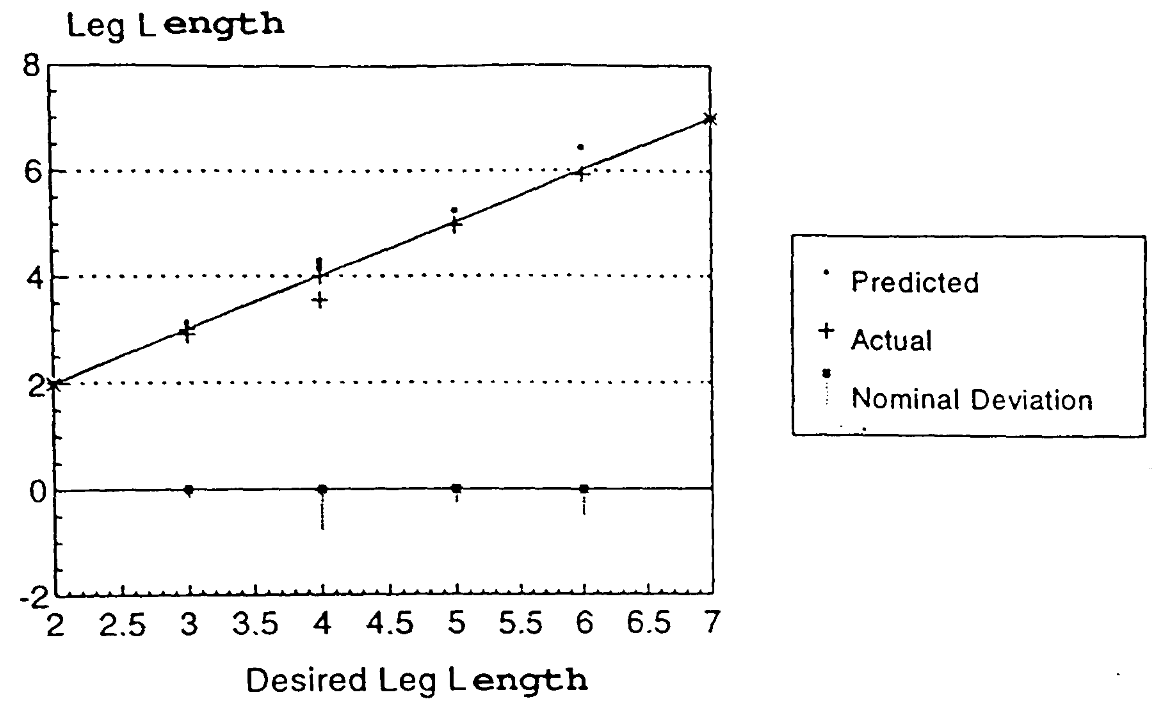
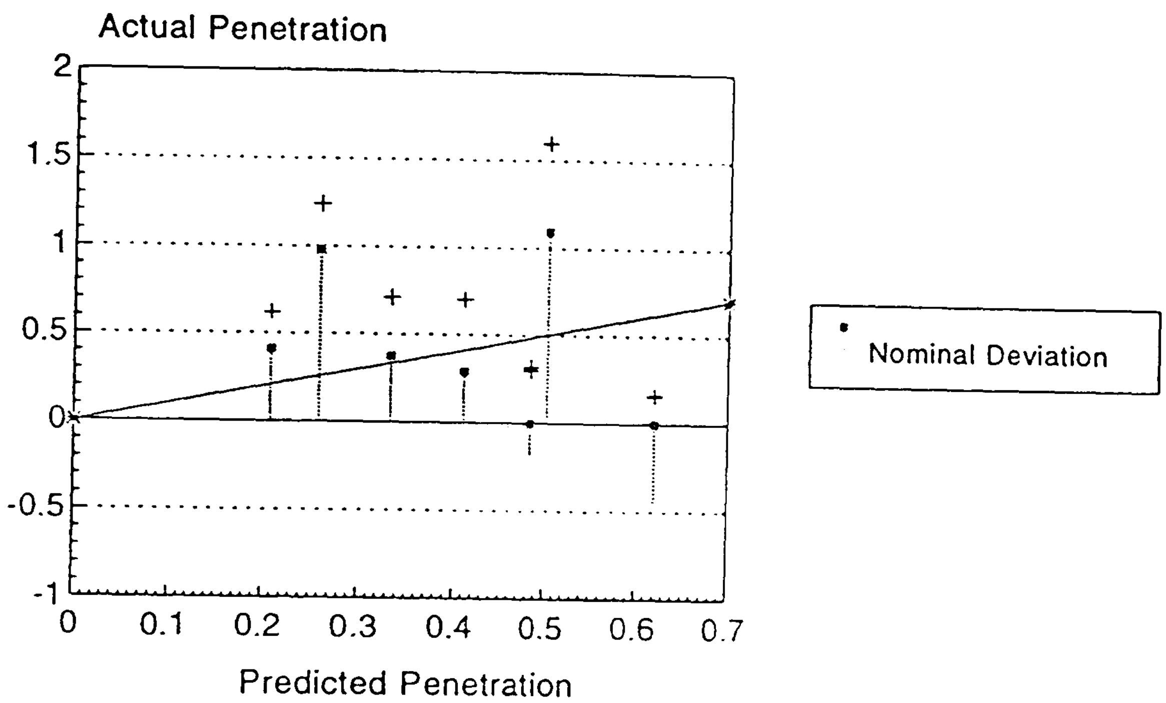


Figure 6.3: Testing Manual Mode Optimisation Algorithm: Plate Thickness=3.2mm

a) Leg Length



b) Bottom Plate Penetration



c) Side Plate Penetration

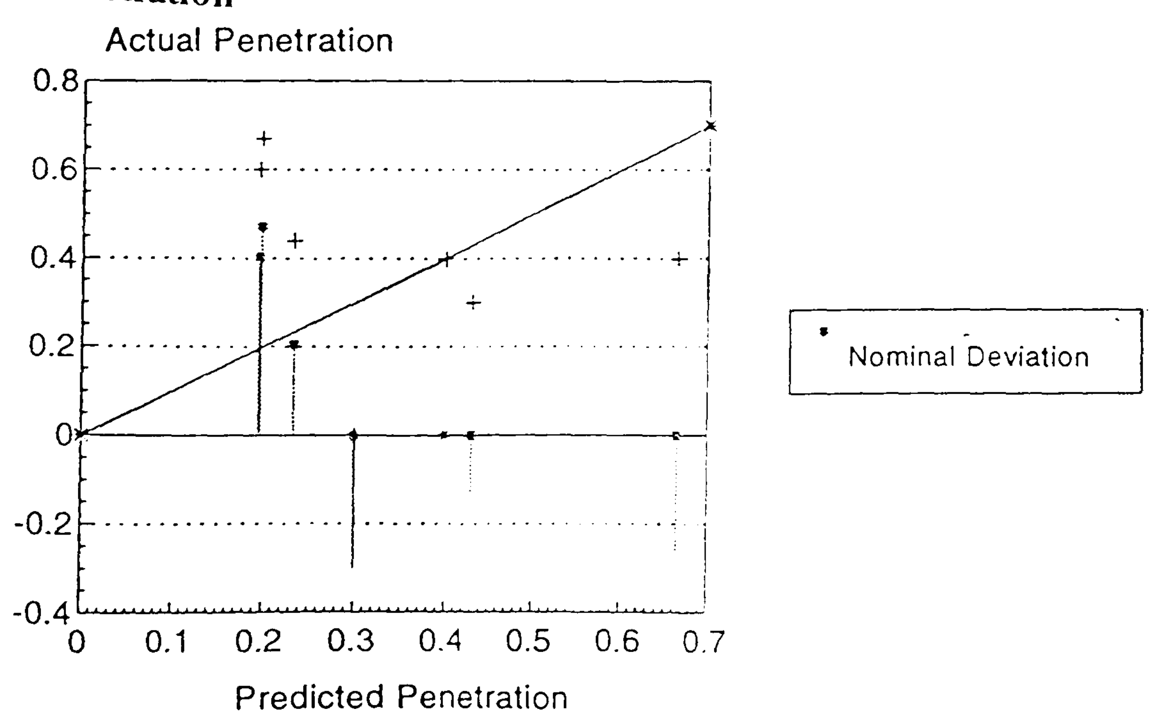


Figure 6.4: Testing Manual Mode Optimisation: Vertical Down Welds

Chapter 7

Adaptive Quality Control Algorithm

It should be noted that weld quality control would involve continuous on-line changes to welding procedure to ensure acceptable quality. As already mentioned in section 3, it is very important to start with an optimum procedure. Then, any changes required should be minor and the transition between the procedures should be stable.

The control algorithm involves the integration of the various regression models correlating the quality and disturbance parameters to the welding parameters. The main objective is to minimise deviation from desired quality requirements.

Gap and standoff variation are the most commonly occurring quality problem in robotic welding of thin sheet. Control algorithms were developed to control their effects on weld quality. It is assumed that the joint will be properly located and seam of joint followed accurately by the robot.

It is obviously very important to have good algorithms to detect any disturbance because without detection control is impossible. The models developed have the capacity to detect gap, standoff variation, arc stability, metal transfer and ignition problems.

Figure 7.1 shows the conceptual algorithm architecture proposed for weld quality control. The five algorithms found necessary to implement the control are described below:

1. Procedure Optimisation Algorithm

The algorithm is to be used to select the welding procedure. The algorithm is fully illustrated in Section 6.

2. Synergic and Metal Transfer Control Algorithm

The algorithm is used to select optimum voltage level. The algorithm is fully illustrated in Section 5.3.5.

3. Monitoring Algorithm

The monitoring algorithm is the collection of models for transfer mode and stability assessment (Section 5.3.2-5.3.3), on-line weld quality assessment (Section 5.5), standoff estimation (Section 5.4.1) and gap detection (Section 5.4.2).

4. Control Algorithm

The control algorithm would mainly compensate for the effect of gap and standoff on final weld quality. The gap and standoff control algorithm are illustrated below in section 7.1 and 7.2 respectively. Note that gap control takes priority over standoff control. However the parameters adaptation for gap should only take place when the gap size exceeds 1mm; based on the observation of the gap detection algorithm (section 5.4.2) it will be assumed that gap size is zero if the prediction is less than 1. Table 7.1 gives an illustration of the control cycle.

Table 7.1 Quality Control Cycle

1.	Start of weld
2.	Get procedure; wire feed speed, voltage, speed and standoff.
3.	Calculate appropriate reference values from the procedure for Imean (equation 5.18), I_{bk} (equation 5.23), GI_{bkmin} (equation 5.50), V_{bk} (equation 5.22), GV_{bkmin} (equation 5.49).
4.	Select appropriate sample rate, sample size and interval
5.	Begin welding
6.	Collect samples of welding wavefom
7.	Calculate wavefom statistics
8.	Implement Monitoring and Reporting Algorithm
9.	IF "Arc stable" GOTO 10 ELSE 6
10.	Control Algorithm Priority IF gap<1 GOTO 11 else 12
11.	Implement Standoff Control Algorithm THEN GOTO 13
12.	Implement Gap Control Algorithm THEN GOTO 13
13.	IF "End of weld" GOTO 1 ELSE 6

5. Reporting Algorithm

The reporting algorithm will raise an alarm (audible or printer) if abnormalities, such as arc outage during weld, burnthrough, etc occurs. Also, systematic variation in any of the developed models can be charted for maintenance and quality assurance purposes.

7.1 Control Algorithm for Gap

The presence of a gap implies that the weld size and deposition rate must increase. The leg length for a fillet weld must be increased by the gap size.

It is well established that to minimise the damaging effect of gap, the welding current (wire feed speed) and welding speed should be reduced with increasing gap size in order to reduce the risk of burnthrough and undercut.

A proportionality approach was adopted to adjust the welding parameters if gap variation is detected. Therefore, starting with an optimum welding condition the change necessary in the welding parameter is related by a linear equation to the gap size.
The wire feed speed can be estimated using the equation

$$WFS = WFS_0 - \frac{gap}{pt}\,(WFS_0 - WFS_{min}) \qquad (7.1)$$

where

WFS_0	*is the setup wire feed speed;*
WFS_{min}	*is the minimum wire feed speed (fixed priori to welding);*
WFS	*is the new (setup) wire feed speed;*
pt	*is the plate thickness;*
gap	*is the gap size.*

The appropriate welding voltage would then be calculated using the synergic algorithm. And the welding speed is estimated by rearranging equation 5.7 as

$$S = \frac{WFS}{(L_{avg}+gap)^{\frac{1}{\beta}}} \qquad (7.2)$$

where

S	*is the new (setup) welding speed;*
Lavg	*is the average leg length;*

However, from experimental data it was observed that to ensure quality and minimise productivity loss, the welding speed should not be less than 0.4 m/min.

Therefore, if predicted welding speed is less than 0.4m/min then the welding speed should be fixed at 0.4m/min and the wire feed speed re-estimated using

$$WFS = S\,(L_{avg}+gap)^{\frac{1}{\beta}} \tag{7.3}$$

7.2 Control Algorithm for Standoff Variation

If standoff changes, it can either be corrected through the welding robot program or by maintaining the welding current at a reference value by controlling the wire feed speed. This can be done by reversing equation 5.18, that is,

$$WFS = \frac{(I_{ref}-\alpha_3)}{(\beta_3+\delta_3 SO_i)} \tag{7.4}$$

where

I_{ref} *is the reference welding current estimated from procedure using equation 5.18;*

SO_i *is the standoff at interval i.*

It was assumed that this would keep penetration relatively consistent inspite of standoff variation. However, increasing wire feed speed to compensate for reduction in current will lead to an increase in bead size unless speed is increased to take bead size into consideration.

The welding speed control equation is

$$S = \frac{WFS}{(L_{avg})^{\frac{1}{\beta}}} \tag{7.5}$$

The appropriate welding voltage would then be calculated using the synergic algorithm. If any control action is taken, then the constant in the standoff estimation model must be recalculated using the new wire feed speed and standoff as the reference input values.

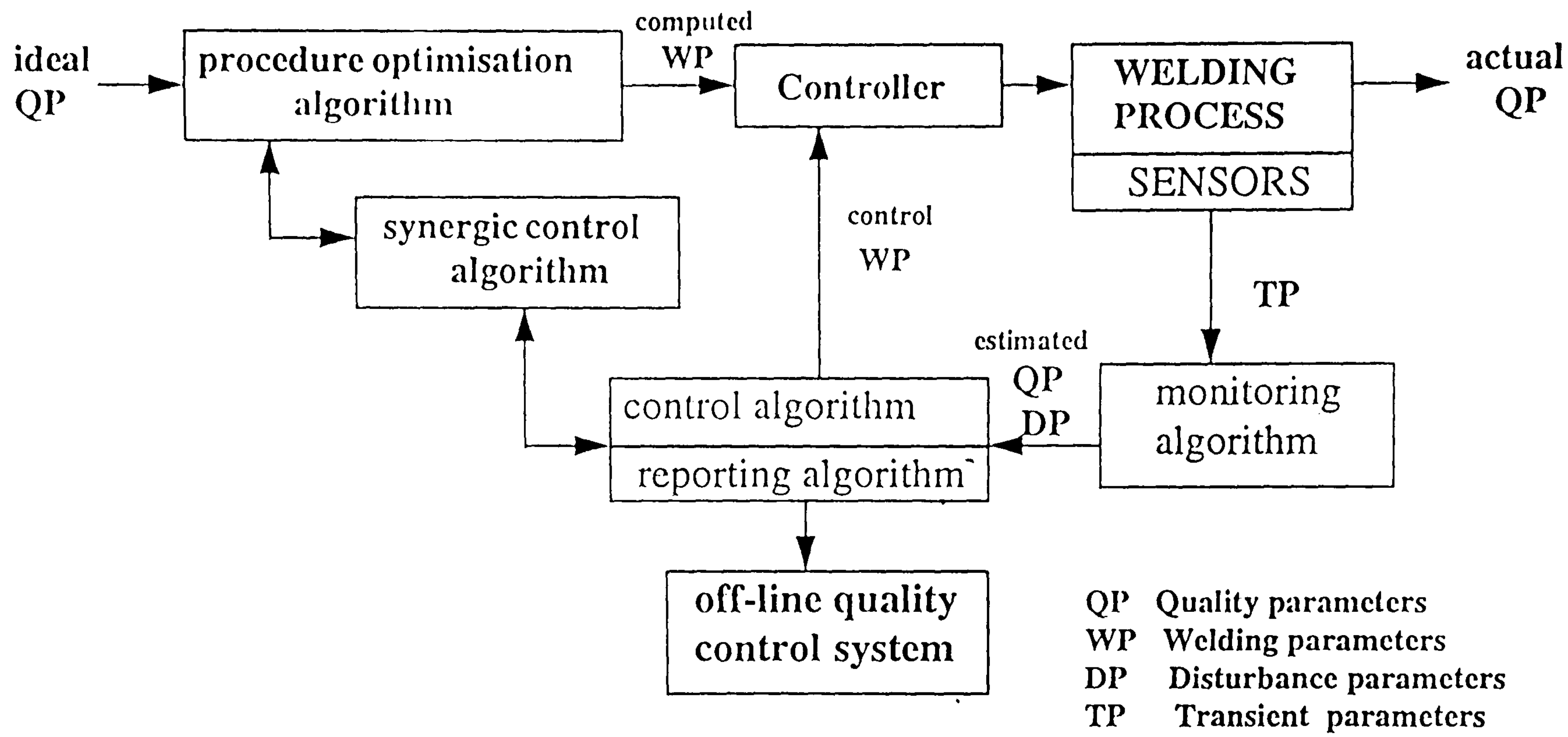


Figure 7.1: Adaptive Quality Control Concept Algorithm Architecture

Chapter 8

Process Modelling and Procedure Generation using Artificial Neural Networks

Modelling was an integral part of this work; as a feasibility study of alternative approach, some of the regression models were remodelled using artificial neural network. It should be noted that this is not an indepth analysis of modelling using neural network but an investigation to see if any improvement can be made on the regression models and identify the scope for its usage.

Backpropagation neural networks were used to develop models that will estimate weld quality parameters and assess the risk of defects such as inadequate penetration and undercut at the procedural stage. However, unlike regression models which can be inverted for procedure development, backpropgation network is not invertible, so the inverse model of the process has to be learned.

8.1 Modelling Strategy for Backpropagation ANN

The main task in neural modelling is to define the network configuration. This involves specifying the number of hidden layers, neurons per layer and the network parameters. The network parameters are the gain, momentum and maximum output error.

In section 2.7.3 some automatic selection of parameters have been suggested and these were found useful. The most important contribution being the assertion that, to avoid overfitting and overtraining, the number of weights must be less than the total number of input parameters[171]. This provides a way of constraining the network size to the available experimental data. It was decided to start with the one hidden layer with number of neurons equal to the input layer. The number of hidden layers and neurons can be increased but subject to this constraint.

Another main concern is when to stop training a network, the common approach is to train a network, to a specified small error. However, the backpropagation algorithm is similar in some ways to the least square method. Therefore, the network can be assessed from a statistical perspective of curve fitting.

It was assumed, as in regression analysis, that the total sum of squares of the actual output data must be equal to or less than the sums of squares of fitted values by Artificial Neural Networks. It was assumed that the condition for over fitting and learning is when the coefficient of determination(R^2) is greater than one (see Section 2.7.2)

The network training is done in stages and its prediction performance assessed. In the commercial artificial neural network (NT 5000™) software used, the maximum output error must be specified. The starting point was fixed at 0.2 (20%).

