DEVELOPMENT AND TESTING OF AN INTELLIGENT CONTROLLER FOR OPTIMIZATION OF RESISTANCE SPOT WELDING PROCESS

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Development and Testing of an Intelligent Controller for Optimization of Resistance Spot Welding Process

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other university.

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This thesis has been submitted for examination with our approval as the University supervisors:

Sign.. Date..........................

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JKUAT, Kenya

DEDICATION

I dedicate this work to my wife, Mirfat and my lovely daughter Nur.

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All the praises and thanks be to Almighty God, without whom this work would not have even started. I thank Him for giving me the opportunity to undertake this course to completion.

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LIST OF ABBREVIATIONS

AC	Alternating Current
A/D	Analogue to Digital interface
AI	Artificial Intelligence
ANFIS	Adaptive Neural Fuzzy Inference System
ANOVA	Analysis of Variance
BBN	Bayesian Belief Networks
D/A	Digital to Analogue interface
DAQ	Data Acquisition System
FIS	Fuzzy Inference Systems
FLC	Fuzzy Logic Control
LVQ-NN	Learning Vector Quantization Neural Network
MFDC	Medium Frequency Direct Current
MLP	Multi-Layer Perceptron
SCR	Silicon Controlled Rectifier
SOM	Self Organizing Maps

NOMENCLATURE

$\boldsymbol{\alpha}$	Firing angle (rad)
$\boldsymbol{\theta}$	Conduction angle of SCR (rad)
$\boldsymbol{F_{max}}$	Maximum electrode force (N)
$\boldsymbol{I}$	Current applied to unknown resistance (A)
$\boldsymbol{I_{2cc}}$	Secondary short circuited current (A)
$\boldsymbol{N}$	transformer turn ratio
$\boldsymbol{u_1}$	instantaneous applied primary voltage (V)
$\boldsymbol{u_2}$	instantaneous applied secondary voltage (V)
$\boldsymbol{i(t)}$	Weld current time function(A)
$\boldsymbol{f}$	Supply frequency (Hz)
$\boldsymbol{R}$	Resistance of conductor (Ohm)
$\boldsymbol{V}$	Voltage applied to unknown resistance(V)
$\boldsymbol{S_{max}}$	Maximum welding power (W)

ABSTRACT

Resistance spot welding (RSW) is one of the most widely used welding processes for sheet metal joining, especially in the automotive industry. One of the challenges facing RSW is inconsistencies in quality of the weld. This challenge can be addressed by implementing an on-line weld quality assessment and control. In this study an on-line quality assessment and control model based on Learning Vector Quantization Neural Network (LVQ-NN) system and Adaptive Neuro-Fuzzy Inference System (ANFIS) is developed.

The ANFIS model is realized for identifying the RSW dynamical system based on given input output data. It can be used to approximate nonlinear systems with minimum training data, quicker learning speed and higher precision.

An indirect estimation of the weld quality employing an LVQ-NN type classifier was designed to provide a real time assessment of the weld quality.

Experiments were conducted to establish the effects of various parameters, such as the welding time and the welding current on the quality of the weld produced. A set of important parameters was then selected as the input data to train the proposed LVQ-NN type classifier and ANFIS controller. Once the monitoring and control system had been trained, it was then tested to evaluate their validity in the RSW process.

The results show that the classifier based on LVQ-NN was able to classify the weld quality into normal, cold and expulsion based on their corresponding dynamic resistance curves obtained as a function of welding time. The recognition rate was 82 percent for the test data. The proposed control algorithm based on ANFIS demonstrated robust performance reducing the number of expulsion welds by 30%

compared to the conventional controller, while increasing the number of normal welds by 31% in RSW process.

CHAPTER ONE

INTRODUCTION

1.1 Background

Resistance spot welding (RSW) is one of the methods for joining metals and has been widely employed, especially in automotive industries. RSW is an electro-thermal process, in which the electrical energy is converted to heat, which is generated at the interface of the parts to be joined. Welding is accomplished by passing an electrical current through the parts for a precisely controlled time period and under a controlled pressure to form a molten nugget at the interface.

Although it has been used in mass production for several decades, RSW poses some problems, most notably, large variation in weld quality [3]. These problems include sources of variability, noise, and errors which are caused by factors such as the fluctuation of power line voltages, fluctuation of electrode pressure, wear of electrodes, variation of secondary circuit impedance and difference of condition of workpieces surfaces.

Any of these makes it difficult to automate the process, leads to reduced weld quality, demand over-welding and increases production cost. For this reason, ensuring weld quality remains a major challenge and goal.

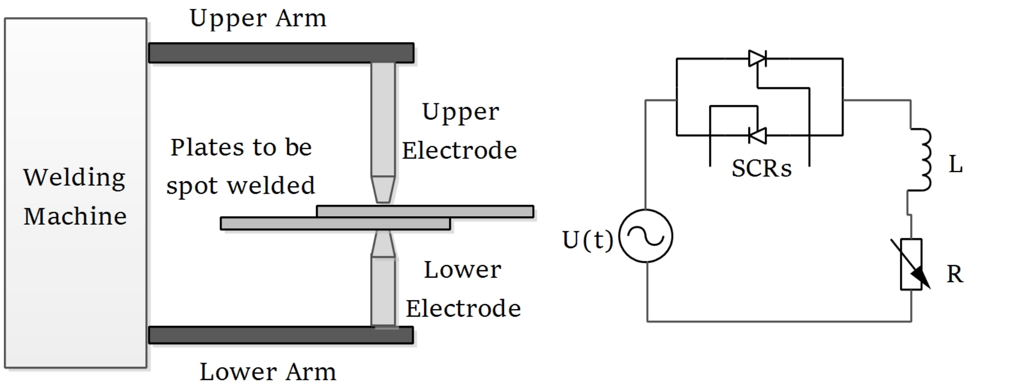
This study presents a structured and systematic approach developed to design an effective controller that will improve the reliability of the resistance spot welding process. Due to the extensive use of resistance spot welding, even a small improvement would bring significant economic benefits.

1.1.1 Electrical system of RSW

The parameters of the electrical system of RSW machine, such as welding current, voltage and welding time, play an important role in the functionality and performance of a welding machine, and subsequently influence the welding process and weld quality. Controlling an RSW system involves control of the amount of electrical energy which is delivered into the system. There are two types of resistance spot welding machines used in modern industry, namely single phase Alternating Current (AC) RSW and three-phase Medium Frequency Direct Current (MFDC) RSW. The proposed research will involve the use of a single-phase AC RSW which is predominantly used in modern industry [4].

A typical single-phase AC RSW electrical system consists of a low frequency power supply connected in series with a pair of anti-phase silicon-controlled rectifier (SCR) to the primary side of a step-down transformer. In the control operation, the firing angle α of SCR is the controllable variable; its value decides the value of welding current. The process setup, that is welding machine and workpieces/electrodes combination is connected to the secondary side of the transformer which can be modeled as time-varying resistance and inductance elements connected in series.