Preliminary investigation shows that the assumptions made above are valid, the comparison of neural networks and statistical model output on new data gives comparatively the same results.

8.2 Synergic Mode Neural Network Models

Tables 8.1 - 8.4 gives details of the neural network models developed. The network for procedure development was trained with the experimental data that provided penetration greater than ten percent of the plate thickness and with no apparent defects.

Table 8.1 **Neural Network Modelling of Leg Length and Throat Thickness: Synergic Mode**

Network Details

Name	DIPA23
Training Data	Table 5.2
Objective	*To predict leg length and throat thickness.*
Input	Current, Standoff and Welding Speed
Output	Side and Bottom Leg Lengths and Throat Thickness

Training Parameters

Topology	3,4,3
Number of Weights	31
Momentum of Learning	0.95
Learning Rate	0.15
Transfer Function	Sigmoid
Gain	3

Statistical Characteristics

R^2	0.8234
Number of Iteration	334
Validation Result	Table 1 in Appendix G

Table 8.2 **Neural Network Modelling of Inadequate Penetration and Undercut Risk: Synergic Mode**

Network Details

Name	DIPA13
Training Data	Table 5.1
Objective	*To predict risk of inadequate penetration and presence of undercut.*
Input	Current, Standoff and Welding Speed
Output	Pr(Sp), Pr(Bp), Pr(und)

Training Parameters

Topology	3,3,3
Number of Weights	24
Momentum of Learning	0.95
Learning Rate	0.3
Transfer Function	Sigmoid
Gain	3

Statistical Characteristics

R^2	0.91057
Number of Iteration	13339
Validation Result	Table 2 in Appendix G

Note:
Pr(Sp), Pr(Bp) and Pr(und) are possibility values for risk of inadequate side and bottom plate penetration and presence of undercut (see Section 5.2.1).

Table 8.3 **Neural Network Modelling of Penetration: Synergic Mode**

Network Details

Name	DIPA11
Training Data	Table 5.2
Objective	*To predict penetration depth.*
Input	Current, Standoff and Welding Speed
Output	Side and Bottom Plate Penetration

Training Parameters

Topology	3,4,2
Number of Weights	26
Momentum of Learning	0.9
Learning Rate	0.3
Transfer Function	Sigmoid
Gain	3

Statistical Characteristics

R^2	0.99816
Number of Iteration	4962
Validation Result	Table 3 in Appendix G

Table 8.4 **Neural Network Procedure Development: Synergic Mode**

Network Details

Name	DIPA24
Training Data	Table 5.2
Objective	*To predict welding procedure giving required bead size and the standoff distance.*
Input	Side and Bottom Leg Lengths and standoff
Output	Current and Welding Speed

Training Parameters

Topology	3,6,2
Number of Weights	38
Momentum of Learning	0.95
Learning Rate	0.15
Transfer Function	Sigmoid
Gain	3

Statistical Characteristics

R^2	0.90106
Number of Iteration	29445
Validation Result	Table 4 in Appendix G

Testing the Networks - Synergic Mode

The neural network models are tested on the same data used to test the regression models for the synergic mode. The network models give a maximum prediction error of -0.722mm for leg length, -0.404mm for throat thickness, 0.568mm for side plate penetration and -0.552mm for bottom plate penetration (see Figure 8.1). The undercut model was not very accurate. The possibility model of penetration was satisfactory. Pr(Sp) also gives high value at low current.

The artificial neural network was used to generate welding conditions for leg length between 2.5-4mm on 1.6mm plate thickness. The standoff was fixed at 12mm. All welds produced from the network prediction are of marginal quality with undercut or traces of undercut present. It can be seen from the quality of weld obtained that while penetration is adequate, the dimensional accuracy was not satisfactory (see Figure 8.2).

8.3 Manual Mode Neural Network Models

Tables 8.5-8.8 gives details of the neural network models developed. The experimental data present a problem that was resolved by a novel modelling logic. The problem was that the experimental contains spatter and undercut response data. It is perceived possible to specify acceptable risk of defects, in this case spatter and undercut at procedure stage.

Table 8.5	**Neural Network Modelling of Leg Length and Throat Thickness: Manual Mode**
Network Details	
Name	DIPC1
Training Data	Table 5.4
Objective	*To predict leg length and throat thickness.*
Input	Wire feed speed, Welding voltage, Welding speed and Standoff
Output	Side and Bottom Leg Length and Throat Thickness
Training Parameters	
Topology	4,2,3
Number of Weights	19
Momentum of Learning	0.95
Learning Rate	0.15
Transfer Function	Sigmoid
Gain	3
Statistical Characteristics	
R^2	0.7514
Number of Iteration	1428
Validation Result	Table 5 in Appendix G

Table 8.6 **Neural Network Modelling of Penetration: Manual Mode**

Network Details

Name	DIPC3
Training Data	Table 5.4
Objective	*To predict penetration depth.*
Input	Wire feed speed, Welding voltage, Welding speed and Standoff
Output	Side and Bottom Plate Penetration

Training Parameters

Topology	4,6,2
Number of Weights	44
Momentum of Learning	0.95
Learning Rate	0.15
Transfer Function	Sigmoid
Gain	3

Statistical Characteristics

R^2	0.9454
Number of Iteration	5340
Validation Result	Table 6 in Appendix G

Table 8.7 **Neural Network Modelling of Spatter and Undercut Risk: Manual Mode**

Network Details

Name	DIPC5
Training Data	Table 5.4
Objective	*To assess risk of spatter and undercut from procedure.*
Input	Wire feed speed, Welding voltage, Welding speed and Standoff
Output	Pr(spatter), Pr(und)

Training Parameters

Topology	4,6,2
Number of Weights	44
Momentum of Learning	0.95
Learning Rate	0.15
Transfer Function	Sigmoid
Gain	3

Statistical Characteristics

R^2	0.9425
Number of Iteration	4297
Validation Result	Table 7 in Appendix G

NOTE

Pr(spatter) and Pr(und) are possibility values for presence of spatter and undercut.

Table 8.8 **Neural Network Procedure Development: Manual Mode**

Network Details

Name	DIPC6
Training Data	Table 5.4
Objective	*To predict welding procedure giving required bead size, Standoff and Acceptable defect risks.*
Input	Side and Bottom Leg Lengths, Standoff, Pr(spatter), Pr(und), Standoff,
Output	Wire feed speed, Voltage and Welding speed

Training Parameters

Topology	5,7,3
Number of Weights	66
Momentum of Learning	0.95
Learning Rate	0.15
Transfer Function	Sigmoid
Gain	3

Statistical Characteristics

R^2	0.8568
Number of Iteration	1369
Validation Result	Table 8 in Appendix G

Testing the Networks - Manual Mode

Using the same three weld runs for testing the manual mode regression models on the neural networks; the maximum prediction error for throat thickness was -0.682mm, for leg length was -0.914mm, for bottom plate penetration was 0.267mm and for side plate penetration was 0.436. The response data for undercut model suggest that Pr(und) greater than 0.20 corresponds to presence of undercut. The response data for spatter does not show a clear cut cluster.

The welding conditions that were generated by the neural network for leg length between 2.5-6mm on both 1.6 and 3.2mm plate thickness gave very satisfactory welds. The penetration was adequate and the dimensional accuracy was satisfactory (see Figure 8.3).

8.4 Comparison between Regression Models and ANN

Models in welding are generally used for estimating weld quality from the setup parameters. Comparisons were made between the regression models and neural networks prediction. Initial comparison of the test data suggest that neural networks produces better models for penetration while regression models produces better models for the leg length and throat thickness.

However the data was not representative of the process range; the predicted data from procedure optimisation routine was used as the comparison data (Tables 1 and 2 in Appendix F) as they are the most representative data available for a wide range of bead size and welding parameters.

From the results, it can be deduced that neural networks offers no significant improvement over regression models (see Figures 8.4-8.6); comparative results were obtained and neither of the modelling methods gave satisfactory prediction for penetration. An objective comparison of risk of inadequate penetration, spatter and undercut models was difficult, as their performance is dependent on the level of decision threshold set. Figure 8.7 shows the correlation between neural networks and regression models used for prediction possibility of undercut.

The neural network developed for procedure development in the synergic mode was not very satisfactory. However, in the manual mode model, good welding conditions were generated. The main drawback is that neural network approach only gives one solution which might not be satisfactory; while statistical approach gives a series of conditions satisfying the quality objectives to select from. Figures 8.8 and 8.9 shows pictures of the welds produced by both approaches.

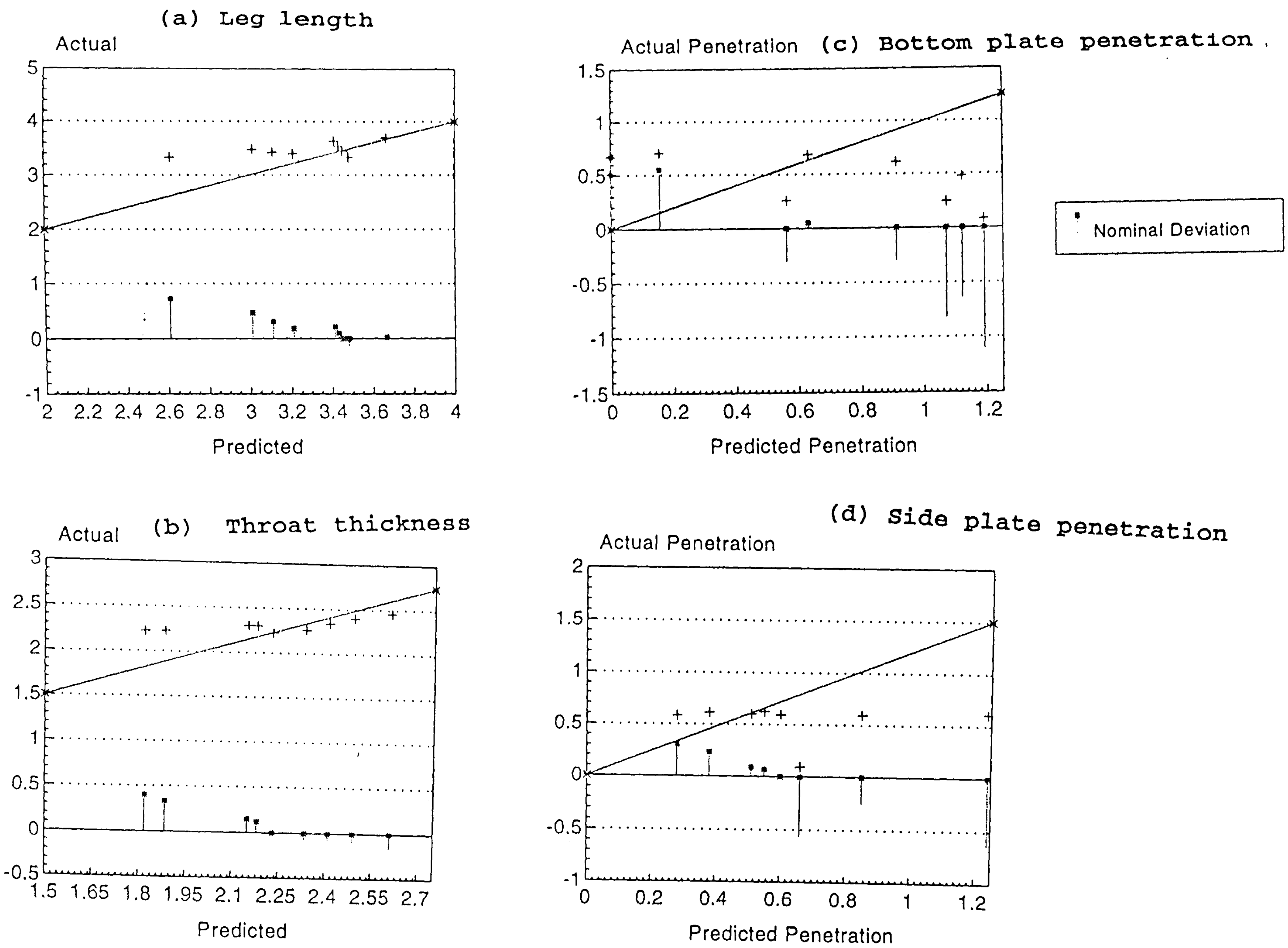


Figure 8.1 Testing Neural Network Models for Synergic Mode

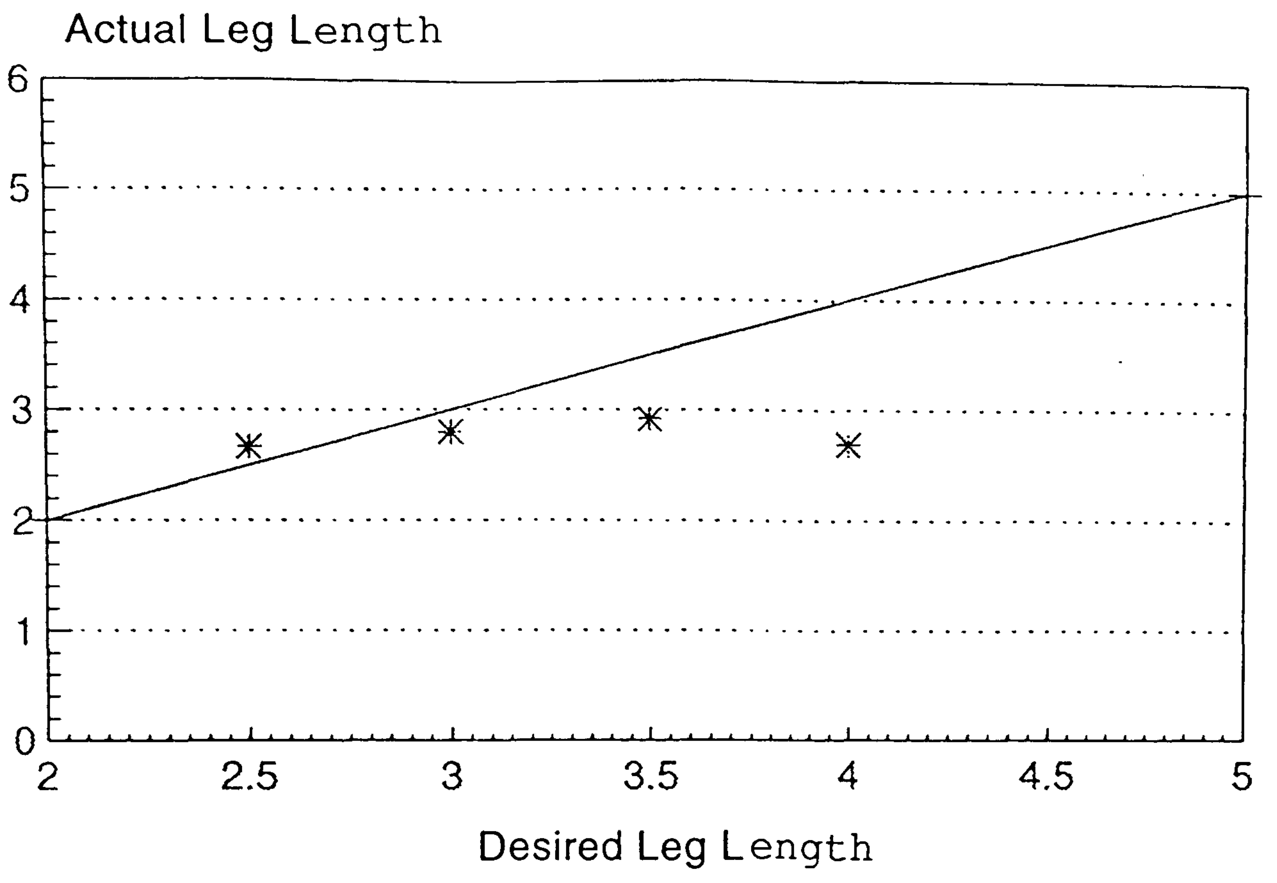


Figure 8.2 Testing Neural Network Procedure Development: Synergic Mode

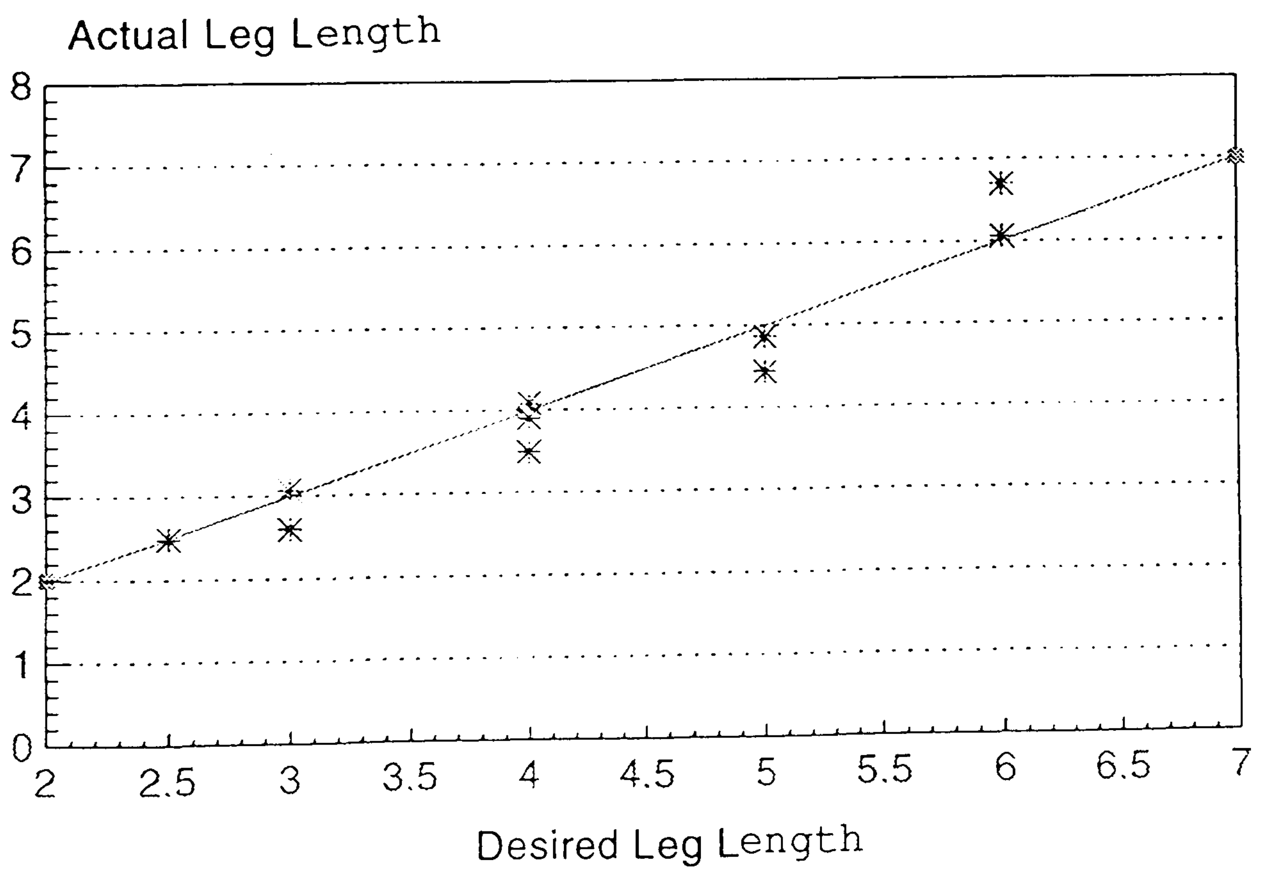


Figure 8.3 Testing Neural Network Procedure Development: Manual Mode

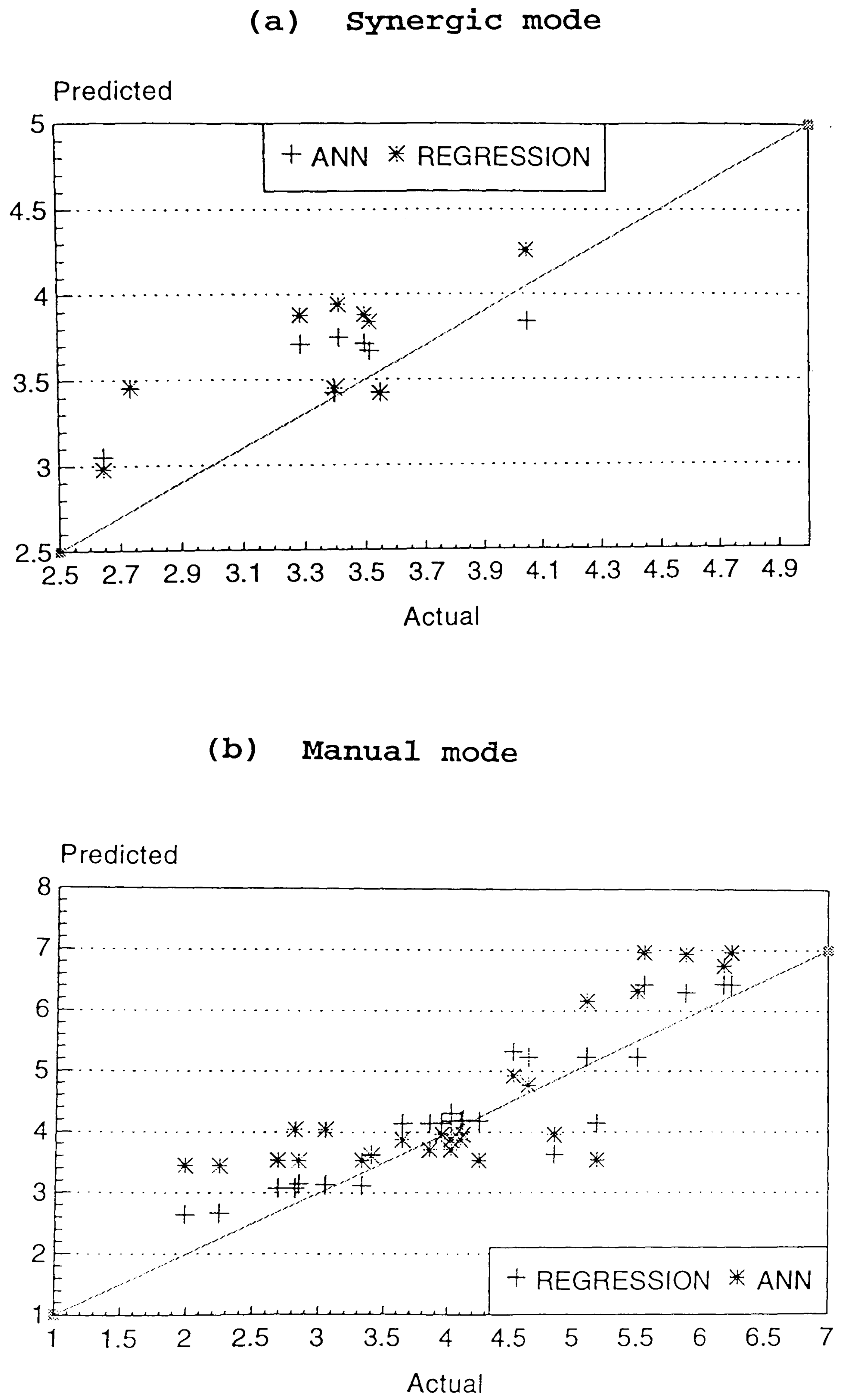
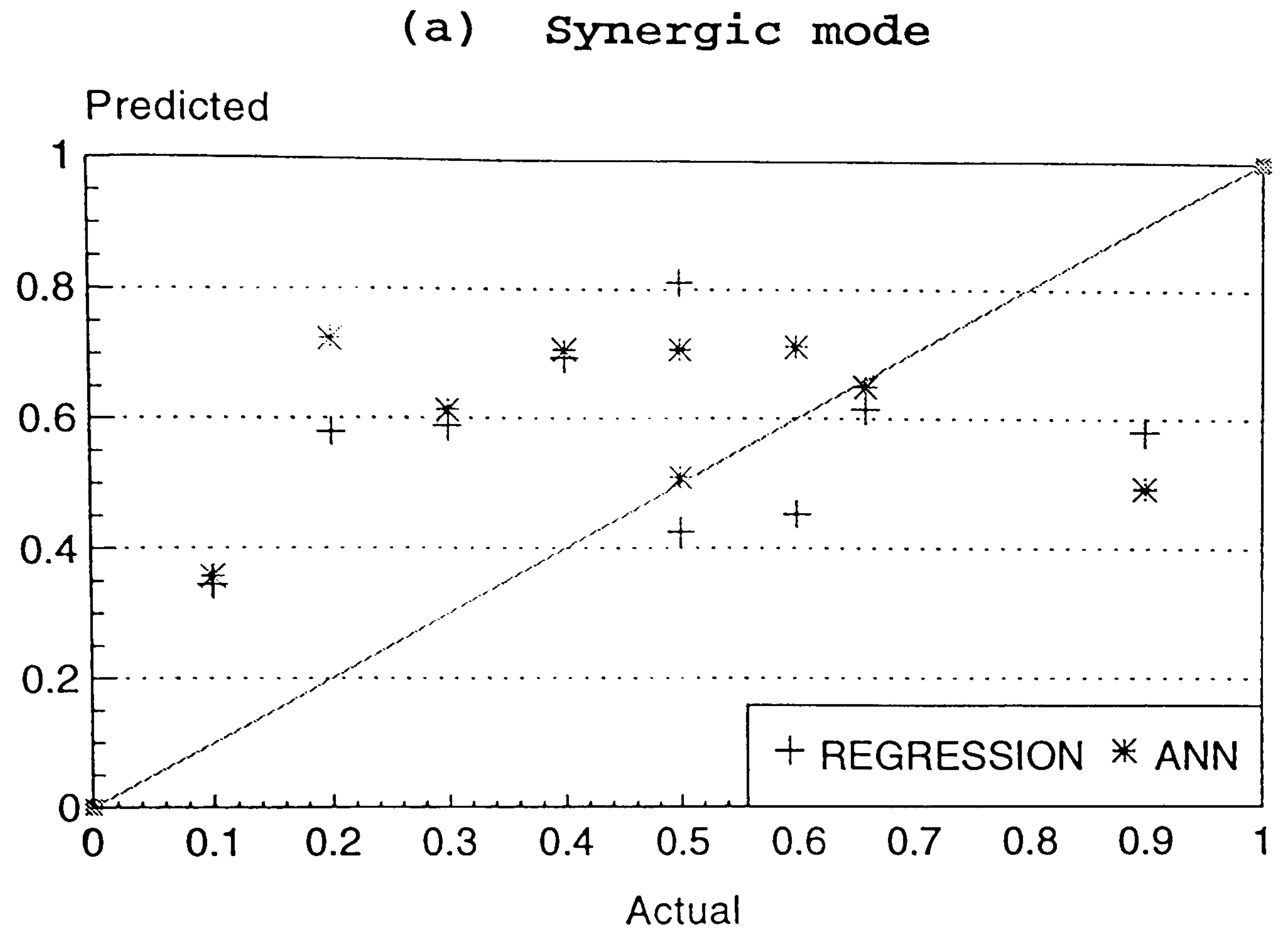


Figure 8.4 Comparison between Statistical and Neural Network Models: Leg Length



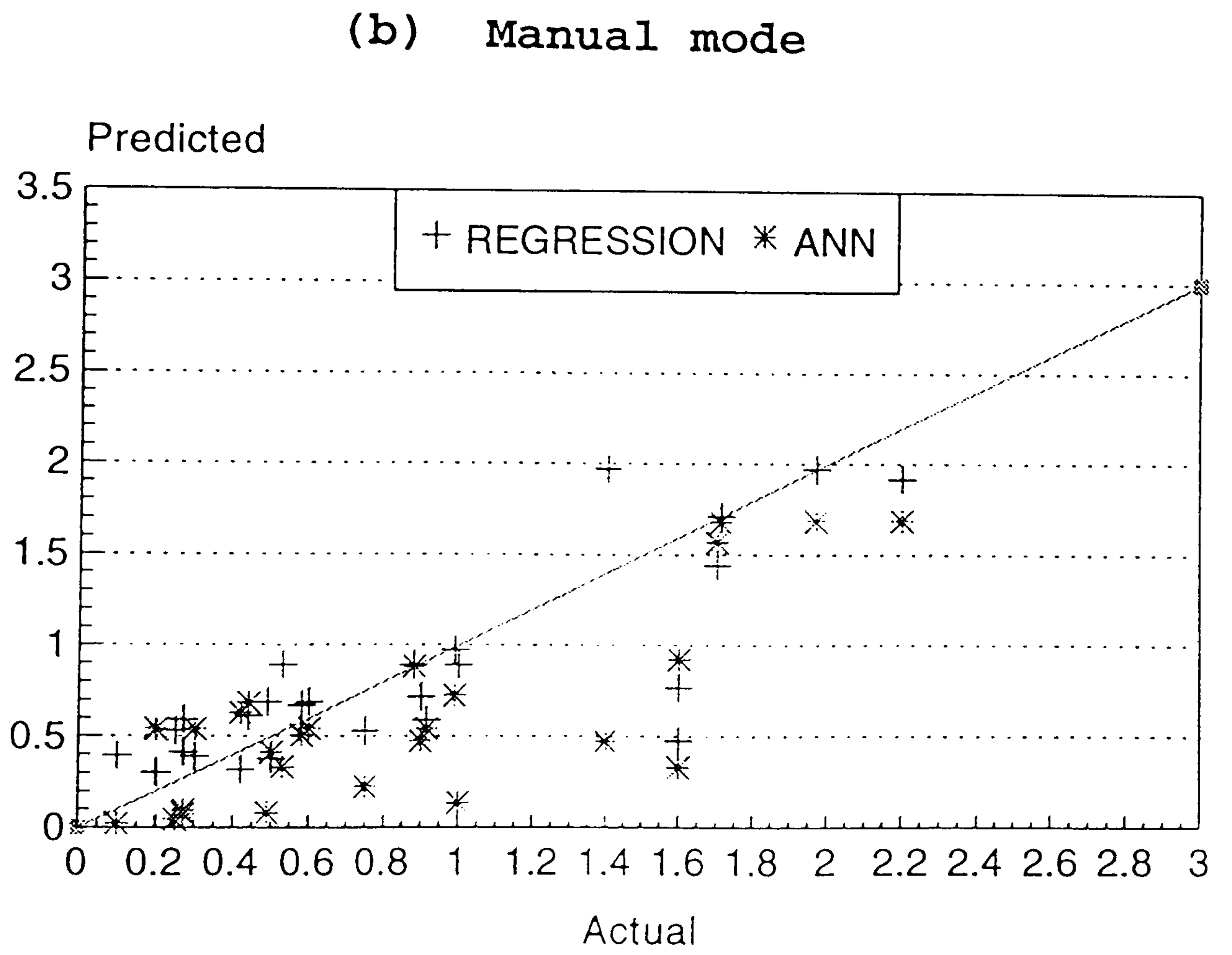
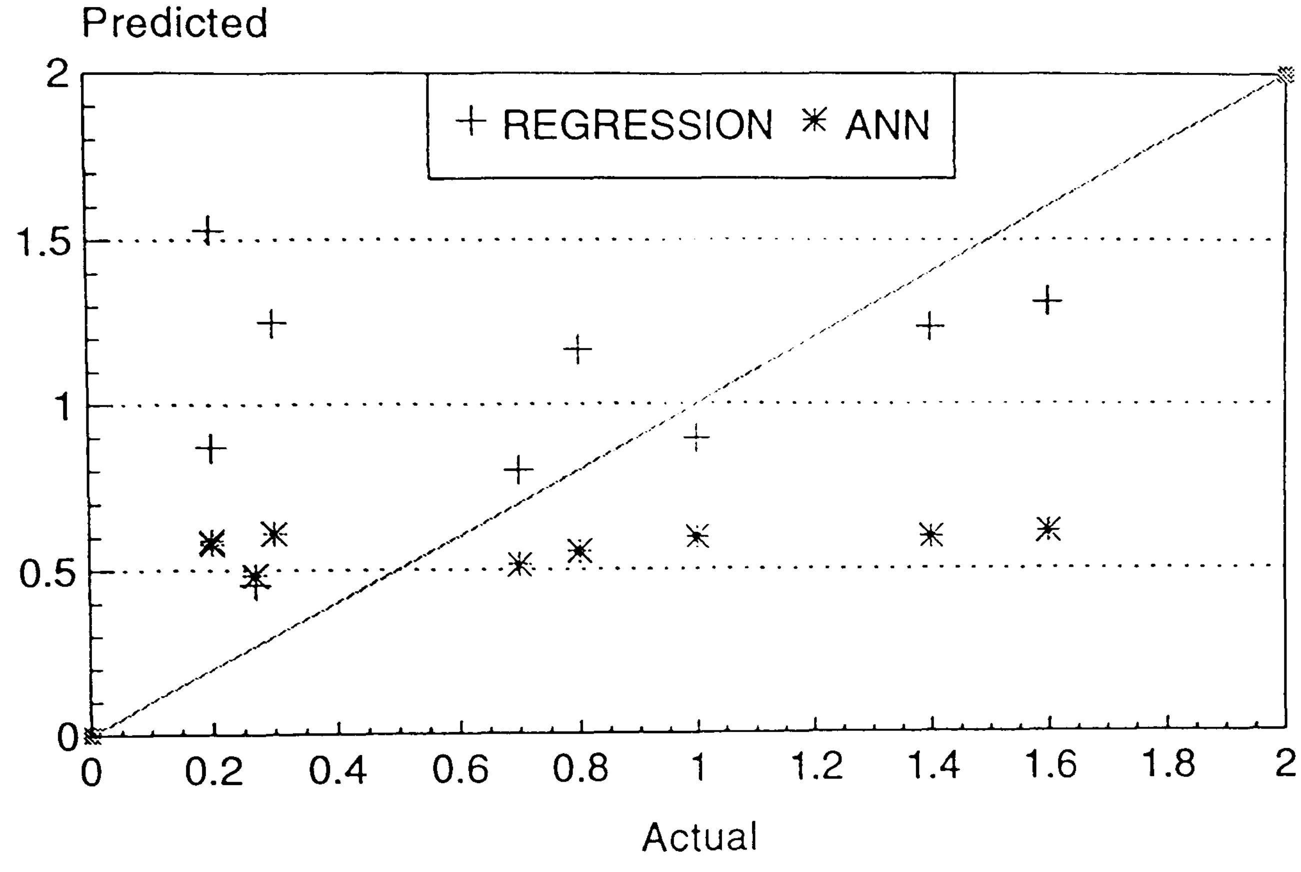


Figure 8.5 Comparison between Statistical and Neural Network Models: Bottom Plate Penetration

(a) Synergic mode



(b) Manual mode

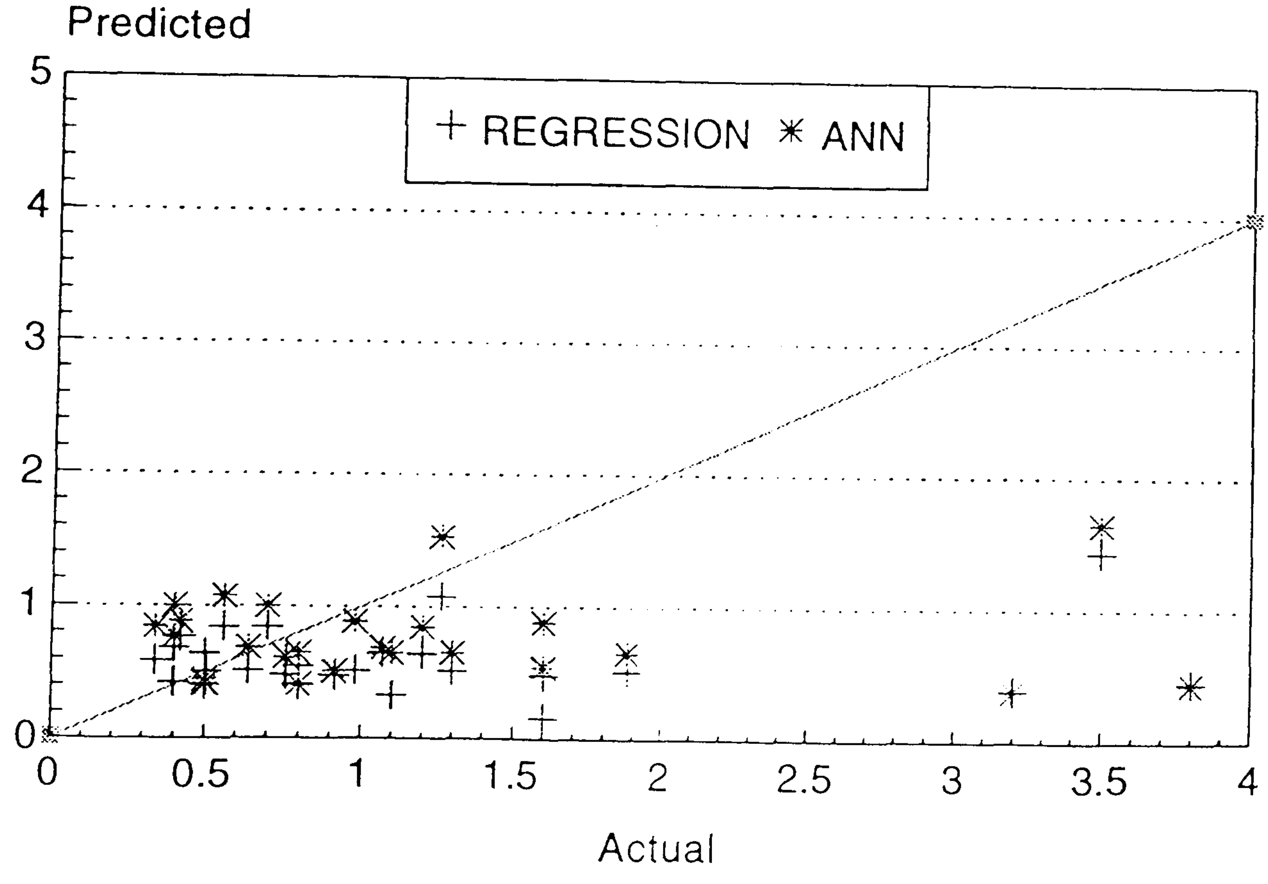


Figure 8.6 Comparison between Statistical and Neural Network Models: Side Plate Penetration