The detailed schematic of the electrical system is shown in Figure 1.1 [5, 6].



(a) Physical diagram of resistance spot welding

(b) Schematic diagram of resistance spot welding

Figure 1.1: Schematic diagram of resistance spot welding

1.1.2 Weld nugget formation

In RSW process the welding nugget starts to form when sufficient heat has been generated at work-piece interface. The size of the weld nugget diameter formed is dependent on the resistance offered, the welding current and the welding time [3]. The electrodes exert a concentrated force on the outer surfaces of the parts to be joined. The electrode force produces a local deformation at the common interface to align the workpiece properly and to establish good electrical contact before current flow. Figure 1.2 shows simplified representation of the RSW process.

The RSW process consists of four stages as follows:

1. Squeeze cycle time during which the upper electrode is brought into contact with the sheets and a force is exerted at the region that needs to be welded.

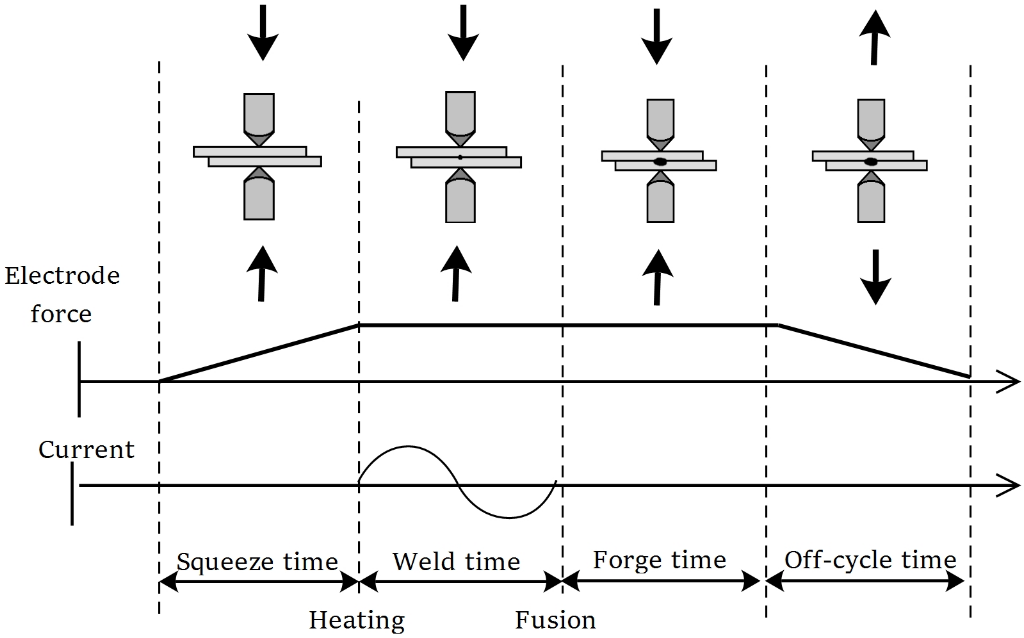


Figure 1.2: Phases of resistance spot welding process

2. Weld cycle time during which current is turned on and resistance to current flow at the sheet interface produces a nugget.

3. Hold cycle time during which the current is turned off and the fully grown nugget is allowed to cool and solidify slowly under constant pressure.

4. Off cycle time during which the electrode is raised from the welded sheets.

It is very important that the welding parameters such as the welding current, the welding force and the welding time are chosen correctly. There are two major flaws that can arise from wrong choice of RSW parameters. These are cold weld and expulsion.

A cold weld is a weld made with an insufficient amount of energy and is a consequence of the welding current being too low and/or welding time being too short and/or welding force being too high.

A well-known defect mode in RSW is expulsion, where molten metal is ejected from the sheet metal interface during the process. Expulsion occurs when the diameter of the weld nugget increases to such an extent that electrode pressure is insufficient to contain the high pressure caused by volumetric expansion of the liquid metal. There have been studies that focus on the effect of expulsion in RSW [7]. Since expulsion reduces the amount of molten metal available for form the final weld, it generally leads to surface indentations and internal voids, the latter reducing the strength of the joint [7]. Expulsion also contributes to welding fume in the working environment.

As a consequence there is an optimal window of welding parameter selection (no cold weld nor expulsion). The position of the optimal window is, however, dependent on a variety of welding parameters that can be determined as well as on the indeterminable parameters such as impurities, poor fit-up, oxidized surface and electrode wear. It is therefore extremely difficult to maintain the optimum parameters for all welds.

1.1.3 Optimum welding parameters

The optimum welding parameters can be obtained from weldability lobe diagram, and are normally used by the resistance welder to preset the welding schedule for satisfactory welding results. The lobe diagram is generated by experimental tests and defines a window of welding parameters, weld current and weld times, which produces quality welds [8].

The formation, size and growth rate of weld depend on the welding parameters used. Figure 1.3 shows the effect of variation of welding current on the size of the weld nugget.

A good spot weld has sufficient diameter and nugget penetration. The minimum acceptable diameter of weld nugget is considered to be $4\sqrt{t}$, where t is workpiece thickness [9]. Welds with smaller diameters do not have sufficient penetration and the size of the weld is not enough to bear the calculated loads. The recommended weld diameter is $5\sqrt{t}$, and any weld nugget above this value is considered to be an expulsion weld [9]. This value of weld nugget diameter is usually achieved slightly under the splash limit (expulsion), where the weld nugget growth is stabilized and small variation in the welding current or workpiece surface quality do not significantly change the size of the weld [10].

1.2 Problem statement

Resistance spot welding (RSW) is one of the most widely used welding processes for sheet metal joining. One of the challenges facing RSW is inconsistencies in quality of the weld. This challenge can be addressed by implementing an online weld quality assessment and control. One of the phenomena that causes the deterioration in quality is the eruption of molten material, which is referred to as expulsion. This is undesirable and should be avoided especially when the resulting weld is to be subjected to dynamical loading, such as in motor vehicles.

One of the strategies employed by the industries to reduce the risk of part failure and to compensate for this variance is to increase the welding points by 20-30% [3], but such over-welding results in higher costs and lower productivity.

Although some conventional quality assessment methods have been developed during the past decade, their accuracy, flexibility and reliability remain insufficient [3]. Hence, the present work aims at combining the important aspects of intelligent control approach to ensure less variation in weld-bonding quality and improved weld strength in RSW process.

1.3 Objectives

The overall objective of this study is to develop a robust on-line monitoring and control system for the optimization of resistance spot welding process.

The following are the specific objectives:

1. To investigate the effect of welding current and welding time of the RSW on the resulting weld quality

2. To design an on-line weld quality evaluation system based on Learning Vector Quantization Neural Network (LVQ-NN).

3. To design and implement an Adaptive Neuro-Fuzzy Inference System (ANFIS) based controller for the RSW process.

1.4 Justification of the study

In the recent years, global competition in automobile industry has led to exploration of better means and more efficient welding machines. In particular, a resistance spot welding machine has become the predominant tool in auto body assembly process. The strategies employed by the automobile industries to reduce the risk of part failure and to compensate for this qualitative variance is by increasing the welding points, yet such over-welding results in higher costs, lower productivity, and expulsion [3]. Consequently, the tests of weld quality tends to be predominantly off-line or end-of-line processes. However, to apply the destructive methods to on-line quality estimation there is often too much delay in the collection of the information for controlling the process.