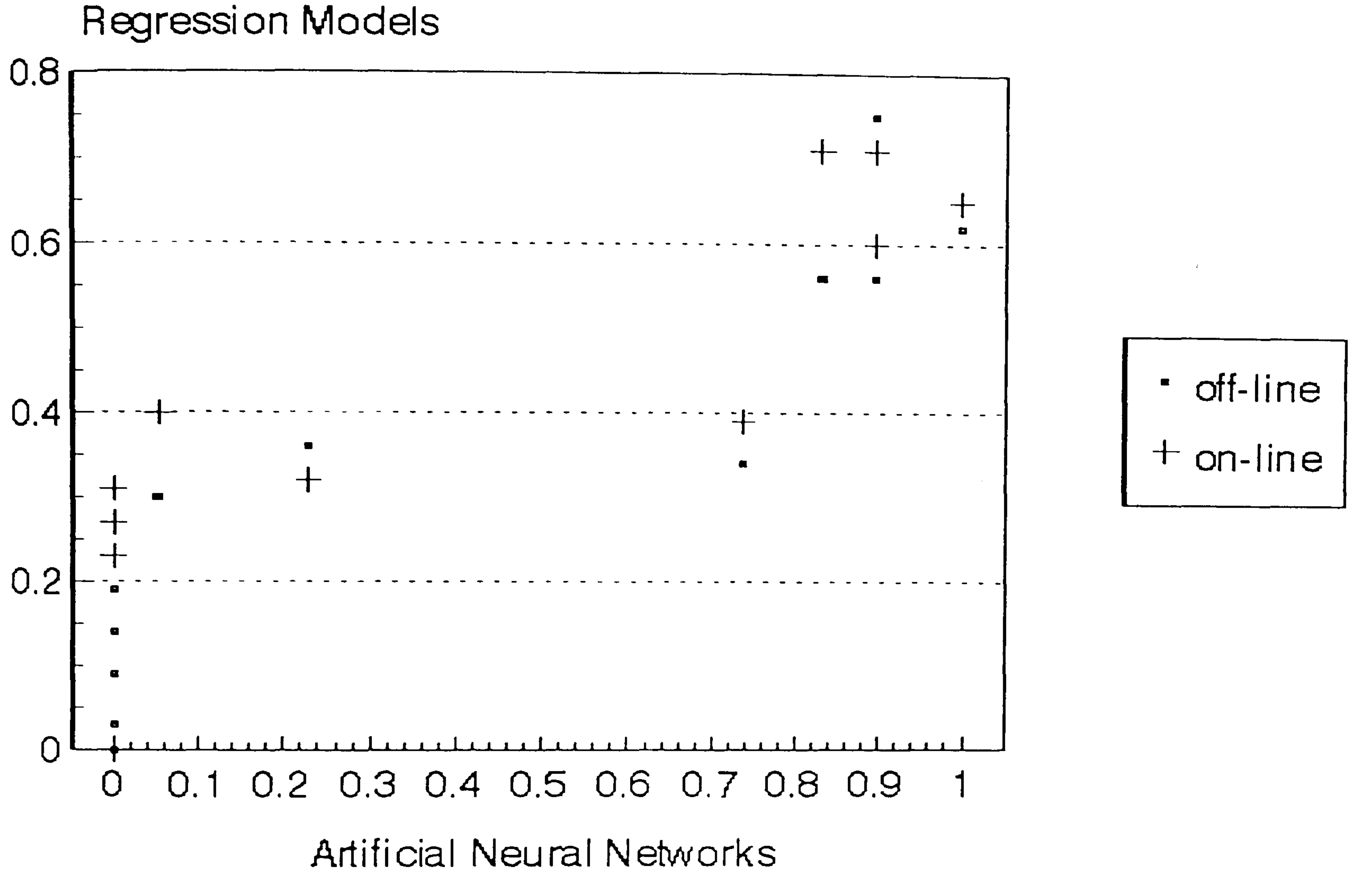


Figure 8.7 Comparison between ANN, on-line and off-line prediction for undercut

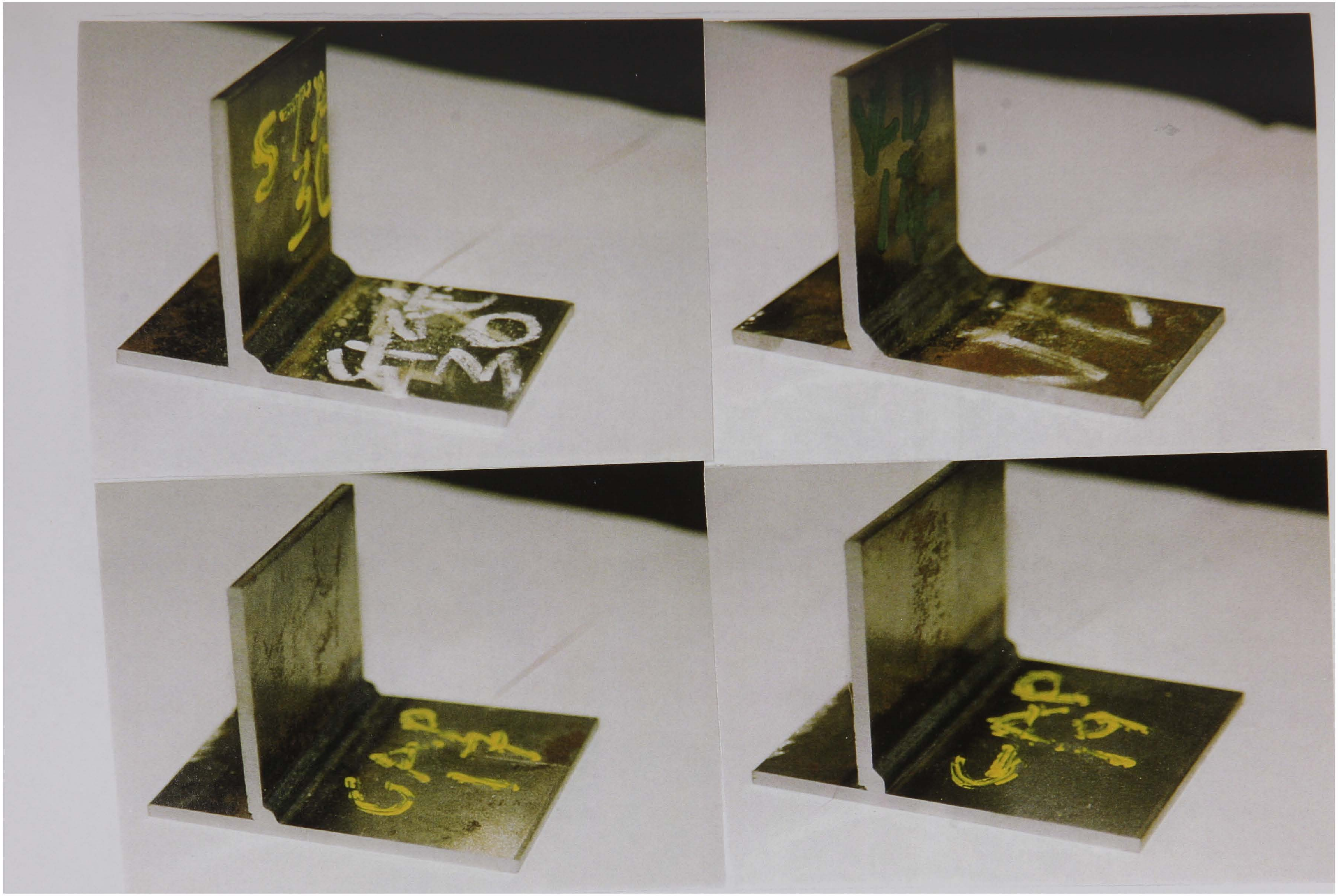


Figure 8.8 Photograph of Welds Produced using Regression Model Approach

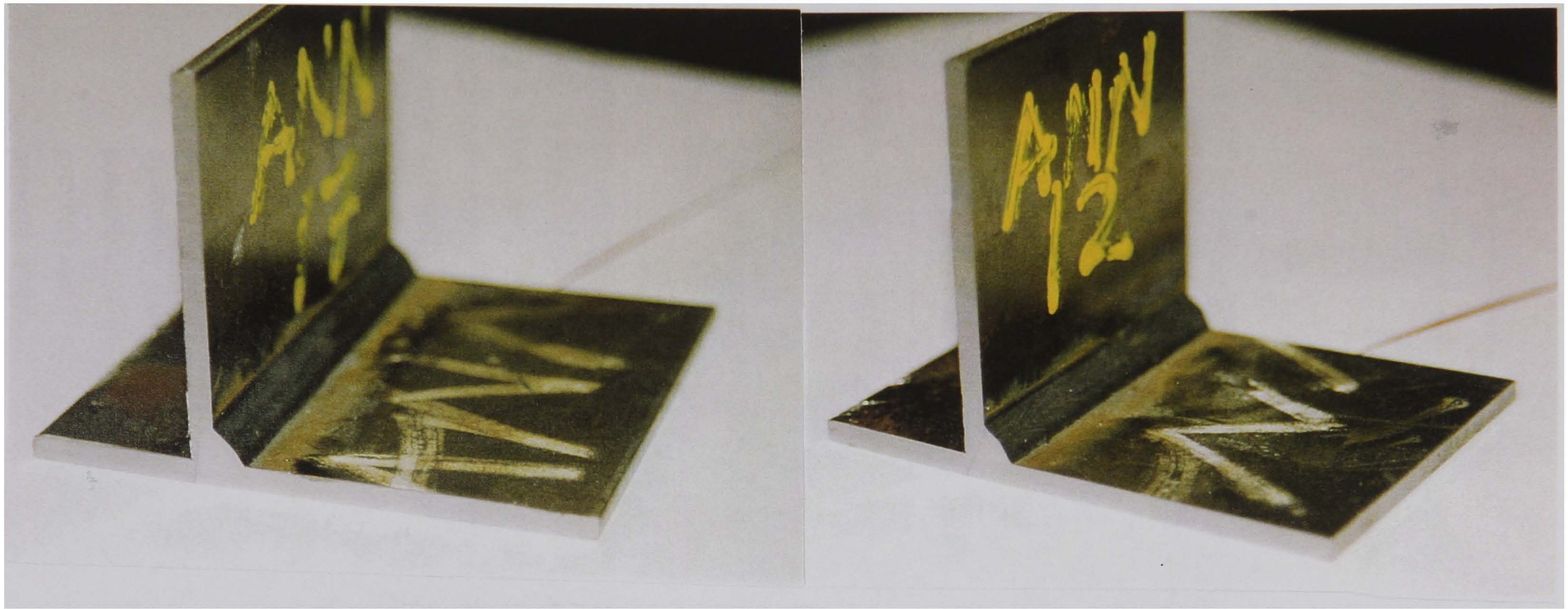


Figure 8.9 Photograph of Welds Produced using Artificial Neural Network Approach

Chapter 9

Discussion

9.1 Introduction

The aim of this project was to develop an adaptive quality control strategy for robotic gas metal arc welding although the work carried out is also applicable to mechanised welding systems. The work was motivated by the industrial need for on-line quality control. The target application area, is the manufacturer of welded steel sheet and tubular components. Typical production is usually high volume and involves producing components with multiple welds in different welding positions. Each weld could have different quality requirements, defined by the customer's need.

It has already been established that the reject rates are not high but the manual quality control method used to monitor and maintain this is expensive[7]. Their profitability or even financial survival therefore depends on producing good quality welds at low cost. Hence, the need for a quality control system with the ability to correct or identify any quality variation during welding.

Quality is more effectively achieved by avoiding defects. It is therefore important to establish procedures for producing the required quality welds and for preventing, detecting and correcting critical quality problems. The critical defects encountered in thin sheet welding are identified in section 1.1. The strategy for controlling them presented in section 3.1. A three point approach was proposed; off-line optimisation (procedural control), on-line control (adaptive control), and post weld analysis for long term assessment.

These were used to:

optimise welding procedure;
control bead geometry;
prevent insufficient penetration;
prevent undercut;
detect and control metal transfer;

assess welding arc stability;
detect variation in joint geometry;
detect variation in standoff;
provide information on process trends.

9.2 Process Modelling

Welding is a special process[q] that requires skilled operators to achieve optimum operation. In modelling the welding process, it is important that the models can be easily interpreted and understood in terms of the system. The models developed in this work were aimed at emulating the welders' control actions.

A welder in producing welds of adequate quality would ensure that he has good arc ignition and a stable arc, before moving the arc at a speed that gives appropriate bead size and good fusion. The action is in fragmented but interrelated stages, hence models were developed to reflect this situation. The following welding phenomena were modelled:

Phenomena	Modelling Objective
1. arc ignition	assess risk of bad ignition;
2. process stability	assess stability and transfer;
3. undercut	assess risk of undercut;
4. penetration	quantify penetration depth;
5. gap detection	detect gap and burnthrough;
6. bead size	quantify bead size;
7. standoff variation	quantify standoff variation.

The complete modelling of the welding process involves the integration of various models each defining a specific aspect of the process. The models were used to monitor and control the process. It should be noted that the models required were determined from the specification of quality features and any physical phenomena that affects quality.

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[q] **As defined in BS5750: Part 1: 1987.**

The models are classified as either off-line or on-line depending on the parameters used in developing them. The off-line models are developed using the welding setup and quality parameters. While, the on-line models are based on process disturbance, transient response and quality parameters.

It should be noted that the relevant parameters defining weld quality depend on the welding parameters used. Therefore, the quality control problem in welding was treated as regression problem. Three basic assumptions were made in order to model the process, using regression methods:

1. It was assumed that the process input parameters have a proportional relationship although not necessarily linear over a wide operating range (see section 2.6) with the output parameters;
2. It was assumed that if the arc is stable, then the features of the welding waveforms are relatively static. Therefore, the transient features which are interdependent can be modelled empirically. The ability of new generation of power sources equipped with setpoint controllers makes this assumption plausible;
3. It was also assumed that the data used for modelling are representative of all relevant operating conditions and was sufficient to realistically represent the normal process behaviour.

The process quality output are further classified as qualitative and quantitative. Qualitative data are features which cannot be defined numerically; whist quantitative data can be described numerically. Examples of qualitative parameters are undercut and spatter, while quantitative parameters include leg length and penetration.
The quantitative parameters are modelled using a multiple regression method, while the qualitative parameters are modelled using a fuzzy regression method. The fuzzy regression output gives a "possibility measure" of a defect occurring. Undercut and plate fusion were modelled using fuzzy regression.
The benefits of using regression analysis for the process models developed are:

1. it is a standard procedure and easy to use;
2. good for quick model development;
3. statistical software package widely available;
4. models can be built to reflect process understanding;
5. the models can be easily programmed into controllers.

The basic drawback however is that, due to simplicity of regression approach, it can easily be misused and misunderstood. The main source of difficulty in regression modelling is in determination of a model's structure. It should be noted that the models are used mainly for predictive purposes in welding applications. Hence, the models' structure should only be subject to the constraint that they fit the experimental data used. Although where possible the structure should incorporate any understanding of the process physical phenomena. It is also proposed that a specification for regression analysis be established. The minimum values for the correlation coefficient and statistical significant (α) level for estimated coefficient in final model, should be specified.

9.3 Process Monitoring

The ability to monitor the process is very critical to the quality control approach presented here. It should be noted that, **"what can't be detected can't be controlled"**. The basic objective of monitoring was to provide control signals and report abnormalities.

From the published work surveyed (section 2.3 and 2.4), it was concluded that defect diagnosis and quality control for an arc welding process could be achieved by monitoring the arc electrical characteristics. This implies the need to acquire reliable data and develop the necessary sensing strategy (including data processing algorithms). The advent of computers made this task easier, giving the scope for innovative data processing, process modelling and diagnosis[219,222].

The sensitivity of the arc to disturbances is one of the main requirements for process monitoring. Process disturbances are reflected as changes in the arc transient and/or steady state (average) characteristics. The transient features used to detect, monitor or estimate some process phenomena are shown below:

Phenomena	Relevant Features
1. bead profile	mean current and voltage;
2. arc stability	minimum and maximum current;
3. metal transfer mode	background voltage, minimum and maximum current;
4. penetration	mean current and voltage;

5. undercut — mean current and voltage;
6. standoff — mean current and voltage;
7. gap sensing — background current and voltage;
8. burnthrough — background current and voltage .

The fault detection methods outlined in section 2.3.4, were used in hybrid form in this work. The most commonly used techniques are model-based diagnosis and pattern recognition. The models are developed using regression analysis. Sections 5.4 and 5.5 illustrate the models used for monitoring. The models developed utilises the novel windowing technique developed by Chawla[219]. The technique involves the use of a data acquisition system to capture data in small blocks (windows) of transient data.

This effectively divides the data into a fixed number of segments representing the whole weld run. It is therefore possible to treat each segment as independent. This also means that the on-line models can provide output prediction at regular intervals based on each window data.

However, care is needed in using regression models for monitoring. Regression analysis is normally based on the assumption that predictor variables in a model are fixed. The on-line parameters are normally corrupted with randomness due to the process physical phenomena. The degree of randomness depends on the overall process stability. It should be noted therefore that the models for predicting bead geometry, penetration and risk of undercut (section 5.5) are only valid if the arc is established and reasonably stable (that is have reached equilibrium).

Scope for Statistical Process Control

The main scope for statistical process control would be for post weld analysis. This would involve the development of a quality management and supervision (reporting) system or network. The traditional statistical process control (SPC) techniques can be integrated with the models for monitoring (Sections 5.4 and 5.5). The historical output of the models can be used to detect systematic or sudden changes in process characteristic such as the occurrence of burnthrough or sudden break in arc.

Implementing adaptive control is a sign that something is wrong, hence any control action initiated can be reported and logged. The SPC charting of the frequency of control over a long period can be used to develop a predictive maintenance strategy. For example, adapting the procedure frequently for gap in a joint that is supposed to be a tight fit can be deemed as an indication of wear in bending and cutting tools.

The stability of the welding arc is greatly influenced by the condition of the contact tip[223]. Starting with a stable arc, trends in the stability and transfer indexes developed in this work over a period can be used as indication of possible wear in the contact tip.

9.4 Procedure Optimisation

Although this work shows that, it is possible to monitor and predict defects, it is clear from an economical point of view that prevention is even better than identification. Many potential weld defects can be prevented by proper quality control practice. The first step in quality control is to weld with an optimum procedure. Welding with an optimum procedure is important as the damaging effect of any quality disturbance should not then be very drastic giving time to detect and change the procedure as necessary.

Statistical and neural network based optimisation methods have been successfully evaluated during this work. The statistical approach offers more flexibility, because it is based on an iterative strategy. It produces a series of welding procedures that satisfy the required quality criteria, while artificial neural network predict only one procedure, the quality of which depends on the design of the network and the validity of the training data.

The statistical based optimisation technique was an adaptation of multiobjective optimisation concept introduced by Deringer and Such[204]. The technique was illustrated section 6.5, the primary advantage of this approach lies in its modularity, new models and constraints can be easily added. The main optimisation objective was the minimisation of the welding arc power subject to satisfying required quality criteria.

An optimisation routine must not only ensure a stable welding arc, it must also ensure that the weld pool is in dynamic equilibrium. While the objective of the present work does not involve the study of weld pool behaviour, its indirect influence on the final weld quality is recognised, based on the detailed analysis presented[37] in section 2.1.4.

The decision to optimise the welding procedure by minimising the arc power (subject to satisfying the quality requirements) is based on the fact that thin sheets are susceptible to fitup problems[1,2], which means defects such as burnthrough and undercut could occur frequently if excessive arc power is used. Therefore, it is assumed that, if the lowest arc power possible (subject to satisfying the quality requirements) is used, the resulting procedure is more tolerant to fitup problem and positional welds.