If the weld quality enhancements offered by the proposed intelligent resistance welding system can result in reduction in the number of welds, this will lead to lower costs, higher production rates, and less expulsion.

1.5 Outline of thesis

This thesis contains five chapters. The first chapter provides an introduction to the research by highlighting the existing problem, the objective and the scope of the research work. Chapter 2 is a literature review on the various methods employed in monitoring and control of RSW process. Chapter 3, outlines the experimental procedure for investigating the relationship between the input welding parameters and the welding quality. Finally chapter 4 presents the experimental results obtained. The conclusion and recommendations are made in chapter 5.

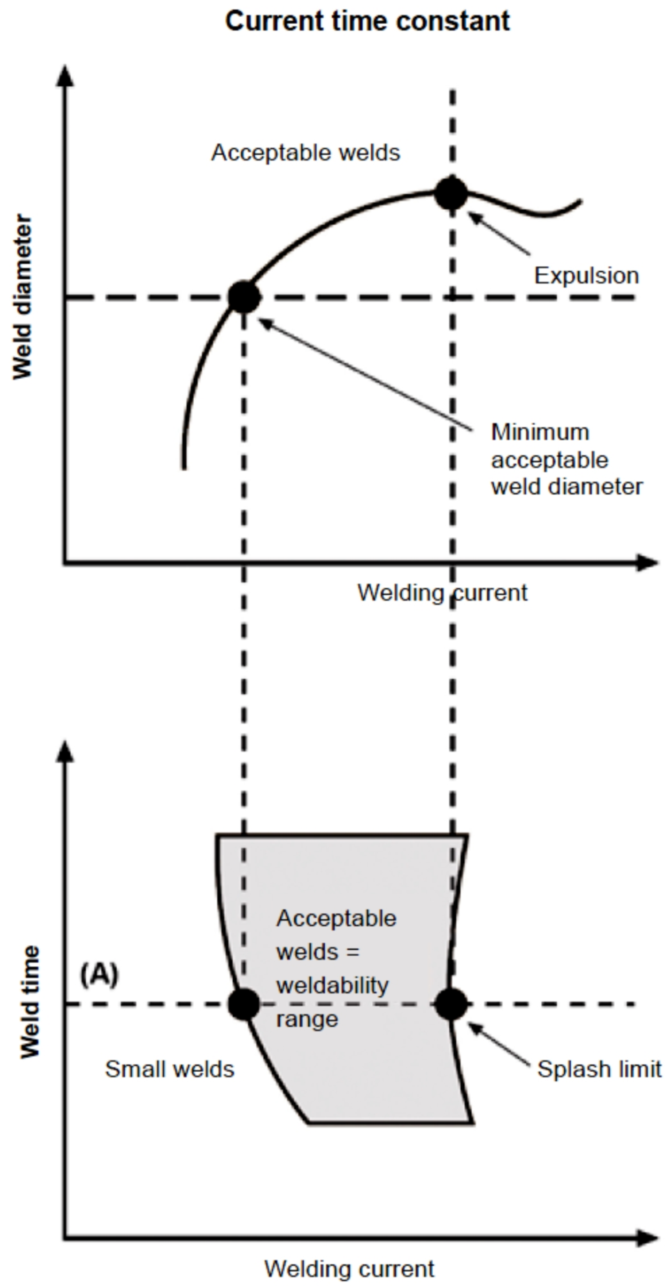


Figure 1.3: Weld nugget growth curve and weldability range [1]

CHAPTER TWO

LITERATURE REVIEW

A considerable attention has been devoted to monitoring the RSW process in order to gain information about weld quality, and to control the process to ensure quality welds. This is due to uncertainty associated with individual weld quality affected by factors such as tip wear, fluctuations in power supply, etc.; a strong emphasis is placed on improving the quality of the welds [11, 12].

On-line quality assessment has become one of the most critical requirements for improving the efficiency and the autonomy of automatic resistance spot welding processes. Some of the research carried out on the RSW, especially on optimization, is outlined in this section.

2.1 Techniques used for weld quality monitoring in RSW process

Methods developed for weld quality evaluation have followed two major trends, namely destructive testing and non-destructive testing (NDT). A variety of available destructive testing methods are useful in order to establish weld nugget strength and can provide vital information on weld quality. These tests include tension shear, cross-tension shear, twist and peel tests. However, such conventional methods can only ensure the quality of specific spot samples and have limitations in the widely used assembly line system [8]. In addition, the product wastage and the labour costs incurred while performing this type of testing make this approach unattractive.

The welding parameters such as electric current, voltage, force, displacement, and dynamic resistance signals are the most widely used in a monitoring and control system to evaluate weld quality [13]. Effective control algorithms can be developed based on information obtained from the monitoring of the above stated welding parameters.

The most common techniques employed in modern weld control systems can be classified into four major groups namely ultrasonic, thermal force, displacement and dynamic resistance technique [14].

2.1.1 Ultrasonic technique.

Ultrasonic technique has been explored by many researchers including Doyum *et al.* [15] and Blatnik *et al.* [16] to estimate the spot weld quality. The consistent results from literature is that the geometry of the weld nugget can be determined by measuring the transit time and the attenuation of the ultrasonic wave (or echo) propagated through the weld nugget in a direction perpendicular to the faces of the sheet metal stack, which can then be used to estimate the quality of the weld joint. While the ultrasonic methods have shown good promise in laboratory environments, from a practical point of view, acoustic sensors cannot be easily mounted and maintained on weld guns (calibration will be necessary at regular intervals).

2.1.2 Thermal force technique.

Thermal force technique has also been widely explored by many researchers [13, 17, 18]. Thermal expansion caused by the growing weld nugget will be felt by the welding gun as 'thermal forces'. This will indicate to the controller whether sufficient weld nugget growth has been achieved. The thermal force feedback system exploits the fact that thermal forces precisely reflect the state of the metal during the welding process. From a practical point of view, the fundamental drawback with this system is that the weld gun has to be structurally rigid (heavy) so as to be able to accurately transfer (and measure) the very small displacements to the load cell. Hence, it has only limited success on certain type of resistance spot welding machines.

2.1.3 Displacement technique.

The displacement technique directly measures nugget formation and expansion displacement between the electrodes [13, 19]. A number of control systems have been based on this principle. A Linear Variable Differential Transformer (LVDT) is typically used to measure electrode displacement. In order to avoid the noise from the magnetic field, in some cases, the displacement is measured with a digital optical encoder.