The implication of minimising arc power however is that, the welding speed predicted might be low; the benefit of this is that, there is more time to control and detect disturbances with more certainty. It should be noted however that as speed increases the process is less tolerant to disturbances. It is presumed that any industrial productivity requirement can be satisfied easily from the predicted procedures, as the results in Appendix F shows; however if required a minimum productivity requirement can be added as constraint into the optimisation routine.

It should be noted the work carried our was intended for implementation on thin sheets welding applications, therefore there is a limit to the extrapolation of minimum arc power as the procedure optimisation criteria on thicker plates.

9.5 Process Control

The process control involves the adjustment of the welding procedure in a pre-specified manner. The objective is to counteract the effect of disturbances while ensuring the stability of the process and acceptable quality welds are produced in accordance to quality requirements.

The main control parameters are wire feed speed, voltage, standoff and travel speed. The changes necessary are obtained by reversing the regression models based on the assumptions that the model accuracy is satisfactory. The stability of the control loop is maintained by the synergic control. It should be noted that the control stability would also depend on the ability of the welding power source to implement fast and smooth set point changes.

The control emphasis is on bead size only. The penetration models developed were not robust enough to be used for control. It was therefore assumed that maintaining current at a set level will keep penetration adequate. This emphasises the need to start welding with an optimum procedure.

The proposed control strategy illustrated in sections 3 and 7 is "anticipatory in nature"; that is excessive control are avoided as corrective actions are initiated only if there is going to be a violation of quality requirement. The overall control architecture is shown in figure 7.1.

The modular structure of the strategy means that each individual module can be used independently. The modules were independently tested satisfactory off line with the exception of the control algorithm.

The control algorithm presented in section 7 was implemented in an industrial environment on a VME (Versa Modular Eurocard) bus system[224-225]. The communication between the VME system and the welding system (robot and power source) was done via a Robot Interface built by Migatronic.

The transfer of welding parameter before and during welding to the power source was successful; but it was not possible to change robot speed and position during welding. Hence, the control strategy presented was not fully validated in a closed loop situation.

The software implementation of the control algorithm however shows that with reference to the quality of welds already obtained, the control routine would maintain good weld quality and a stable arc.

9.6 Analysis of Investigation

The work done is mainly empirically based. It was based on the premise that there is a sufficient amount of experimental data representative of the process operating conditions to develop all the necessary models. It is however difficult to validate this.

The regression models were developed with data from experimental trials. The aim of the experimental design was to obtain representative data. The most common experimental approach being used in welding is factorial design; but the result of parameter selection in this work shows it is not always feasible to use factorial design. The combinations of some parameters do not produce good fusion welds. It was found necessary to adjust parameters to get good welds hence restricting the welding parameter range.

Factorial experimental design was used for trials conducted using the synergic mode of the power source (section 5.2.1). However, it was found difficult to apply factorial design in manual mode (section 5.2.2), due to the difficulty in the selection of voltage.

This led to the use of "unplanned" experiment for welding with the power source in manual mode. It can be argued that, this could lead to unrepresentative and biased data. However, the prediction error of the models developed were acceptable. The importance of systematic approach to experimental design must however be stressed.

The main problem encountered (which could result in modelling errors) is bead asymmetry, that is, unequal leg length. This was attributed mainly to robot programming problems. Welding in horizontal vertical position is likely to make tendency towards bead asymmetry increase with current. To reduce the misalignment effect on modelling, the leg length would be expressed in this project as the average of both leg lengths. The bead asymmetry range observed in the experimental study is shown in Table 1 in Appendix H.

The independent parameter range can also affect the ability to produce representative models. The independent parameters for synergic mode were found to be too limited. The range of variables which may be used produce no defects apart from the fusion problem encountered, may be due to the speed range used (0.8-1.6m/min), although the models were tested for speed as low as 0.4m/min and satisfactory results were obtained as is shown in Appendix A. This gives an indication of the effectiveness of the synergic control algorithm used.

The problem identified was rectified in experimental trials for manual mode, the speed was set between 0.3-1.6m/min. Tables 2 and 3 in Appendix H gives the welding and bead response parameter range respectively. However, investigating a wide range of parameters leads to some difficulty as voltage is not easily controllable. This however in the author's opinion is not a setback, since experimental studies are supposed to represent the process behaviour. The use of synergic welding has the benefit of automatic control of critical parameter such as voltage, but at the expense of establishing potential defect patterns and parameter tolerance.

Evaluation of the Models

Due to the fact that the models are integrated, it was found necessary to evaluate each model individually. The models developed for bead size, undercut, gap detection, spatter generation and arc ignition are found to offer good performance. The penetration model accuracy was not good but gives satisfactory results in terms of expressing the posssibility that penetration is adequate or inadequate. That is, using "**if-then**" (rule based) approach.

The difficulty in modelling penetration can be attributed to the experimental response level and complexity of the phenomena. The penetration depth is very limited often less than 1mm hence not giving the scope for good generalisation. The industrial requirement for penetration is very specific; it is either adequate or inadequate; which suggests the need for fuzzy regression approach for different plate thickness.
Most manufacturing companies do not however have the time for extensive modelling work. In the automotive industry the design thickness of plate may vary from 1 to 6mm. In this case intuitive judgment was used to compensate for the absence of the desired model precision and adaption of penetration models to different plate thickness. It was assumed that the penetration models would be valid for plate thickness up to 6mm. Although, the models were not accurate, satisfactory results were achieved when the manual and synergic models were transferred to 1.6 mm (thinner) and 3.2mm (thicker) plates respectively.

Main concern was the attainment of adequate fusion on thicker plates and prevention of overpenetration or burnthrough on thinner plate. The risk of fusion problem is greater with dip transfer welding of thicker plates. It should be noted that the heat from the arc is used to melt the plate and as plate thickness increases the energy required to achieve melting also increases. Middleton[226] states that the volume of parent plate melted is dependent on the arcing current; the arcing current has direct correlation with voltage and wire feed speed. This is in line with the observation made in section 6.2, that a minimum voltage exists for a given plate thickness especially in dip welding with the welding speed set accordingly for the required weld size subject to having a stable arc.

Evaluation of the Algorithm

The models developed were used to design algorithms for synergic control (section 5.3.5), gap detection (section 5.4.2), standoff estimation (section 5.4.1), process stability assessment (section 5.3.2), procedure optimisation (section 6) and quality control (section 7).

The algorithms all give satisfactory results and have been validated in the laboratory and tested in an industrial environment where the component welded was a car rear axle. Appendix I shows an example of the test results; the overall accuracy of welds obtained was satisfactory, although some of the welds showed bead asymmetry associated with positioning problems; which can be corrected.

The results show that the models can be transferred to other power sources. The validation in the industrial environment was carried out on a different power source Migatronic BDH 550; during monitoring the predicted geometry was recorded and compared with actual welds, the overall accuracy of the welds obtained was satisfactory. The monitoring rules (see Table 5.7 and Figure 5.11) were also tested on a Murex TransMIG 450i power source with different gas mixtures; good results were obtained(see Appendix C).

The gap detection algorithm requires more study so as to develop a more precise modelling approach. The parameters in the algorithm were "fine tuned" to produce a good fit with simulated gap conditions. The procedure optimisation algorithm developed was adapted successfully to weld joints with fit-up problems and/or in position by limiting the operating range of the process to dip transfer. This however depends on the ability to constrain the metal transfer by integrating the optimisation algorithm with the synergic control algorithm developed.

9.7 Modelling using Artificial Neural Networks

It has to be noted that there has always been debate between statisticians and neural networks researchers on the effectiveness of both approaches for emperical modelling, judgement however depends on personal bias as can be seen in the published work by Sarle[227] and several postings on comp.ai.neural-nets newsgroup on the Internet. The objective of the present comparison in this work is not to contribute to this debate but as exploration of alternative modelling tools for the welding process.

Regression models have been commonly used for process modelling in welding [182-188]; however artificial neural networks are now being used to solve problems that have been satisfactorily modelled using regression methods. The limitation associated with the regression models include the difficulty in capturing the complexity and non-linearity of the welding process.

The main advantage of regression models over neural network is that they can reflect physical understanding of the process while the inner workings of neural networks are difficult to understand and are viewed as a black box. However, the significant advantage of neural network techniques over regression models is that they offer a non-linear and multi-dimensional (parallel) modelling process with high processing speed.

Modelling work using neural networks have been undertaken widely[196-198] but none of the investigators have compared their results with alternative regression models. This comparison was made in this work. It was concluded from the comparison between some of the regression models, that the neural network approach offered no significant improvement over regression models. The accuracy of neural network is comparable with the accuracy achieved by regression models (see Figures 8.4-8.6) when the objective was to predict weld quality from a given welding procedure.

However, using backpropagation neural network models for procedure development requires practical welding experience. A real process representative input-output response (experimental) data is fundamental to good model performance. The poor performance of the synergic mode neural network for procedure development shown in figure 8.2 illustrates this. The procedure development neural network for the manual mode shows that the network must be trained on data containing information on potential defects and problems.

The results of the work carried out shows that both techniques satisfactorily model the welding process and can therefore be used to complement one another. Although this is not an extensive study, it was identified that neural networks can be integrated into the strategy developed. Neural networks can be used to replace the fuzzy regression models because they produce output between 0 and 1 without the need for the constraints employed on the fuzzy regression models output. They can also be used for process monitoring and diagnosis.

For example the stability rules in Table 5.7, are very subjective and involve knowing how the process behaves to establish the thresholds. A neural network was used to reduce the complexity of the IF..THEN rules. The neural network can be used to classify transfer mode and assess stability by using the transfer, transfer stability and dip consistency indexes as input into the network.

To do this, it was assumed that metal transfer consist of both dip and spray components. The spray component (Pr(spray)) represent the tendency for a droplet to transfer without short circuiting and dip component (Pr(dip)) vice-versa. The amount of each component present depends on how unstable the process is. The actual transfer mode and stability depends on the dominant component.

The use of a threshold is unavoidable but its complexity can be reduced using the ANN approach. The applicable thresholds would have upper and lower value within which the process would be considered unstable. Section 2.3.5 discussed the issues involved in threshold selection. The network tested in this work was trained on data used for validating the synergic algorithm (Table 5.10). The data was coded as follows:

if dip transfer Pr(dip)=1 and Pr(spray)=0
if spray transfer Pr(dip)=0 and Pr(spray)=1

The trained neural network details are shown in Table 9.1

Table 9.1 Neural Network Modelling of Metal Transfer Mode Detection

Topology	3,3,2
Number of connections	20
Input	TI, TSI, DCI
Output	Pr(dip), Pr(spray)
Momentum	0.95
Learning Rate	0.15
Gain	3
Iteration Number	158
Output Error	0.004

It should be noted that regression models can also be used. The regression models developed are:

$$Pr(spray) = 0.485 + 0.655TSI - 1.1983DCI - 2.601TI \quad (9.1)$$

$$Pr(dip) = 1 - Pr(spray) \quad (9.2)$$

The regression models however seem very sensitive compared with neural network. The table in Appendix J shows the response of the neural networks and regression models to the manual mode experimental data (Table 5.8).

9.8 Possible Industrial Applications

As already stated, this work was motivated by the industrial need. The algorithm developed has been implemented on a VME computer system and tested in an industrial environment[225]. The trials were satisfactory and point to the following possible industrial applications:

1. *Adaptive control system for weld quality;*

   The major industrial benefit of this work is the design of a flexible adaptive control and monitoring system for arc welding processes with the emphasis on weld quality.

2. *Design of intelligent power sources;*

   The most significant contribution of the work is probably the monitoring rules for stability assessment developed (section 5.3). The simplicity of the models means that they can easily be built into a power source controller. The rules could be used as basis for the design of an intelligent power source using fuzzy logic and/or neural networks.

3. *Testing and Optimisation of consumable and power sources welding performance;*

   It has already been established that the indices in the monitoring rules (section 5.3) seem to be equipment and consumable independent. The indices in the rules provide a way for testing and optimising the welding performance of power sources and/or consumable. Dixon[220] used the rules for assessing gas mixture optimisation for robotic welding. The stability models can also be used to give an objective assessment of inductance and slope requirement for shielding gases as the results of independent experiment performed by Bassett and Norrish in Appendix C suggest.

4. *Development of software tools for welding.*

Most modelling work in welding results in application based software, ranging from monitoring software, numerical and expert system based procedure optimisation software[179,180,182,184,219]. Following the same route, a BASIC demonstration software package was written. The software demonstrates how the models and algorithm developed were used for quality assessment, defect prediction, procedure optimisation and enables the simulation of welding parameter generation and defect prediction. The demo disk is available with the thesis and the instruction for use are presented in Appendix K.

9.9 Limitations and Possible Improvement for Industrial Application

Some of the limitations identified are based on discussion with a welding equipment manufacturer in Europe, in an attempt to establish whether the work could be exploited industrially.

The quality control strategy presented is empirically based and requires some commitment to experimentation. *The first concern was that the design of experiment and building the models might be too time consuming.* There is also a problem of establishing model structure; and ensuring that the experimental data available is adequate. These concerns can be resolved by automating the design of experiment and model building technique. This has the added benefit of ensuring consistency and reliability of the concept presented.

The models have fixed coefficients and are restricted to specific conditions, such as gas, wire and joint types. For different conditions trials have to be carried out and new coefficients calculated. The coefficients are normally stored in the equipment in board memory. *The second concern was that the maintenance of different coefficients and thresholds involved in the models for a wide range of different gases, wire type and sizes could lead to memory problem.* To resolve this concern, practical judgement could reduce the experiment trials significantly. The models can be developed; however, for standard joints, gases and wire diameters and programmed into the power sources. The most important part of the model requirement being to set stable voltage for the wire feed level.

If a new condition is demanded, the programmed condition closest to the new situation should be selected. The arc could be made stable by increasing or decreasing voltage as necessary, to ensure stability. It should be noted that most power sources already have voltage trim facility for doing this. The monitoring rules in section 5.3 and fuzzy logic (and/or neural network) can be used here to make the fine tuning systematic. An example of such application can be seen in the published work by Won and Cho[144]. The authors used fuzzy logic and rule based method to establish stable arcs for dip welding trials.

The third concern was how fast the welding signal must be sampled and model output calculated for closed loop control. It has to be stated that the concept does not require high sample rate. In setting sampling rate, sampling theorem suggests that signals should be sampled at twice the rate of the highest signal frequency that needs to be monitored. Consideration must be given to the sample size also referred to as window. A window in the Arcwatch™ contain 512 data points as default but can be set to 256, 1024 and 2048 data points.

It was assumed that a window must contain approximately 10 process cycles. A cycle is the time taking to transfer a droplet; typical cycle time obtained for a series of stable welding conditions, using the developed synergic algorithm was between 2 and 16milliseconds (see Table 5.10). The sample rate (per channel) should be set to achieve this. It was found adequate to set the sample rate in kHz, at the number of data points per window divided by ten times the cycle time in milliseconds. For the default sample size of 512 data points, the sampling rate would therefore be between 3 and 25kHz and the approximate sampling time will be between 25 and 128milliseconds.

The model output would only be constrained by the speed of the computer being used. On a 33MHz DX2 personal computer it took approximately 1second to implement the procedure optimisation routine. It is estimated that it will takes approximately 3milliseconds to calculate the welding waveform statistical features for a window (sample); the features are then used as inputs in to the on-line models and monitoring rules hence no processing overhead perceived. It is therefore estimated that the control cycle illustrated in Table 7.1 will take roughly 3milliseconds.

It should be noted that with the techniques used here there is an inherent control delay time corresponding to the sampling time. The control frequency depends on the rate at which the welding equipment (power source and robot) can recieve control intructions (error signals) and update the welding procedure; typical rates of control reported in published work is of the order 5Hz. The sampling times are generally set to accommodate this and are found to be up to 500milliseconds[112]. However the control system can be designed to have different update rate for process control and monitoring. It is perceived from the result of the current work that reliable high monitoring and reporting update rate of between 7 to 40Hz is achievable with the system providing on-line graphical display of the models output for the operator(s).

Chapter 10
Conclusions and Recommendation for Further Work

10.1 Conclusions

1. The welding process can be effectively modelled by breaking down the process into well defined sequence of sub-objectives; and integrating the resulting models;

2. A robust optimisation technique using statistical models and rules derived from weld quality specifications was developed;

3. It was found sufficient to monitor weld quality using welding current and voltage transient signals only and travel speed;

4. The control strategy shows the feasibility of using regression models for adaptive control of weld quality;

5. A general quality control algorithm architecture has been successfully developed for gas metal arc welding process;

6. A novel method has been developed for metal transfer detection and process stability assessment;

7. A thru-arc sensing strategy has been developed for monitoring and estimating the size of joint geometrical variation (gap);

8. A novel synergic and metal transfer algorithm that combines the transient and steady state dynamic of the welding arc was developed;

9. Backpropagation neural network models were found to offer no significant improvement over regression models;

10. The possibility of using backpropagation neural network to reduce complexity of monitoring rules for some parameters was identified.

10.2 Recommendation for Further Work

This project has demonstrated the possibility of developing a flexible quality focused adaptive control strategy for robotic welding of thin steel sheet. The following further work is suggested to enhance the usefulness of the results:

1. Development of Knowledge based Experimental Design System

It is important for any experimental design to produce process representative data. The result of this study has illustrated the difficulty in applying standard experimental design to welding over a relatively wide range. Hence, a knowledge based system for experimental design in welding could be developed. The guiding aim should be to collect data representative of all possible process characteristics.
Welding is a special process, which depends on the skill of the operator. Therefore in designing an experiment it is important to use the welder's skill. The system should interact with the welder(s) and be designed to get maximum welder experience by recording experimental observations. An extension of such a system could include automating data collecting, analysis, correlation, transformation of observations and process modelling.

The typical experimental design is envisaged to be evolutionary, taking into consideration welders' skill and experience. An expert systems could be used to advise on the next experimental point or whether to continue, based on the response of interest which must be defined by the quality specification.

2. Extension of Experimental Scope and Range

The experimental work done and models developed could be extended to thicker wire (say up to 2mm), flux-cored wires, different shielding gases, thicker plate thicknesses (upto 12mm), other joint geometry, and multi-pass welds. The possibility of integrating the synergic algorithm developed with a pulse synergic algorithm could also be investigated.

3. Process Modelling and Control using Spreadsheet

Commercial spreadsheet software is becoming very powerful with built-in analytical and statistical function libraries together with powerful charting facilities. Some neural network software is now being provided as an "add-in" for standard spreadsheets.

A standard spreadsheet package such as Excel and Lotus could be used to develop a software environment for interactive procedure generation and assessment environment based on models developed using neural networks and/or statistical methods.

The final system could allow the user to asses the impact of changing welding parameters by generating alarms for out of specification conditions and offering corrective advice. The scope for automatic on-line weld quality control and documentation should be explored.

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APPENDICES

Appendix	Description
A	The test data for testing synergic mode regression models.
B	The test data for testing manual mode regression models.
C	The data in this appendix gives the response of a fixed welding parameters to the monitoring rules in Table 5.7 on different gas types and power source characteristics settings. The photographs of resulting welds were attached.
D	This appendix consists of selected good dip and spray transfer welding.
E	The test data for testing on-line quality models.
F	This appendix contains the result of testing of manual and synergic mode optimisation algorithm.
G	The test result of neural network models.
H	The bead dimension and assymetry range.
I	An example of industrial test result.
J	Comparison of neural networks and regression models for metal tranfer classification.
K	How to use the demo disk.