Xiaoyun *et al.* [20] developed a method of extracting electrode indentation from servo encoder of a resistance spot welding system, whereby an electrode was driven by a servomotor to generate welding pressure. Weld indentation depth was then measured by using the feedback function of electrode displacement, considering the feedback characteristics of the servo encoder. A weld lobe based on indentation was determined which was then used for on-line weld quality inspection according to the indentation range.

Xianfeng *et al.* [21] studied the effect of electrode displacement fluctuation characteristics on the quality of weld nugget produced in a RSW process, the electrode displacement was measured in real time using grating displacement sensor, and the displacement signals were then sampled by the monitoring system developed using LabVIEW software. One group of samples was welded under the fixed electrode pressure and welding time but the different welding current, and the fluctuation characteristics of the electrode displacement curves were mined and analyzed. Based on the electrode displacement fluctuation characteristics, the HMM was built with the electrode displacement as the observation and the tensile-shear strength as the state. The simulation results showed that the maximum estimation error can be 2%, which is 3% lower than the one when performing the same HMM simulation using the displacement curve filtered as observation

The fundamental limitation with this technique is the lack of robustness. From a practical point of view, there is susceptibility of the signal to mechanical vibrations and magnetic field fluctuations hence, affecting the accuracy of the results obtained.

2.1.4 Dynamic resistance technique.

Several studies on the secondary dynamic resistance have been performed. Through these studies, the relationship between the pattern of secondary dynamic resistance and the nugget growth has been determined for uncoated steel. While the dynamic resistance is very promising for online spot-weld quality estimation, it has many limitations. The fundamental issues have to do with the location of the voltage measuring device and the increased cost of installing the monitoring device.

Based on better emerging monitoring techniques new approaches were adopted. With the current development of measuring devices and hardware, many methods for measuring dynamic parameters have been considered [13]. A system of measuring the dynamic resistance using a microprocessor was proposed by Patange *et al.* [22]. In their study, the welding current, which was detected by the current transformer (CT) on the secondary circuit, was converted to instantaneous dynamic resistance.

Klopcic *et al.* [23] studied a theoretical analysis of the dynamics of transformer iron core saturation for a middle-frequency resistance spot welding system. For better utilization of the transformer iron core, the author proposed an advanced hysteresis controller (AHC), which keeps transformer iron core saturation within prescribed bounds regardless of how unequal the ohmic resistances and diodes‘ characteristics in the transformer‘s secondary circuits are. The unequal ohmic resistances of the two transformer’s secondary circuits and the different characteristics of the diodes of output rectifier lead to the magnetic saturation which, consequently, causes the unwanted spikes in the transformer’s primary current and over-current protection switch-off. The proposed advanced hysteresis controller (AHC) was achieved by a combined closed-loop control of the welding current and closed-loop control of the iron core saturation level. A circuit model of the welding transformer with full-wave current rectification was developed and analyzed with different ohmic resistances and different characteristics of the output rectifier diodes which causes undesired asymmetry of the spot welding system. It was shown that a highly asymmetric welding system can be obtained if this differences sustain each other [23].

Kang *et al.* [24] developed an online quality control system for RSW, for generating welds of a satisfactory quality. In their study the quality criterion was based on the dynamic resistance curve, which has a particular variation tendency during the welding process, and was employed to analyze the nugget formation and growth process. The slope of the dynamic resistance curve was used to determine the appearance of the first melting point. With the online detection of the first melting point, the nugget diameter could be estimated according to the heat energy absorbed by the weld after the first melting point.

In their study the proposed online nugget diameter estimator was considered as a nugget diameter sensor. The welding time was then determined according to the error between the desired nugget diameter and the calculated nugget diameter from the online nugget diameter estimator. If the calculated value of nugget diameter approaches that of the predetermined goal within the given tolerance, welding action was terminated.

A mathematical model of the relation between the heat energy and nugget diameter, which was used for estimation of weld quality was established. Based from data of this model an online nonlinear controller was designed and was implemented on a constant current control (CCC).

They showed that performance of the proposed controller was better than that of the PID controller in terms of Overall Average Absolute Value of the Error (OAAE).The improvement ranged from 10% to 50%. The performance of the proposed controller was also better than of the PID controller in terms of Integral of the Square of the Error (ISE) in most cases.

Cho and Rhee [25] monitored the process variables in the primary circuit of the welding machine to obtain the variation of the dynamic resistance across the electrodes. This allows the dynamic resistance monitoring system to be applied to the in-process system without any extra monitoring devices in the secondary circuit. In addition, to test the reliability of such a system, an artificial intelligence algorithm was developed to estimate the weld quality using the primary dynamic resistance. The authors used uncoated steel welding to verify their model. They also used shear strength as weld quality metric.

Wang and Wei [26] showed that dynamic resistance can also be obtained by taking the sum of temperature-dependent bulk resistance of the work pieces and contact resistances (at the faying surface and electrode-work piece interface) within an effective area corresponding to the electrode tip where welding current primarily flows.

Lee *et al.* [27] studied a quality assurance technique for resistance spot welding using a neuro-fuzzy algorithm. Four parameters from an electrode separation signal, in the case of non-expulsion, and dynamic resistance patterns, in the case of expulsion, were selected as the fuzzy input parameters. These parameters were determined using a neuro-learning algorithm and then used to construct a fuzzy inference system. They also used the displacement and the voltage signals as inputs to their model. Displacement signal is not very practical in industry due to the presence of backlash within the movements of the electrodes.

Hongjie *et al.* [28] presented a quality estimation technique based on Genetic K-Means Cluster Analysis. Where the electrode displacement signal of resistance spot welding process was monitored and mapped into a 15 by 25 element bi-polarized matrix by means of some method of fuzzy theory. The electrode displacement pattern matrices from different welding current were treated as gene to construct chromosome.

The genetic K-means algorithm (GKA), which combines the simplicity of the K-means algorithm and the robust nature of the genetic algorithm, was utilized to realize clustering analysis and quality estimation of welded spots. The results of the clustering analysis indicated that the electrode displacement pattern matrix can provide adequate quality information of welded spots for machine learning. At the same time, the results of clustering can realize quality estimation of the resistance spot welding and also can be used as a prior knowledge to provide the necessary support for the supervised machine learning to evaluate the weld quality.

Liang Gong *et al.* [29] proposed a method to determine the optimal control parameters and help to assess the weld quality. Where a causal model is built with the offline trained Bayesian Belief Networks (BBN) as a pattern determination net which deals with the optimal pattern of the electrode displacement, i.e. the ideal parameter combination between the maximum electrode displacement and its expansion velocity, to provide more reliable welding process and qualified welds.

Podrzaj *et al.* [18] proposed a linear vector quantization neural network (LVQ-NN) system to detect expulsion. The network was analyzed with different sensor combinations and different materials. The results showed that the LVQ-NN was able to detect the expulsion in different materials. They also identified welding force signal as the most important indicator for the expulsion occurrence, availability of force signal is limited to certain types of welding guns, and they are more expensive than other types of sensors.

They concluded that the LVQ-NN is a promising tool that needs to be further researched in connection with expulsion detection as a basis for resistance welding control.