APPENDIX A

Test Data for Synergic Models

Table 1

RN	CUR	S	SO	Ips	Vps	Imean	Vmean
S1	95	0.4	12	126	16.9	121.21	16.61
S2	135	0.6	12	174	18.9	171.13	18.48
S3	95	0.6	12	129	16.9	125.79	16.60
S4	135	1	12	173	19.1	173.84	18.04
S5	120	0.6	16	138	18.2	136.38	17.59
S6	150	0.9	16	160	21.1	160.65	18.80
A53	145	1	15	178	19.0	173.8	18.00
A54	150	1	12	190	19.0	190.3	18.10
A55	120	0.8	15	149	17.9	147.2	17.05

Table 2

RN	Lavg	Lavg*	Error %, mm	T	T*	Error %, mm
S1	3.41	3.42	0.29 **-0.01**	2.49	2.29	8.03 **0.20**
S2	3.665	3.79	3.41 **-0.125**	2.61	2.60	0.38 **0.01**
S3	3.01	3.27	8.64 **-0.26**	2.15	2.17	0.93 **-0.02**
S4	2.61	3.36	28.74 **-0.75**	1.82	2.26	24.18 **-0.44**
S5	3.43	3.35	2.33 **0.08**	2.41	2.20	8.71 **0.21**
S6	3.11	3.55	14.15 **-0.44**	2.18	2.30	5.50 **-0.12**
A53	3.48	3.38	2.87 **0.10**	2.23	2.25	0.90 **-0.02**
A54	3.45	3.50	0.57 **-0.05**	2.335	2.38	1.93 **-0.045**
A55	3.21	3.22	0.31 **-0.01**	1.885	2.11	11.93 **-0.225**

*** predicted values**

Test Data for Synergic Models (contd)

Table 3

RN	Sp	Sp*	Error %,mm	Bp	Bp*	Error %,mm
S1	0.66	0.96	45.45 **-0.30**	1.19	0.15	87.39 **1.04**
S2	0.55	1.18	145.45 **-0.63**	1.12	0.44	60.71 **0.68**
S3	0.66	0.83	25.76 **-0.17**	0.56	0.07	87.50 **0.47**
S4	0.51	0.81	58.82 **-0.30**	0.63	0.29	53.97 **0.34**
S5	0.38	1.05	176.32 **-0.67**	1.07	0.11	89.72 **0.96**
S6	0.28	1	257.14 **-0.72**	0.91	0.27	70.33 **0.64**
A53	0.60	0.87	45.0 **-0.27**	0	0.24	* **-0.24**
A54	0.85	0.89	4.71 **-0.04**	0.155	0.43	177.42 **-0.275**
A55	1.24	0.88	29.03 **0.36**	0	0.08	* **-0.08**

Table 4

RN	Pr(Sp)	Pr(Sp)*	Pr(Bp)	Pr(Bp)*	Pr(und)	Pr(und)*
S1	0	0.745	0	0	0	0
S2	0	0.296	0	0	0	0
S3	0	0.745	0	0	0	0
S4	0	0.296	0	0	0	0.32
S5	0	0.464	0	0	0	0
S6	0	0.128	0	0	0	0
A53	0	0.184	1	0	0	0
A54	0	0.128	1	0	0	0.34
A55	0	0.464	1	0	0	0

*** predicted values**

APPENDIX B

Test Data for Manual Models

Table 1

RN	WFS	S	V	SO	T	T*	Error %,mm
C20	4	0.6	20	12	2.43	2.34	3.70 **0.09**
C23	8	1.2	22	12	2.22	2.34	5.41 **-0.12**
C24	10	1.4	22	12	1.92	2.41	25.52 **-0.49**

Table 2

RN	Lavg	Lavg*	Error %,mm	Sp	Sp*	Error %,mm
C20	3.54	2.99	15.54 **0.55**	0.66	0.40	39.39 **0.36**
C23	3.24	2.99	7.72 **0.25**	0.48	0.40	16.67 **0.08**
C24	2.625	3.12	18.86 **-0.495**	0.38	0.44	15.79 **-0.06**

Table 3

RN	Bp	Bp*	Error %,mm
C20	0.44	0.31	29.55 **0.13**
C23	0.51	0.31	39.22 **0.20**
C24	0.58	0.34	41.38 **0.24**

Undercut Model Response Data

Table 4

RN	WFS	S	V	SO	undercut	Pr(und)
D1	12	1	24	12	none	0.09
D2	6	0.4	19	12	none	0
D4	8	0.4	22	12	none	0
D5	8	0.9	22	16	none	0.30
D7	12	1.2	28	16	present	0.56
D8	16	1.4	32	16	present	0.75
D11	10	0.8	22	16	none	0.19
D12	8	1	24	20	present	0.56
D14	12	1	28	20	present	0.62
C19	4	0.4	20	12	none	0.03
C20	4	0.6	20	12	present	0.14
C23	8	1.2	22	12	present	0.34
C24	10	1.4	22	12	present	0.36

APPENDIX C

The data in this appendix gives the response of a fixed welding parameters to the monitoring rules in Table 5.7 on different gas types and power source characteristics settings.

Power Source	TransMIG 450i
Standoff	20mm
Gas Flow Rate	201/min
Average Current	125 Amps
Average Voltage	18 Volts
Travel Speed	0.3m/min
Experimenters	John Bassett & John Norrish

Key to Slope and Inductance setting

F .. Flat Characteristic(1V/100A)	0 .. Minimum Inductance
M .. Medium Characteristic(3V/100A)	5 .. Medium Inductance
H .. Steep Characteristic(5.75/100A)	10 ..Maximum Inductance

Note:
All comments are the actual observations made by the experimenters.

GAS TYPE: Ar 8%CO2 2%O2

RUN	SLOPE	INDUCTANCE	CURRENT	VOLTAGE	WFS
1	F	0	123	18	3.56
2		5	122	18	3.42
3		10	127	18	3.24
4	M	0	121	18	3.25
5		5	129	18	3.19
6		10	128	18	3.15
7	H	0	123	18	2.92
8		5	124	18	2.95
9		10	124	18	2.94

RUN	OBSERVATION
1	not a good condition, lots of large spatter, lot of spatter arc very slappy not a good strike.
2	better than the last run but don't sound nice, bead shape better, spatter level above average and improved better strike.
3	much better sounding and reduced spatter level.good bead shape
4	not such a good condition,spatter levels got worse and not a good strike.bead shape has got worse
5	better run and strike,good spatter levels
6	good strike and weld and very low spatter,good bead shape
7	spatter increased,not a good bead shape
8	bead size improved slightly,spatter level very low
9	better looking bead and very low spatter

RUN	TSI	DCI	TI	Applicable Rule
1	3.77	0.06	0.43	5
2	2.89	0.13	0.45	5
3	1.98	0.27	0.39	2
4	3.30	0.18	0.37	5
5	1.94	0.42	0.35	2
6	1.57	0.49	0.33	2
7	2.68	0.35	0.33	5
8	1.61	0.57	0.30	2
9	1.39	0.61	0.27	2

GAS TYPE: Ar5%O2

RUN	SLOPE	INDUCTANCE	CURRENT	VOLTAGE	WFS
1	F	0	127	18	3.46
2		5	120	18	3.32
3		10	123	18	3.24
4	M	0	126	18	3.31
5		5	127	18	3.32
6		10	128	18	3.36
7	H	0	128	18	3.35
8		5	129	18	3.33
9		10	129	18	3.33

RUN	OBSERVATION
1	large amounts of spatter very large and globy, sounds very slappy. not a lot of wash to the bead
2	improved bead appearance but arc even more slappy than before spatter still in large globules but not as many.
3	again an improvement to bead, spatter has reduced, arc still globy and slappy, bead has narrowed.
4	very similar to above , bead a bit narrower
5	slight improvement to the wash but still very slappy. bead appearance is quit good,spatter levels about the same as previous two beads
6	again not a lot of difference
7	again its difficult to see or hear any visible signs that things are changing
8	same as above
9	same as above

RUN	TSI	DCI	TI	Applicable Rule
1	3.54	0.05	0.46	5
2	3.49	0.07	0.33	5
3	2.52	0.11	0.35	5
4	3.43	0.07	0.34	5
5	2.32	0.14	0.29	5
6	1.95	0.23	0.27	2
7	2.8	0.11	0.27	5
8	1.88	0.21	0.23	2
9	1.62	0.24	0.22	2

Conclusion: None of these condition seems particularly good,all very slappy,no crispness in the sound of the arc. this gas is for spray higher voltage required.

GAS TYPE: Helishield 101

RUN	SLOPE	INDUCTANCE	CURRENT	VOLTAGE	WFS
1	F	0	129	18	4.58
2		5	132	18	4.18
3		10	123	18	3.74
4	M	0	128	18	3.99
5		5	124	18	3.56
6		10	123	18	3.47
7	H	0	125	18	3.55
8		5	126	18	3.49
9		10	125	18	3.53

SLOPE	OBSERVATION
1	bead appearance not good, arc very slappy not crisp plenty of spatter very large globules.
2	bead seems cold no ah to it, little spatter much reduced from previous run
3	arc seems cold, less spatter than previous run
4	cold arc, spatter as previous run, sounds slappy not a crisp sounding arc
5	reduced spatter but still visible globule size reduce.
6	same as above
7	low spatter, not such a good strike
8	again not a good strike, welding arc starts to hunt, sign of possible instability
9	very unstable to strike, increased arc hunting, low spatter level

RUN	TSI	DCI	TI	Applicable Rule
1	3.92	0.11	0.79	5
2	2.42	0.28	0.73	5
3	2.05	0.41	0.71	5
4	2.96	0.31	0.74	5
5	1.90	0.41	0.61	2
6	1.62	0.52	0.58	2
7	2.45	0.44	0.65	5
8	1.63	0.60	0.59	2
9	1.52	0.61	0.49	2

GAS TYPE: CO2

RUN	SLOPE	INDUCTANCE	CURRENT	VOLTAGE	WFS
1	F	0	125	18	5.46
2		5	126	18	3.35
3		10	130	18	3.36
4	M	0	123	18	3.86
5		5	127	18	3.25
6		10	119	18	3.24
7	H	0	125	18	3.60
8		5	126	18	3.26
9		10	126	18	3.2

RUN	OBSERVATION
1	very bad spatter that I could sweep up,very cold, ugly bead
2	good bead very nice sound, spatter level very good ie low
3	again good looking bead, spatter level low
4	not a good condition,difficult to achieve
5	good weld condition
6	not a good condition even though the finished bead doesn't look too back, it was difficult to strike, spatter level about average
7	again bad strike took time to settle down, not a good condition
8	not a good strike, seems to run nice good condition resulting bead looks good
9	bead looks okay, lots of spatter

RUN	TSI	DCI	TI	Applicable Rule
1	3.96	0.21	0.80	5
2	1.84	0.62	0.74	2
3	1.72	0.67	0.70	2
4	2.94	0.55	0.74	5
5	1.73	0.70	0.61	2
6	2.03	0.59	0.62	2
7	2.52	0.60	0.54	5
8	1.48	0.70	0.43	2
9	1.46	0.70	0.38	2

GAS TYPE: Argonshield TC

RUN	SLOPE	INDUCTANCE	CURRENT	VOLTAGE	WFS
1	F	0	125	18	3.65
2		5	122	18	3.25
3		10	127	18	3.22
4	M	0	126	18	3.3
5		5	126	18	3.11
6		10	127	18	3.14
7	H	0	125	18	3.03
8		5	125	18	3.0
9		10	125	18	3.09

RUN	OBSERVATION
1	not a good run, very spattery in very large globy, arc very globy not a nice looking bead
2	marginally better run, doesn't sound brilliant spatter level still not good but an improvement on run1
3	much better looking and sounding run spatter level low
4	back to a very globby transfer, very spattery in large globy
5	improvement on run4, spatter level above average
6	beast run so far, spatter level very low
7	spatter very globy, spatter level quite high
8	good condition, sounds okay, spatter level low
9	same as above

RUN	TSI	DCI	TI	Applicable Rule
1	3.75	0.07	0.44	5
2	3.05	0.13	0.47	5
3	2.06	0.28	0.42	2
4	3.41	0.17	0. 37	5
5	2.17	0.36	0.37	2
6	1.69	0.49	0.34	2
7	2.72	0.34	0.34	5
8	1.62	0.59	0.30	2
9	1.41	0.61	0.29	2

APPENDIX D

Ideal Process Data

RN	Imean	SO	Imax	Imin	Ibk	Vbk	Vmean
C2*	114.73	12	201.75	69.98	96.43	4.12	16.65
C4*	203.02	12	304.58	87.26	166.85	6.12	18.55
C7	243.84	16	266.54	227.98	239.91	26.45	27.39
C10	301.63	16	315.58	285.01	297.97	29.91	31.28
C14	183.61	20	204.69	168.88	180.6	24.56	25.56
C15	227.94	20	250.54	212.42	224.53	26.64	27.43
C18	291.63	20	306.56	279.49	288.7	30.33	31.33
D2*	159.70	12	278.90	91.31	**	5.93	18.55
A11*	178.56	12	323.97	111.28	144.86	5.56	17.51
A12*	216.48	12	378.47	138.43	176.63	8.32	19.00
A14*	176.83	12	290.64	115.98	147.29	4.92	17.33
A16*	152.15	12	272.55	93.46	123.14	5.11	16.67
A20*	168.27	15	280.30	110.45	142.63	5.47	17.57

*** dip transfer else spray tranfer**
**** missing data**

APPENDIX E

Table 1 On-line Prediction of Bead Geometry

RN	Lavg	Error %, mm	T	Error %, mm	Sp	Error %, mm	Bp	Error %,mm
S1	4.05	18.77 **-0.64**	2.87	15.26 **-0.38**	0.622	5.76 **0.038**	0.602	89.91 **0.588**
S2	4.03	9.96 **-0.365**	2.86	9.58 **-0.25**	0.728	32.36 **-0.18**	0.683	39.02 **0.437**
S3	3.2	6.31 **-0.19**	2.27	5.58 **-0.12**	0.55	16.66 **0.11**	0.493	11.96 **0.067**
S4	2.98	14.78 **-0.37**	2.11	15.93 **-0.29**	0.548	7.45 **-0.038**	0.428	32.06 **0.202**
S5	3.43	0 **0**	2.43	0.83 **-0.02**	0.603	58.68 **-0.223**	0.550	48.6 **0.52**
S6	3.08	0.97 **0.03**	2.18	0 **0**	0.575	105.36 **-0.295**	0.472	48.13 **0.438**
A53	2.98	14.34 **0.50**	2.11	5.69 **-0.12**	0.548	8.67 **0.052**	0.428	* - **0.428**
A54	3.14	8.98 **0.31**	2.22	4.93 **0.115**	0.602	29.18 **0.248**	0.485	212.9 **-0.33**
A55	3	6.54 **0.21**	2.12	12.47 **-0.235**	0.531	57.18 **0.709**	0.441	* **-0.44**
C20	3.32	1.23 **0.22**	2.35	3.29 **0.08**	0.585	11.36 **0.075**	0.531	20.68 **-0.09**
C23	3.20	1.23 **0.04**	2.26	1.80 **-0.04**	0.636	32.5 **-0.156**	0.490	3.92 **0.02**
C24	3.20	21.91 -0.575	2.26	6.22 **0.15**	0.635	67.11 -0.255	0.458	21.03 **0.122**

Table 2 On-line Prediction of Risk of Undercut

RN	Imean	Vmean	S	undercut	Pr(und)
D1	256.52	23.50	1	none	0.27
D2	159.70	18.55	0.4	none	0
D4	203.4	21.49	0.4	none	0
D5	177.91	21.52	0.9	none	0.40
D7	230	27.44	1.2	present	0.71
D8	306.20	31.26	1.4	present	0.71
D11	207.07	21.42	0.8	none	0.23
D12	174.63	23.56	1	present	0.60
D14	231.65	27.53	1	present	0.65
C19	118.95	19.73	0.4	none	0
C20	118.28	19.67	0.6	present	0.31
C23	203.34	21.35	1.2	present	0.39
C24	234.46	21.60	1.4	present	0.32

APPENDIX F

Table 1 Testing Synergic Mode Optimisation

Predicted Procedure and Expected Quality Response

REF	Desired Lavg	CUR	S	Sp	Bp	Pr(und)	Predicted Lavg*
STAT1	2.5	160	1.45	0.455	0.344	1	2.98
STAT2	3	155	1.05	0.871	0.453	0.42	3.45
STAT3	3	150	1	0.895	0.426	0.34	3.46
STAT4	3	175	1.20	0.801	0.579	0.67	3.42
STAT5	3.5	160	0.75	1.232	0.614	0	3.88
STAT6	3.5	155	0.70	1.247	0.588	0	3.88
STAT7	3.5	175	0.90	1.165	0.694	0.24	3.84
STAT8	3.5	150	0.60	1.311	0.58	0	3.94
STAT9	4	175	0.60	1.529	0.81	0	4.26

Actual Quality Response

REF	Ls	Lb	Sp	Bp
STAT1	2.45	2.84	0.27	0.10
STAT2	3.30	3.50	0.20	0.60
STAT3	2.77	2.70	1	0.5
STAT4	4	3.1	0.7	0.2
STAT5	3.29	3.29	1.04	0.66
STAT6	3.5	3.5	0.3	0.3
STAT7	3.78	3.25	0.8	0.4
STAT8	3.4	3.43	1.6	0.9
STAT9	4	4.1	0.2	0.5

Table 2 Testing Manual Mode Optimisation: Horizontal Vertical

Standoff 12mm Plate Thickness 1.6mm

Predicted Procedure and Expected Quality Response

REF	Desired Lavg	WFS	V	S	Sp	Bp	Pr(und)	Predicted Lavg*
STAT11	2.5	6	17.6	1.10	0.422	0.395	0.24	2.67
STAT12	2.5	7	18.4	1.30	0.516	0.415	0.32	2.65
STAT13	3	7	18.4	1	0.516	0.533	0.17	3.08
STAT14	3	8	19.2	1.10	0.586	0.593	0.20	3.15
STAT15	3	10	20.7	1.40	0.648	0.613	0.32	3.12
STAT16	4	9.5	20.3	0.80	0.641	0.892	0	4.18
STAT17	4	7	18.4	0.60	0.516	0.690	0	4.14
STAT18	5	7	18.4	0.40	0.516	0.769	0	5.32

Actual Quality Response

REF	Ls	Lb	Sp	Bp
STAT11	2.30	2.20	0.4	0.1
STAT12	1.94	2.04	0.64	0.27
STAT13	2.84	2.54	0.98	0.25
STAT14	2.84	2.86	0.34	0.27
STAT15	3.73	2.93	1.07	0.44
STAT16	3.55	4.50	1.20	0.53
STAT17	4.30	3.6	1.30	0.60
STAT18	4.62	4.42	1.88	1.60

Table 2 (contd)

Standoff 15mm and Plate Thickness 1.6mm

Predicted Procedure and Expected Quality Response

REF	Desired Lavg	WFS	V	S	Sp	Bp	Pr(und)	Predicted Lavg*
STAT22	3	6.5	19.2	0.90	0.405	0.303	0.25	3.14
STAT23	3	7	19.6	1	0.482	0.319	0.29	3.08
STAT24	4	7	19.6	0.60	0.482	0.476	0.09	4.14
STAT25	4	6	18.9	0.50	0.329	0.391	0.06	4.20
STAT26	4	7.5	19.9	0.60	0.548	0.531	0.08	4.31

Actual Quality Response

REF	Ls	Lb	Sp	Bp
STAT22	3.3	3.1	0.8	0.2
STAT23	2.86	2.78	0.76	0.42
STAT24	2.93	4.35	*	1.6
STAT25	4.24	4	1.1	0.3
STAT26	4.05	4	0.80	0.75

*** missing data**

Table 2 (contd)

Plate Thickness 3.2mm

Predicted Procedure and Expected Quality Response

REF	Desired Lavg	WFS	V	S	Sp	Bp	Pr(und)	Predicted Lavg*
STAT19	4	9.5	20.3	0.80	0.641	0.892	0	4.18
STAT20	4	7	18.4	0.60	0.16	0.69	0	4.14
STAT21	3.5	6.5	18.0	0.70	0.472	0.590	0.04	3.63
STAT27	3.5	6.5	19.2	0.70	0.405	0.376	0.15	3.63
STAT28	4	10.5	22.1	0.90	0.843	0.718	0.19	4.14
STAT29	4	9.5	21.4	0.80	0.768	0.669	0.15	4.18
STAT30	5	10.5	22.1	0.60	0.843	0.894	0.02	5.23
STAT31	5	14	31.3	0.80	0.506	1.71	0.21	5.23
STAT32	6	14.5	31.5	0.60	0.454	1.914	0.04	6.30
STAT33	6	15	31.8	0.60	0.39	1.969	0.03	6.43
STAT34	5	7	27.0	0.40	0.684	1.969	0.22	5.23
STAT35	6	10	28.4	0.40	1.077	0.974	0.20	6.43
STAT36	6	15	30.7	0.50	1.439	1.439	0.34	6.43

NOTE: Standoff is 12, 15 and 20mm for STAT19-21, STAT27-33, and STAT34-36 respectively.