Park and Cho [30] proposed LVQ-NN as well as a Multi-Layer Perceptron (MLP) neural network to classify the weld quality by using the force signal. The authors classified the weld quality into five categories. The results showed that the LVQ-NN and MLP neural networks have a success rate of 90% and 95% for the test data, respectively. The authors used shear strength as weld quality metric. Again the availability of force signal is limited to certain types of resistance spot welding machines.

EL-Banna *et al.* [3] also proposed an algorithm framework based on a LVQ-NN for classifying the welds based on the dynamic resistance pattern for cold, normal, and expulsion welds. The author used some features extracted from welding electrode displacement and dynamic resistance to train the LVQ-NN for online estimating the quality of the welds. In this work, the nugget diameter was used as a quality indicator.

2.2 Learning vector quantization neural network as a classification technique

Learning vector Quantization is a neural network invented by Kohonen [31] for pattern classification. This neural network combines competitive learning with supervision. LVQ algorithms are related to other competitive learning algorithms such as self-organizing maps (SOMs) [32] and C-means. Competitive learning algorithms are based on the winner-take-all learning rule and variants in which only certain elements or neighborhoods are updated during learning.

A training set consisting of Q training vector - target output pairs are assumed to be given,

$$\{s^{(q)} : t^{(q)}\} \qquad q = 1,2,...,Q, \tag{2.1}$$

Where $s^{(q)}$ are N dimensional training vectors, and $t^{(q)}$ are M dimensional target output vectors. M is the number of classes, and it must be smaller than Q. The target vectors are defined by

$$t_i^{(q)} = \begin{cases} 1, & \text{if, } s^{(q)} \text{ belongs to class } i, \\ 0, & \text{otherwise.,} \end{cases} \tag{2.2}$$

A two layer LVQ artificial neural network as shown in figure 2.1, is trained in a supervised manner to approximate the mapping between the input vectors and their corresponding target class.

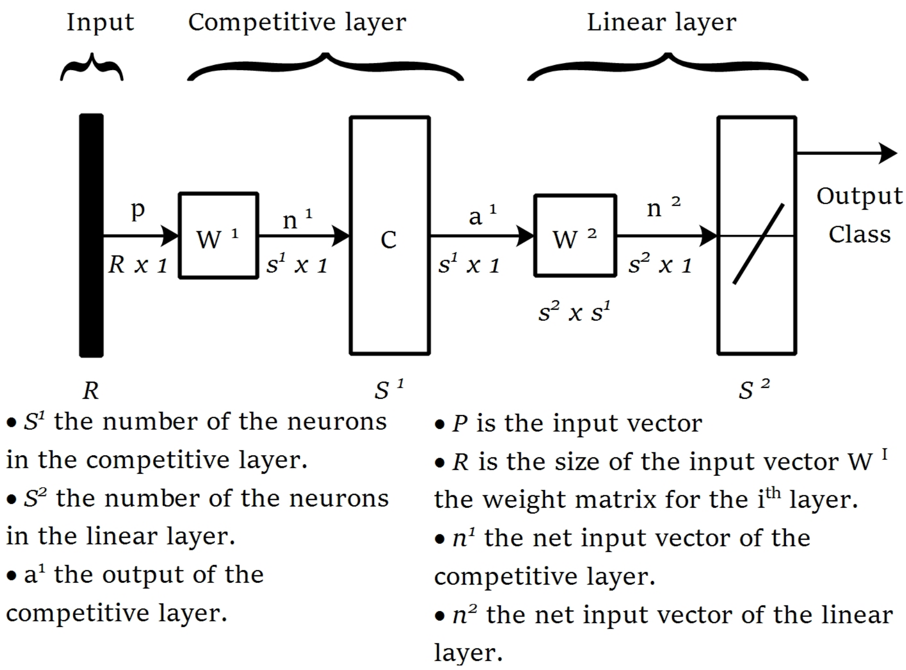


Figure 2.1: Linear vector quantization (LVQ) network [2]

2.2.1 LVQ-NN training rule

At each iteration one of the training vector is presented to the network as input $\mathbf{x}$, and the Euclidean distance from the input vector to each of the prototype vector (forming columns of the weight matrix) is computed.

The hidden neurons compete. Neuron $j*$ wins the competition if the Euclidean distance between $\mathbf{x}$ and the $j*$ prototype vector is the smallest. The $j*$ element of $\mathbf{a}^{(1)}$ is set to 1 while others are set to 0. The activations $\mathbf{a}^{(1)}$ is then multiplied by $\mathbf{W}^{(2)}$ on its right to get the net input $\mathbf{n}^{(2)}$. This produces the output of the entire network $\mathbf{a}^{(2)} = \mathbf{n}^{(2)}$, since the transfer function of the output neurons is an identity function. $\mathbf{a}^{(2)}$ also has only one nonzero element $k*$, indicating that the input vector belongs to class $k*$.

Kohonen SOM is designed to group a set of Q continuous-valued vectors into $M(< Q)$ clusters.

$$s^{(q)} = \left[\begin{array}{cccc} s_1^{(q)} & s_2^{(q)} & \ldots & s_N^{(q)} \end{array} \right], q = 1, \ldots, Q \tag{2.3}$$

The SOM thus consists of an input layer having N neurons, and an output layer having M neurons (cluster units) arranged in some predetermined fashion. Each neuron in the input layer is connected to a neuron in the output layer. Thus output neuron (cluster units) j is connected to each of the input neuron through weights $w_{ij}, i = 1, \ldots, N$, which is referred to as the j-th weight vector. In vector or matrix notation, we denote the j-th weight vector by

$$\mathbf{W}_{.j} = \left[\begin{array}{cccc} w_{1j} & w_{2j} & \ldots & w_{Nj} \end{array} \right] \tag{2.4}$$

It is given by the j-th column of the weight matrix. There is a total of M such weight vectors, one for each cluster units. Each one of these weight vectors serves as an exemplar of the input patterns associated with that cluster. Unless some prior information is known about the clusters, these weight vectors are typically initialize to random values.

2.2.2 Training LVQ-NN

During the training process, each training vector is cyclically or randomly selected and presented to the network. The cluster unit j' whose weight vector $\mathbf{W}_{.j'}$ matches the input pattern $\mathbf{x}$ the most closely is chosen as the winner. Here two vectors are considered closest if the square of the Euclidean distance between them, $\|\mathbf{x}-\mathbf{W}_{.j'}\|^2$

is the smallest. The winning unit and its neighboring units (those located in its first and second neighborhoods) then update their weight vectors according to the Kohonen rule. This process is continued until the weight vectors change by less than a preset amount.

Unless the dot-product is used to measure the closeness of two vectors, the input vector does not get multiplied with the weight vectors, as we have been doing so far. Instead it is the square of the Euclidean distance between the input vector and each of the weight vectors that is computed.

$$d_j = \|\mathbf{x} - \mathbf{W}_{\cdot j}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{W}_{\cdot j}\|^2 - 2\mathbf{x} \cdot \mathbf{W}_{\cdot j} \tag{2.5}$$

Therefore for a given input vector $\mathbf{x}$, the weight vector j' whose $d_{j'}$ is the smallest is always the one which has the largest dot-product with $\mathbf{x}$ only if the variation in the magnitudes of the weight vectors can be ignored.

This happens if the weight vectors are constrained to have the same magnitude.

The general training algorithm is:

1. Initialize M weight vectors. Set topological neighborhood parameters and learning rate, $\alpha(< 1)$.

2. For step $k = 1, 2, \ldots$, do steps a - d by cycling through training set until weight vectors converge

   (a) Set input vector $\mathbf{x} = \mathbf{s}^{(q)}$, one of the training vectors.

   (b) Compute for each cluster unit $j = 1, \ldots, M$ the Euclidean distance

$$d_j = \sum_{i \neq 1}^{N} (x_i - w_{ij}(k))^2. \tag{2.6}$$

(c) Find the index j' such that $d_{j'}$ is a minimum.

(d) For all cluster units j within the specified neighborhoods of j', update the weight vectors

$$w_{ij}(k+1) = w_{ij}(k) + \alpha \left[x_i - w_{ij}(k) \right], \quad i = 1, \ldots, N. \tag{2.7}$$

(e) May reduce the learning rate.

(f) May reduce the radii that define the topological neighborhoods.

The above updating rule moves the weight vectors for the winning neuron and those in its neighborhood towards the input vector. The amount of change is proportional to α. In the extreme limit of $\alpha = 1$, all these weight vectors are set to the input vector.

During training, the learning rate can be decreased linearly, that is

$$\alpha(k) = \frac{\alpha(1)}{k} \tag{2.8}$$

where $k = 1, 2, \ldots$ is the iteration counter.

Geometric decrease of α can also be determined by:

$$\alpha(k+1) = f\alpha(k) \tag{2.9}$$

where $0 < f < 1$, also works.

In general convergence may required many iterations through the training set.

Hence, Modeling with LVQ-NN has a considerable capability for pattern classification based on the input data vectors. Accordingly, this method is preferred for modeling compared to the other methods such as Multi-Layer Perceptron (MLP) neural network and Bayesian Belief Networks (BBN) [29].

2.3 Control Methods for RSW

On-line quality assessment and control has become one of the most important strategies for improving the efficiency and the autonomy of automatic resistance spot welding processes.

Chen *et al.* [33] developed an online control of a spot welding machine using a fuzzy adaptive algorithm. The proposed algorithm was used to evaluate the weld-bonding quality of spot welding using a fuzzy-estimation. However, the proposed algorithm is not industrially applicable because it requires too many input variables and fuzzy-rules, plus it has the potential of failing at local minima because its design point is bound to the range of tensile strength.

Lee *et al.* [27] studied a quality assurance technique for resistance spot welding using a neuro-fuzzy algorithm. The author used an electrode separation signal, in the case of non-expulsion, and dynamic resistance patterns, in the case of expulsion, as the fuzzy input parameters. These parameters were determined using a neuro-learning algorithm and then used to construct a fuzzy inference system.

The displacement signal is not very practical in industry due to the presence of backlash within the movements of the electrodes.

More recently, EL-Banna *et al.* [3] developed an intelligent constant current control based on fuzzy logic for RSW. The algorithm operates as a fuzzy logic controller using a set of engineering rules with fuzzy predicates that dynamically adapt the secondary current to the state of the weld process. The quality of the weld nugget were estimated indirectly using a LVQ-NN for classifying the welds based on the dynamic resistance pattern for cold, normal, and expulsion welds. The author used some features extracted from welding dynamic resistance to train the LVQ-NN for online estimation of the weld quality. In this work, the nugget diameter was used as a quality indicator. The intelligent constant current control for resistance spot welding was implemented and validated on a Medium Frequency Direct Current (MFDC) constant current weld controller.

Kang *et al.* [34] proposed an algorithm for measuring the power factor angle in real time. Which is then used for calculating an appropriate firing angle α for generating welds of a satisfactory quality. In their study they showed that, during the welding process, both inductive characteristics of the welding transformer and variation in the welding load results to a non-sinusoidal welding current which in turn leads to a time-varying power factor angle in AC RSW. Because the power factor angle of the RSW cannot be expressed explicitly with measurable parameters, it is difficult to be directly obtained in real time using the conventional means.

The author presented an integrated algorithm for calculating the power factor on a practical discrete system in real time. Experiments were conducted to validate the effectiveness of the proposed method, and the results showed that the proposed algorithm could be used to obtain more accurate values of the power factor angle than using other methods over a very large operation range.

In their study the quality criterion was based on the dynamic resistance curve, which has a particular variation tendency during the welding process, and was employed to analyze the nugget formation and growth process, which was used for estimation of weld quality. Based from data of this model an online nonlinear controller was designed based on the power factor angle and was implemented on a constant current control (CCC).

This study presents a structured and systematic approach developed to design an effective controller to be implemented on an AC RSW for improving the reliability of the resistance spot welding process. Due to the extensive use of resistance spot welding, even a small improvement would bring significant economic benefits.

2.4 Summary of the gaps

In reviewing past research work, a number of studies have been done on optimal control of RSW phenomena and the following gaps have been identified.

1. Research on the influence of combined effects of varying both the input welding parameters such as welding time and welding current, on the weld quality needs to be explored further. There is still a gap in knowledge as far as optimization of the RSW process is concerned.

2. Application of LVQ-NN needs also to be explored further as it is a good opportunity for improving in the on-line quality assessment process in order to provide real-time weld quality control.

3. There are still no established method of quality control against expulsion using the proposed Adaptive Neural Fuzzy Inference System (ANFIS), as a quality assurance technique for resistance spot welding.

4. Research based on fuzzy algorithm that can evaluate the weld quality using fuzzy-estimation is only effective for the studies in laboratories, but it is difficult to apply these methods to the RSW process in real time due to practical limitations. It requires too many input variables and fuzzy-rules. The present work aims at combining the important aspects of fuzzy logic control and artificial neural networks to come up with an adaptive neuro-fuzzy system that will be used to ensure improved weld strength in RSW process. Such framework makes fuzzy logic control (FLC) more systematic and less reliance on expert knowledge. As a special neural network, ANFIS can approximate all nonlinear systems with less training data, quicker learning speed and higher precision [35–45].

Previous research studies have used different approaches to control the spot welding process. However there is none that can be said to be fully sufficient on its own. This could be due to the complex nature of the process, which makes it difficult to develop analytic models for the process.

Therefore, the current work seeks to develop a control system that would optimize the resistance spot welding process by improving the weld quality without the need for an accurate process model. The controller will minimize expulsion and cold welds by selection of the optimum process and input parameters, hence boosting production while at the same time reducing production cost, and improving the quality of the products.