Actual Quality Response

REF	Ls	Lb	Sp	Bp
STAT19	4	4.5	0.5	1
STAT20	5.17	5.20	1.60	0.49
STAT21	4.57	5.14	0.914	0.914
STAT27	3.50	3.3	0.5	0.5
STAT28	3	4.7	0.7	0.90
STAT29	3.78	4.42	0.42	0.58
STAT30	4.48	4.8	0.56	0.88
STAT32#	4.4	7.36	3.8	2.20
STAT33#	6.4	6.08	3.2	3.2
STAT34	4.6	5.6	0.4	1.4
STAT35	5.96	6.40	1.26	0.99
STAT36#	5.1	6	3.50	1.70

welds with overpenetration.

Table 3 Testing Manual Mode Optimisation: Gap Filling in Horizontal Vertical Position

Plate Thickness 1.6mm

Predicted Procedure and Expected Quality Response

REF	Lavg	SO	Gap	WFS	V	S
GAP1	2.5	12	0-1.6	7	18	0.55
GAP2	3		1	7	18.1	0.60
GAP3	3		1	8.5	19.1	0.70
GAP4	2.5		0-2	7.5	18.2	0.50
GAP5	3		0-2	7	17.9	0.40
GAP6	3		1-1.6	7	18	0.45
GAP7	3	12	1.6	7.5	18.4	0.50
GAP11	3	15	0-1.6	7.5	18.3	0.5
GAP12	3		0-2	7.5	18.3	0.45
GAP13	3	20	1.6	7.5	17.9	0.5
GAP14	3		2	7.5	17.9	0.45

Actual Quality Response

REF	COMMENT
GAP1	overpenetration
GAP2	slight overpenetration; Ls=3.73, Lb=4, Sp=0.8, Bp=1.422
GAP3	gap was overfilled with some sag; Ls=3.8, Lb=3.6, Sp=1.6, Bp=0.8
GAP4	slight overpenetration
GAP5	slight overpenetration with increasing sag as the gap increases
GAP6	more overpenetration
GAP7	overpenetration; Ls=3, Lb=3.4, Sp=2.8, Bp=2
GAP11	cereus overpenetration,humpy at low speed and sag towards the end of the gap
GAP12	cereus overpenetration,humpy at low speed and sag towards the end of the gap
GAP13	overpenetration and slight sag; Ls=3.36, Lb=3.71, Sp=0.84, Bp=1.01
GAP14	overpenetration and slight sag; Ls=4, Lb=4.44, Sp=1.78, Bp=1.52

Table 3 (contd)

plate thickness 3.2mm

Predicted Procedure and Expected Quality Response

REF	Lavg	SO	Gap	WFS	V	S
GAP8	3	12	1.6-3.2	8	18.3	0.3
GAP9			1.6-3.2	9	19	0.35
GAP10			1.6	7.5	18.4	0.5
GAP15		20	1.6	7.5	17.9	0.5
GAP16			1.6	6	17.5	0.4
GAP17		15	1.6	9	18.8	0.6
GAP18			1.6	7.5	18.3	0.5
GAP19			1-1.6	6	17.8	0.4
GAP20			2.5	9	18.8	0.4
GAP21			2	8	18.5	0.45

Actual Quality Response

REF	COMMENTS
GAP8	humpy bead and convex bead at low gap
GAP9	sag towards end of weld
GAP10	good fill; Ls=4.68, Lb=3.03, Sp=2.27, Bp=0.32
GAP15	good fill
GAP16	good fill; Ls=3.31, Lb=4.26, Sp=2, Bp=0.11
GAP17	good fill ; Ls=3.9, Lb=3.30, Sp=2.6, Bp=0.80
GAP18	good fill; Ls=4.20, Lb=2.60, Sp=2.4
GAP19	good fill
GAP20	good fill
GAP21	good fill

Table 4 Testing Manual Mode Optimisation: Positional Welding

Vertical Down

Predicted Procedure and Expected Quality Response

REF	Lavg	SO	PT	GAP	WFS	V	S
VD1	3	15	1.6	0	6.5	17.9	0.90
VD2	3	15			8.5	18.6	1.20
VD3	4	15			6	17.8	0.50
VD4	4	12			7	18.1	0.60
VD5	3	15			6	17.8	0.80
VD6	4	15			6	17	0.50
VD7	4	15	3.2		7.5	18.3	0.60
VD8	4	15			9	18.8	0.70
VD9	4	15			8.5	18.6	0.70
VD10	5	15			7	18.1	0.40
VD11	6	15			7.5	18.3	0.30
VD12	3	15		1.6	5.5	17.6	0.35
VD13	3	15		1.6	5	17.4	0.30
VD14	3	15		3.2	8.5	18.6	0.30
VD15	3	15		1.6-0	5	17.4	0.30

Actual Quality Response

REF	COMMENTS
VD1	good weld ; Ls=3.5, Lb=2.5, Sp=0.71, Bp=0.60
VD2	weld pool running down and undercut present; Ls=2.61, Lb=3.2, Sp=0.16, Bp=0.67
VD3	good weld but misalignment; Ls=4.89, Lb=2.22, Sp=1.24, Bp=0
VD4	good weld; Ls=4.5, Lb=2.6, Sp=1.6, Bp=0.4
VD5	no fusion on lower plate
VD6	good weld; Ls=4.44, Lb=3.55, Sp=0.62, Bp=0.44
VD7	good weld; Ls=3.10, Lb=4, Sp=0.30, Bp=0.40
VD8	bad quality; arc was difficult to maintain
VD9	good weld
VD10	good weld; Ls=4.91, Lb=5, Sp=0.70, Bp=0.30
VD11	good weld; Ls=6, Lb=5.84, Sp=0.32, Bp=0.32
VD12	gap well filled; Ls=3.80, Lb=4.70, Sp=2, Bp=0.4
VD13	gap well filled; Ls=4, Lb=4.80, Sp=2.8, Bp=0.32
VD14	gap well filled; Ls=6.4, Lb= 6, Sp=2.9, Bp=1.28
VD15	gap well filled

Table 4 (contd)

Vertical Up

Standoff 15mm Plate Thickness 3.2mm

Predicted Procedure and Expected Quality Response

REF	Lavg	GAP	WFS	V	S
VU1	4	0	7	18.1	0.6
VU2	5		7	18.1	0.4
VU3	5		7	18.6	0.4
VU4	6		7.5	18.3	0.3
VU5	3	1.6	5	17.4	0.3
VU6	3		7	18.1	0.4
VU7	3		7	18.1	0.45
VU8	3		6	17.8	0.35
VU9	3		8	18.5	0.45
VU10	3		8.5	18.6	0.5
VU11	3	3.2	8.5	18.6	0.3

Actual Quality Response

REF	COMMENTS
VU1	good weld but peaky; Ls=2.9, Lb=3.2, Sp=0.2, Bp=0.3
VU2	good weld
VU3	increasing voltage gives more peaky bead than VU2
VU4	weld pool falling out, very humpy bead, speed too low or weld size too big
VU5	gap filled but with traces of undercut; Ls=5.07, Lb=3.87, Sp=2.13, Bp=1.73
VU6	gap well filled; Ls=3.73, Lb=4.05, Sp=1.71, Bp=0.64
VU7	more sag, more undercut
VU8	more sag, humpy bead, undercut. Conclusion: minimum speed for vertical up is 0.4m/min Ls=3.37, Lb=3.64, Sp=1.78, Bp=0.80
VU9	gap well filled, assumption in VU8 validated
VU10	serious sagging, undercut...arc power too high Ls=2.90, Lb=2.10, Sp=2.8, Bp=1.30
VU11	gap not filled...weld pool was not running, could be filled with bigger wire and maybe weaving.

APPENDIX G

Table 1

RN	Lavg	Lavg*	Error % mm	T	T*	Error% mm
S1	3.41	3.628	7.44 **-0.218**	2.49	2.401	3.57 **0.089**
S2	3.665	3.691	0.709 **-0.026**	2.61	2.457	5.86 **0.153**
S3	3.01	3.475	15.45 **-0.465**	2.15	2.301	7.02 **-0.151**
S4	2.61	3.332	27.66 **-0.722**	1.82	2.224	22.20 **-0.404**
S5	3.43	3.532	2.97 **-0.102**	2.41	2.337	3.03 **0.073**
S6	3.11	3.422	10.03 **-0.312**	2.18	2.301	5.55 **-0.121**
A53	3.48	3.332	4.25 **0.148**	2.23	2.224	0.27 **0.006**
A54	3.45	3.451	0.03 **0**	2.335	2.263	3.08 **0.072**
A55	3.21	3.393	5.70 **-0.183**	1.885	2.224	17.98 **-0.339**

* predicted

Table 2

RN	Pr(und)	Pr(und)	Pr(Sp)	Pr(Sp)*	Pr(Bp)	Pr(Bp)*
S1	0	0.156	0	0.699	0	0
S2	0	0.938	0	0	0	0
S3	0	0.021	0	0.817	0	0
S4	0	0.228	0	0	0	0
S5	0	0.262	0	0.003	0	0
S6	0	0.500	0	0	0	0
A53	0	0.080	0	0	1	0
A54	0	0.831	0	0	1	0
A55	0	0.010	0	0.013	0	0

* predicted

Table 3

RN	Sp	Sp*	Error % mm	Bp	Bp*	Error % mm
S1	0.66	0.10	84.84 **0.56**	1.19	0.084	92.94 **1.106**
S2	0.55	0.621	11.43 **-0.071**	1.12	0.477	57.41 **0.643**
S3	0.66	0.092	86.06 **0.568**	0.56	0.256	54.28 **0.304**
S4	0.51	0.60	17.65 **-0.09**	0.63	0.684	8.57 **-0.054**
S5	0.38	0.615	61.84 **-0.235**	1.07	0.24	77.57 0.83
S6	0.28	0.584	8.57 **-0.304**	0.91	0.613	32.64 **0.297**
A53	0.60	0.593	1.17 **0.007**	0	0.672	* **-0.672**
A54	0.85	0.597	29.76 **0.253**	0.155	0.707	356.12 **-0.552**
A55	1.24	0.61	50.81 **0.63**	0	0.509	* **-0.509**

Table 4

REF	Desired Lavg	CUR	S
ANN1	2.5	171	1.59
ANN2	3	154	1.26
ANN3	3.5	155	0.87
ANN4	4	158	0.72

Actual Quality Response

	Ls	Lb	Sp	Bp
ANN1	2.67	2.67	0.97	0.88
ANN2	2.7	2.90	0.658	0.30
ANN3	2.84	3	0.5	0.27
ANN4	2.66	2.73	0.47	0.27

Table 5

RN	WFS	S	V	SO	T	T*	Error
C20	4	0.6	20	12	2.43	2.725	12.14 **-0.295**
C23	8	1.2	22	12	2.22	2.602	17.21 **-0.382**
C24	10	1.4	22	12	1.92	2.602	35.52 **-0.682**

RN	Lavg	Ls*	Lb*	Lavg*	Error
C20	3.54	3.739	4.017	3.878	9.55 **-0.338**
C23	3.24	3.404	3.674	3.539	9.23 **-0.299**
C24	2.625	3.404	3.674	3.539	34.82 **-0.914**

* predicted

Table 6

RN	Bp	Bp*	Error %,mm	Sp	Sp*	Error
C20	0.44	0.65	47.72 **-0.21**	0.66	0.224	66.06 **0.436**
C23	0.51	0.243	52.35 **0.267**	0.48	0.805	67.71 **-0.325**
C24	0.58	0.805	38.79 **-0.225**	0.38	0.687	80.79 **-0.307**

* predicted

Table 7

RN	WFS	S	V	SO	Spatter	Pr(spatter)	Undercut	Pr(und)
D1	12	1	24	12	present	0.636	none	0
D2	6	0.4	19	12	none	0.341	none	0
D4	8	0.4	22	12	present	0.943	none	0
D5	8	0.9	22	16	none	0.987	none	0.052
D7	12	1.2	28	16	present	0.407	present	0.831
D8	16	1.4	32	16	none	0	present	0.896
D11	10	0.8	22	16	present	0.453	none	0
D12	8	1	24	20	present	0.957	present	0.896
D14	12	1	28	20	none	0.08	present	0.998
C19	4	0.4	20	12	present	0.164	none	0
C20	4	0.6	20	12	none	0.658	present	0
C23	8	1.2	22	12	present	0.998	present	0.737
C24	10	1.4	22	12	present	0.889	present	0.228

Table 8

a) STANDOFF 12mm   PLATE 1.6mm

REF	Desired Lavg	WFS	V	S
ANN5	2.5	4.8	19.7	1.37
ANN6	3	6.2	19.7	1.23
ANN7	4	8.4	21.1	0.80

Weld quality still marginal.

	Ls	Lb	Sp	Bp
ANN5	2.73	2.26	0.56	0.28
ANN6	2.7	2.50	0.4	0.30
ANN7#	3.6	4.20	0.8	1.2

overpenetration of weld

b) STANDOFF 15mm PLATE 3.2mm

REF	Desired Lavg	WFS	V	S
ANN10	3	7.2	22.4	1.42
ANN11	4	9.8	23.6	1.09
ANN12	5	11.8	24.1	0.76
ANN13	6	12.8	25.2	0.48

	Ls	Lb	Sp	Bp
ANN10				
ANN11	3.84	4.22	0.4	0.56
ANN12	4.40	4.48	1.28	1.2
ANN13	7	6.4	1	0.6

ANN10 is a very bad quality weld, very patchy weld.

Table 8 (contd)

d) STANDOFF 20mm PLATE 3.2mm

REF	Desired Lavg	WFS	V	S	Sp	Bp	Pr(und)
ANN14	3	9.1	26.1	1.52	0.613	0.161	0.036
ANN15	4	11.2	26.6	1.37	0.844	0.243	0.104
ANN16	5	12.8	27	1.05	1.331	0.923	0.964
ANN17	6	13.7	27	0.76	1.565	1.245	0.699

	Ls	Lb	Sp	Bp
ANN14	4.352	1.792	0.615	0.615
ANN15	4.5	2.5	0.1	0.3
ANN16	4.92	4.8	0.86	0.86
ANN17	5.97	6.13	0.96	1.92

ANN14 is a very bad quality weld, very patchy weld.

APPENDIX H

Table 1 Bead Asymetry Statistics

δ	Synergic Mode	Manual Mode
δ_{mean}	0.865	0.596
δ_{max}	2.205	1.390
δ_{min}	0.105	0.045

where δ absolute difference between both fillet legs(mm).

Table 2 The Bead Dimensions Range

Dimension	Synergic Mode	Manual Mode
Throat Thickness	1.6 - 2.9	2.5 - 5
Side Leg Lenght	2.42 - 4.83	3.11-7.15
Bottom Leg Lenght	1.87-3.75	3.56-7.35
Side Plate Penetration	0 - 1.53	0-1.69
Bottom Plate Penetration	0 - 1.415	0-1.69

APPENDIX I

An Example of Industrial Test Result

F - 26

INSPECCION Nº / MIAKETA ZENB. 5478

HOJA / ORRIA 2 DE / KOA

LABORATORIO

PROVEEDOR - EKARLE:

CANTIDAD - KOPURUA:

FECHA - DATA 26.9.94 PLANO Nº - PLANO ZENB. E.20.00

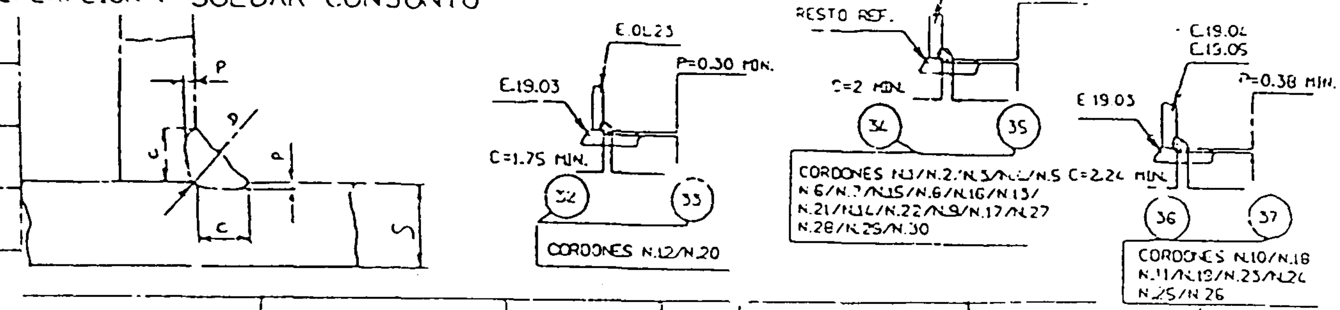
S/PAUTA Nº / ZENBAKI ARAVERA: PAUTA N. 60

FECHA / DATA:

DENOMINACION PIEZA: QUINTO TRAVESAÑO "LARGO"

DIMENSIONES DEL CORDON DE SOLDADURA

OPERACION: SOLDAR CONJUNTO



	PENETRACION "P"	CANTO "C"
1	0,30* - 0,69	3,2 - 3,1
2	1,08 - 0,35	4,4 - 2,6
3	0,73 - 0,61	4,1 - 3,1
4	1,13 - 0*	4,7 - 0*
9	0,75 - 1,79	3,9 - 2,7
10	0,68 - 0,62	4,4 - 4,1
11		
12	0,60 - 1,00	4,2 - 4,9
13	1,19 - 0,50	6,2 - 1,47*
14	0,81 - 0,72	2,3 - 3,7
23	1,92 - *0	5,2 - *0
24	1,15 - 1,04	4,4 - 4,4
27	0,74 - 1,32	4,6 - 2,9
28	0,90 - 0,65	4,7 - 3,0

LA SOLDADURA DEBE ESTAR EXENTA DE GRIETAS, CRATERES, POROSIDAD, RECHUPES Y ANUFTAMIENTOS EN EL METAL BASE. TAMPOCO DEBE SUPERPONERSE A ESTE. LIMPIA Y EXENTA DE IMPUREZAS.

* CORDON Nº 9 Y 24 NOK
PERDIDA MATERIAL.
* Nº 13 PERFORADO.

OBSERVACIONES: / OHARRAK

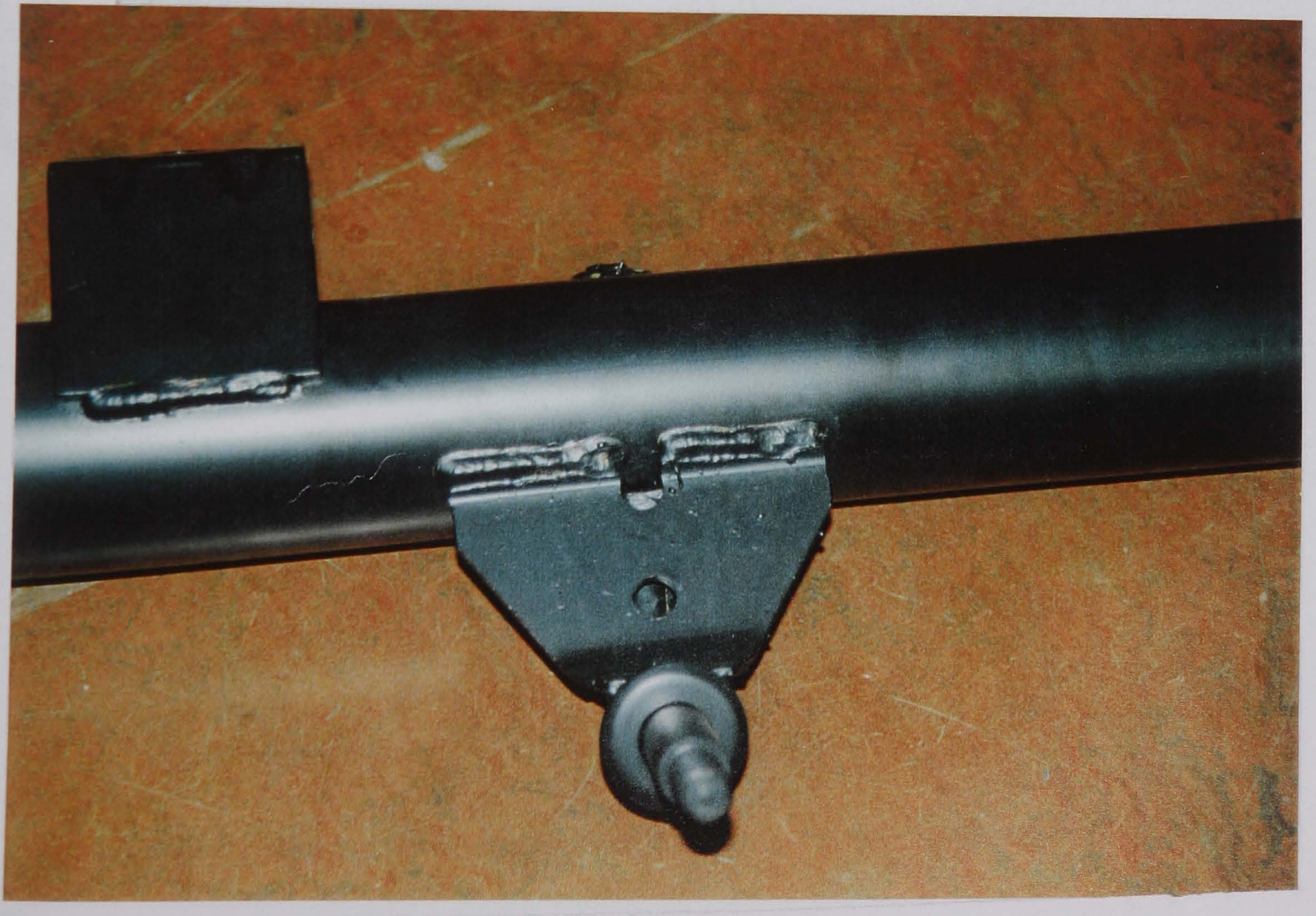
VERIFICADO / EGIAZTATUA — FIRMA: / IZENPEA — FECHA: / DATA 26.9.94

Vº Bº MAESTRO / MAISUAREN ONIRITZIA — FIRMA: / IZENPEA — FECHA: / DATA

Onirizia / Egiaztatua

(a)

(b)



Photographs of the Welded Component

APPENDIX J

Comparison of ANN and Statistical technique for metal tranfer classification

RN	Pr(dip)ANN	Pr(spray)ANN	Pr(dip)STAT	Pr(spary)STAT
C1	0.967	0.040	0.562	0.438
C2	0.979	0.023	1	0
C3	0.040	0.960	0.058	0.942
C5	0.979	0.023	1	0
C6	0.960	0.043	0.547	0.453
C7	0.030	0.970	0.02	0.980
C8	0.407	0.615	0.183	0.817
C9	0.658	0.363	0.282	0.718
C10	0.030	0.967	0.032	0.968
C11	0.104	0.904	0.101	0.899
C12	0.977	0.025	0.974	0.026
C13	0.080	0.919	0	1
C14	0.036	0.964	0.045	0.955
C15	0.030	0.970	0.013	0.987
C16	0.363	0.658	0.126	0.874
C17	0.030	0.967	0.019	0.981
C18	0.027	0.97	0	1

APPENDIX K

About the demonstration software

The attached diskette contains a demonstration programm of the quality control strategy. To run the program type SOFT The software consists of demonstration module for quality assessment, welding procedure generation and quality control. The following pages shows the menu structure for the software.

The weld quality assessment could be done on-line or off-line based on synergic and manual mode of BDH320 power source. The input required for on-line is welding current, voltage,speed and plate thickness. The input for off line synergic is current, standoff, speed and plate thickness. The input for off line manual is wire feed speed, voltage, standoff, speed and plate thickness. The assessment will produce information on the bead dimension and fusion characteristics.

The procedure generation can be carried out for both synergic and manual mode. The synergic mode is dedicated to program 4 of BDH320. The inputs are bead size required, which could be specified as throat thickness or leg length, standoff, plate thickness and welding position; then based on the specified requirement, a series of procedures would be generated.

The quality control involves the demonstration of the standoff estimation, synergic, gap filling and adaptive control algorithm. The standoff estimation requires as input the procedure, the resulting chart also shows how the procedure should be fine tuned based on the standoff estimation. The procedure can be adapted based on detected gap size by creating a look-up for gap. This mode generates series of welding procedures for the gap size.

The synergic algorithm giving the wire feed speed and standoff, predict voltage and gives the user the risk of bad arc start, arc length and estimated metal transfer frequency. The mode also suggests sampling frequency.

The adaptive control issue control instructions and assessment of risk of undercut and penetration ratio in terms of plate thickness; the inputs are the welding procedure and the standoff and gap estimation based sensors input.

INPUT TRANSIENT WELDING PARAMETERS

MEAN VOLTAGE	19
MEAN CURRENT	200
SPEED	0.5

QUALITY ASSESSMENT REPORT

Bead Dimension in mm

Throat Thickness	3.64
Average Leg Length	5.12
Minimum Leg Length	5.12

Fusion Characteristics

Side Plate Peneration	0.88
Risk of lack of fusion	0.00
Bottom plate penetration	0.86
Risk of lack of fusion	0.00
Risk of undercut	0.00

Press any key to return to Quality Assessment Menu

\####* M A I N M E N U *####

[1] WELD QUALITY ASSESSMENT

[2] WELDING PROCEDURE GENERATION

[3] WELD QUALITY CONTROL

[4] ABOUT SOFTWARE

[Esc] EXIT

CHOOSE MODE [?]

\####* M A I N M E N U *####

[1] WELD QU

[2] WELDING

[3] WELD QU

[4] ABOUT S

[Esc] EXIT

CHOO

\### WELD QUALITY ASSESSMENT ###

[1] ON LINE ASSESSMENT

[2] OFF LINE ASSESSMENT:Synergic Mode

[3] OFF LINE ASSESSMENT:Manual Mode

[Esc] MAIN MENU

CHOOSE MODE [?]

INPUT MANUAL MODE WELDING PROCEDURE

WFS	9
SPEED	0.6
VOLTAGE	12
STANDOFF	12
PLATE THICKNESS	3

QUALITY ASSESSMENT REPORT

Bead Dimension in mm

Throat Thickness	3.36
Average Leg Length	4.78
Minimum Leg Length	4.57

Fusion Characteristics

Side Plate Peneration	0.50
Risk of lack of fusion	0.00
Bottom plate penetration	0.28
Risk of lack of fusion	1.00
Risk of undercut	0.00
Risk of bad arc ignition	1.00

Press any key to return to Quality Assessment Menu

The Program Menu Structure 1/2

####* M A I N M E N U *####

[1] WELD QU
[2] WELDING
[3] WELD QU
[4] ABOUT S
[Esc] EXIT

CHOO

WELDING PROCEDURE GENERATION

[1] SYNERGIC MODE
[2] MANUAL MODE
[Esc] MAIN MENU

CHOOSE MODE [?]

####* M A I N M E N U *####

[1] WELD QU
[2] WELDING
[3] WELD QU
[4] ABOUT S
[Esc] EXIT

CHOO

WELDING PROCEDURE GENERATION

[1] SY
[2] MA
[Esc]

CHOO

MANUAL MODE

[1] LEG LENGTH
[2] THROAT THICKNESS
[Esc] Back

CHOOSE MODE [?]

####* M A I N M E N U *####

[1] WELD QUALITY ASSESSMENT
[2] WELDING PROCEDURE GENE
[3] WELD QUALITY CONTROL
[4] ABOUT SOFTWARE
[Esc] EXIT

CHOOSE MODE [?]

WELD QUALITY CONTROL

[1] STANDOFF ESTIMATION
[2] SYNERGIC ALGORITHM
[3] GAP FILLING
[4] ADAPTIVE CONTROL

CHOOSE MODE [?]

INPUT WELDING PROCEDURE
WFS ? 8
STANDOFF ? 15

PROCESS STABILITY AND TRANSFER INDEXES
TI = 0.35 TSI = 1.60 DCI= 0.48

Set Welding Voltage at 20.3 volts
Possibility of free transfer is 4.8 %

PROCESS CHARACTERISTIC
Possibility of bad arc ignition 13.4 %
Arc length 1.8 mm
Short circuiting time 2.4 msec
Arcing time 8.3 msec
Metal transfer frequency 93.2 Hz

RECOMMENDED SAMPLING PARAMETERS
Sample Size ... (256, 512, 1024 or 2048 data points) ? 512
Approximate number of process cycle per sample (10-20) ? 10
Sampling time 107.2 msec at 4.8 KHz sampling rate

Press any key to return to Quality Control Menu

GENERATING WELDING PROCEDURE FOR GAP FILLING

LEG LENGTH 3
GAP SIZE 2
PLATE THICKNESS 3
STANDOFF 15
WELDING POSITION [1] POSITIONAL [0] DOWNHAND 0

SUGGESTED WELDING PROCEDURE

WFS	CURRENT	VOLTAGE	SPEED	Lavg	Pr(ARC)
7.0	181.3	18.1	0.40	5.22	0.33
7.5	189.8	18.3	0.40	5.43	0.35
7.5	189.8	18.3	0.45	5.07	0.35
8.0	198.4	18.5	0.45	5.27	0.37
8.5	207.0	18.6	0.45	5.45	0.38
8.5	207.0	18.6	0.50	5.13	0.38
9.0	215.5	18.8	0.50	5.30	0.40
9.0	215.5	18.8	0.55	5.02	0.40
9.5	224.1	19.0	0.50	5.47	0.41
9.5	224.1	19.0	0.55	5.18	0.41

Press any key to return to Quality Control Menu

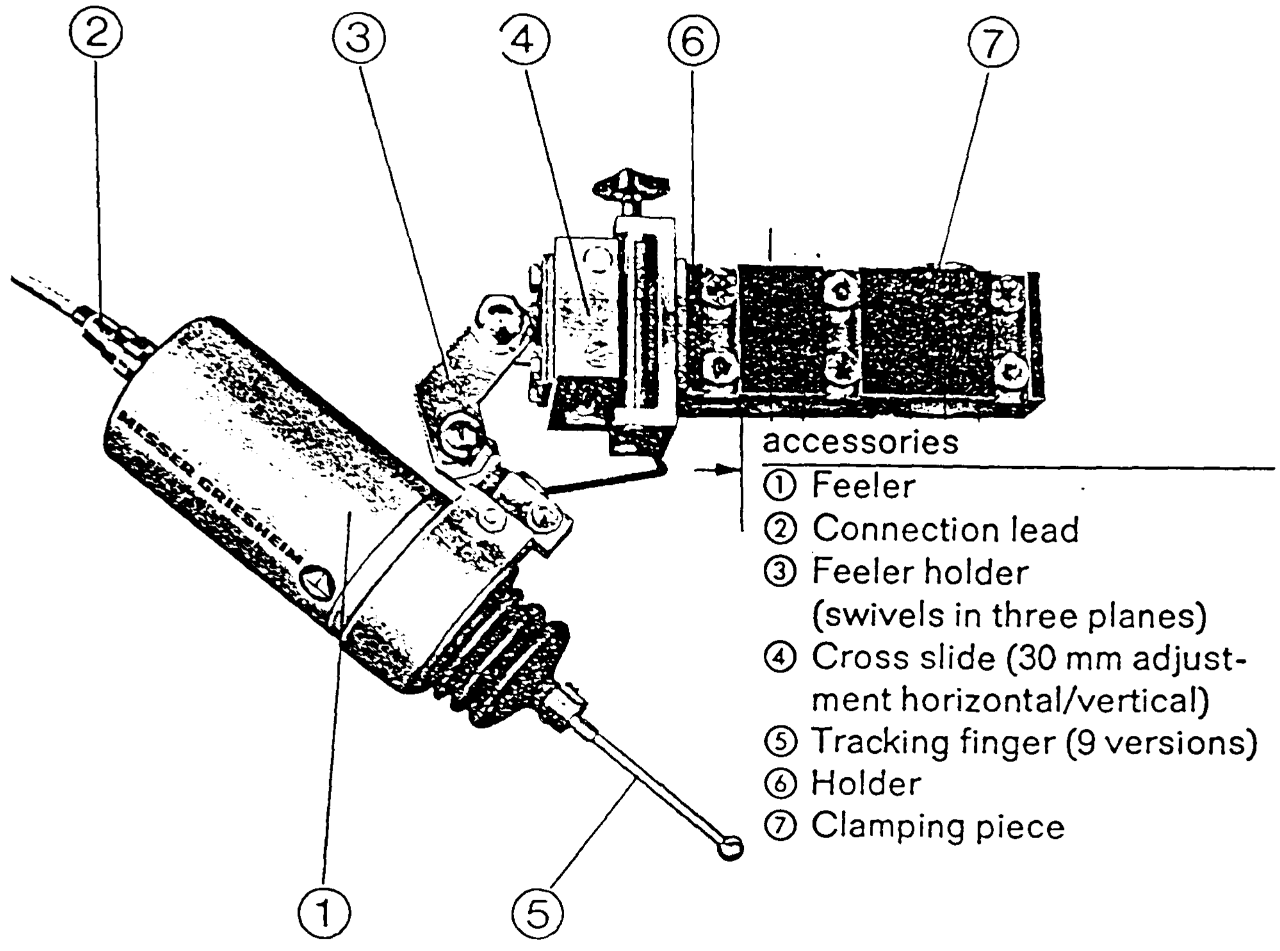


Figure 2.9 An Example of Contact Sensor

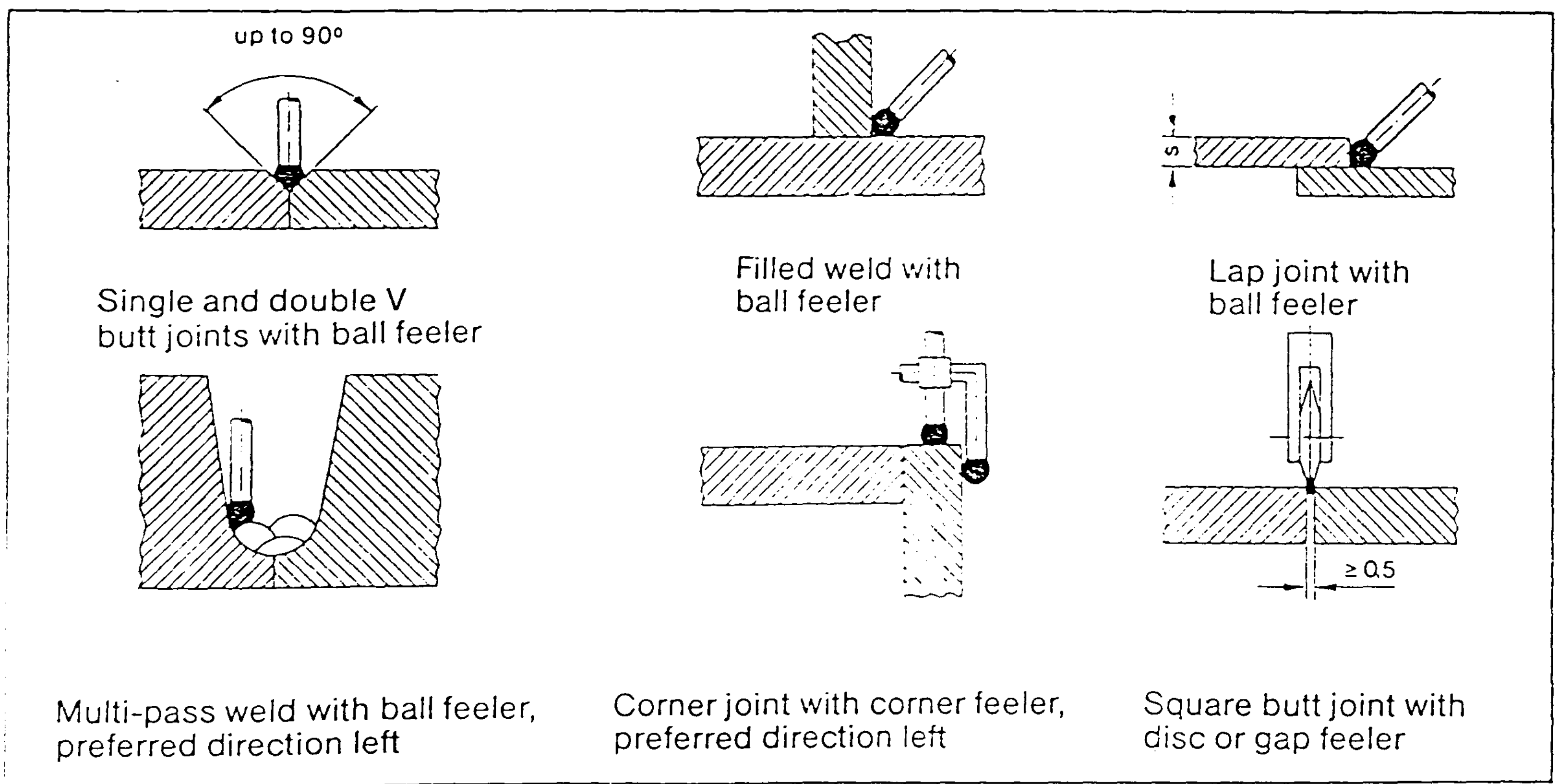


Figure 2.10 Typical Application of Contact Sensing