CHAPTER THREE

METHODOLOGY

3.1 Overview

This chapter describes a series of experiments that were carried out to investigate the effect of welding parameters on the resulting weld quality. Analysis Of Variance (ANOVA) technique was employed to determine the percentage contribution of each parameter against a stated level of confidence. A weld monitoring and control systems were designed for accurate on-line evaluation and control of weld quality based on the dynamic resistance of the RSW. The dynamic resistance was used as quality monitoring signature for characterizing the resistance spot weld. Finally the weld quality monitoring and control systems were tested to evaluate their efficiency and validity.

The workpiece materials used in all the experiments were mild steel sheets of 0.8mm thickness. This material is widely used in the sheet metal fabrication industry.

3.2 Effect of welding current and time on weld quality

3.2.1 Apparatus and experimental procedure

The welding experiments were carried out on a Lecco Annettoni resistance spot welding machine from Costruzioni Elettromeccaniche. Co. Ltd., Italy, as shown in Figure 3.1. The specifications of the machine are given in Table 3.1.

Table 3.1: Specification of Resistance Spot Welding Machine

Single phase input 50/60 Hz, $\boldsymbol{u_1}$	400 V.
Max. welding power, $\boldsymbol{S_{max}}$	23 KVA.
Secondary voltage 50/60 Hz, $\boldsymbol{u_2}$	2.4 - 2.7 V.
Secondary short circuited current, $\boldsymbol{I_{2cc}}$	10.2 KA
Max. welding current, $\boldsymbol{I_{max}}$	10.2 KA
Electrode force, $\boldsymbol{F_{max}}$	2200N
Welding cycle, $\boldsymbol{W_{cycle}}$	8-12 cycles

In this study, the weld nugget diameter was used as the variable to describe the weld quality during the welding process. Previous studies show that the strength of a weld is correlated to the size of the nugget diameter and has been widely used as a quality measure in the automotive industry [46] [47].

A system for monitoring various parameters which provide real-time information of nugget formation and growth for RSW was established. These parameters were welding current, welding time and dynamic resistance. The weld time is the time during which the welding current is applied to the metal sheets and is measured

Figure 3.1: Resistance spot welding machine

and adjusted in cycles of the line voltage as are all timing functions. Where a cycle is 1/50 of a second in a 50 Hz power system. In this study different welding currents, from 1 kA to 10 kA in 1 kA intervals, were used. For each selected welding current, different welding duration were used to obtain the welds with different nugget diameters. The nugget diameter was obtained by destructive peel test after each experiment.

In these experiments, the effect of varying the welding current and welding time on weld quality was studied. The dynamic resistance obtained was used to classify the welding process and improving the weld quality using the proposed method given in the last section.

Figure 3.2 illustrates a schematic diagram of the experimental apparatus for the measurement and the implementation of sensors for the welding process. A Rogowsky coil, with current measurement range of 5 A to 100 kA and a differential voltage probe, rated to measure differential and common mode voltage were used for secondary welding current and voltage measurements, respectively. The signals from the DAQ system were then sampled by the monitoring system developed using LabVIEW®-based software.

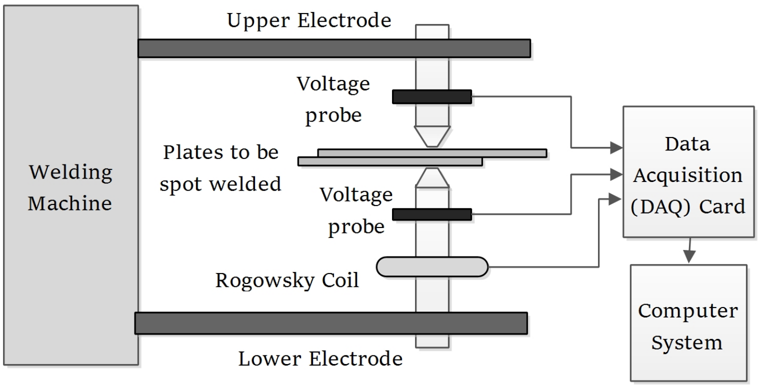


Figure 3.2: Schematic representation of experimental set-up of resistance spot welding

Figure 3.3 shows a pictorial diagram of the experimental apparatus for the measurement and the implementation of the sensors for the welding process.

Figure 3.4 shows a screen shot of the monitoring system implemented on a LabVIEW®-based software.

3.2.2 Determination of weld quality based on peel test

To determine the effect of welding current and welding time on quality of the weld produced, peel test, which is a destructive testing was done as shown in Figure 3.5. ISO10447 (2006) clause 5.2 and 5.3 give details on how to carry out a peel test and how to measure the weld nugget.

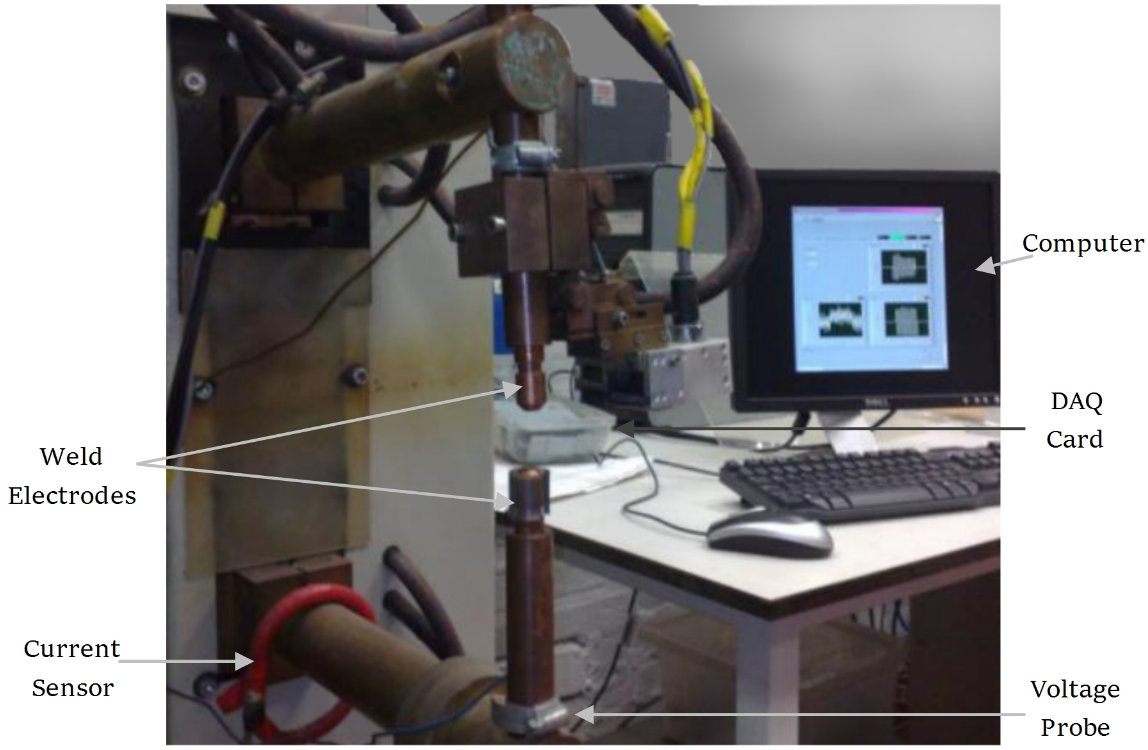


Figure 3.3: Pictorial representation of experimental set-up for resistance spot welding

Two metal stacks of mild steel material were used for tests with the resistance spot welding machine.

Destructive peel testing resulted in a weld zone that has been torn out of one of the metal sheets, the exposed weld area was measured. This measurement of weld size is typically used as an indication of weld quality, i.e. whether the weld is fit for its intended purpose. A good spot weld has sufficient diameter and nugget penetration. The minimum acceptable diameter of a normal weld nugget is considered to be $4\sqrt{t}$ mm, where t is workpiece thickness [9]. Welds with smaller diameters do not have sufficient penetration and are considered as cold welds. The size of the cold weld diameter is not enough to bear the calculated loads. Hence, the recommended weld diameter is $5\sqrt{t}$ mm. Any weld nugget above this value is

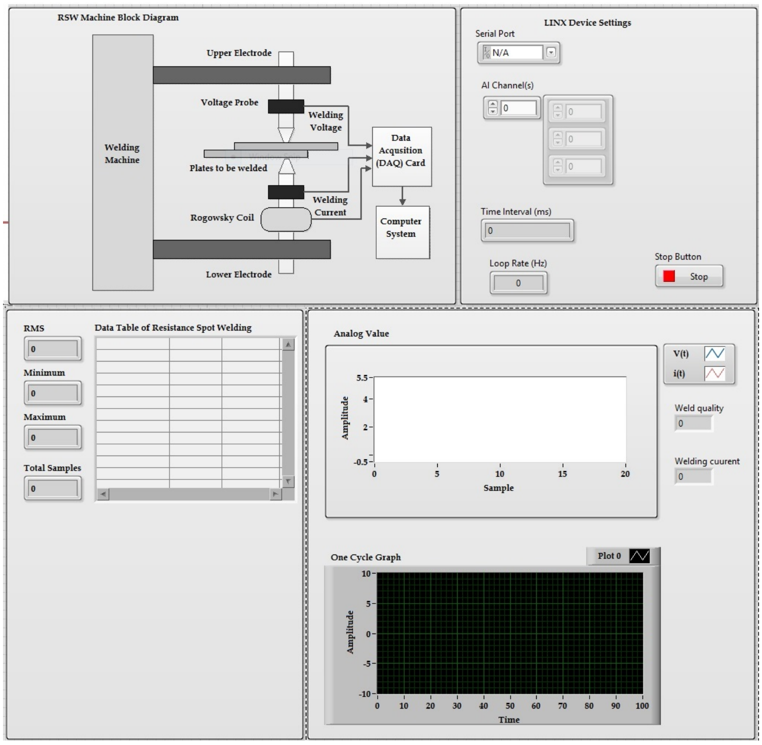


Figure 3.4: A screen shot of the LabVIEW-based control and monitoring software.

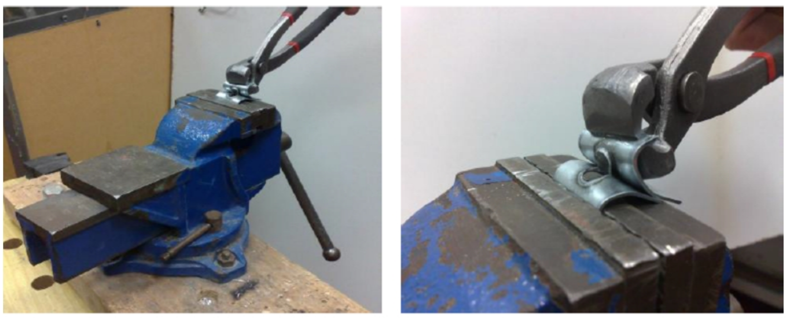


Figure 3.5: Peel test

considered to be an expulsion weld [9, 10].

3.3 Evaluation of weld quality based on dynamic resistance

A weld monitoring system as shown in Figure 3.3 was used to record two important welding parameters during the welding process. The welding current and welding voltage were measured simultaneously throughout the welding process in order to determine the Dynamic Resistance (DR), which is given by Equation (3.1),

$$DR(t) = \frac{v(t)}{i(t)} \tag{3.1}$$

The dynamic resistance obtained for each weld was grouped into one of the following three classes based on quality of the weld nugget: cold, normal and expulsion welds. In order to obtain the weld quality, destructive peel test experiment was conducted for each weld.

The dynamic resistance was used as quality monitoring signature for characterizing the weld nugget, and was selected as the input data to train the proposed on-line monitoring and control system for RSW.

3.3.1 Design of on-line weld quality evaluation system based on learning vector quantization neural network

An accurate and efficient model to perform non-destructive quality estimation is an essential part of RSW for quality and process monitoring. This section deals with the designing, training and testing of the proposed algorithmic framework based on Linear Vector Quantization Neural Network (LVQ-NN) for estimation of weld quality.

Classification is based on a small number of dynamic resistance curves obtained as function of welding time for cold, normal, and expulsion welds that are collected during the stabilization process.

3.3.2 Designing of LVQ-NN algorithm

The LVQ-NN was used to estimate weld quality by classifying the dynamic resistance vectors corresponding to cold, normal and expulsion welds. The inputs to the network were the vectors of dynamic resistance sampled at 1ms during the welding time. Figure 3.6 shows the block diagram of the proposed approach for an online weld quality monitoring system.

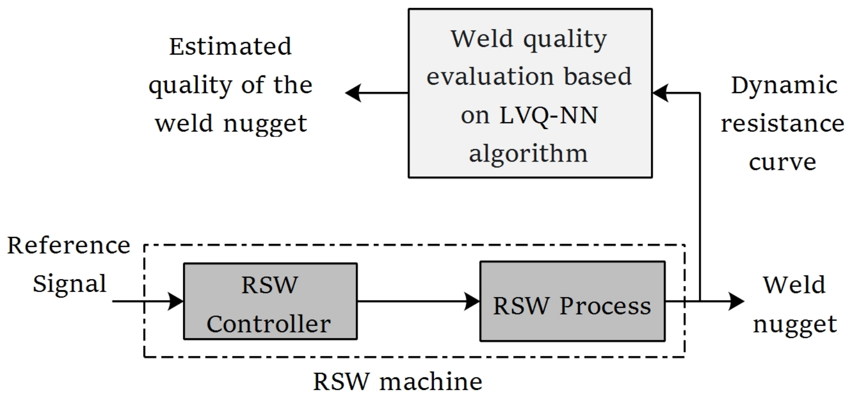


Figure 3.6: Proposed approach for weld quality monitoring system

The LVQ-NN used had six neurons in the first layer that correspond to six subclasses (six weight vectors) and three neurons in the second layer that correspond to three classes which are normal weld class, cold weld class and expulsion weld class. Two neurons in the first layer were associated with each of the class.

Different sets of data are presented to the LVQ-NN, and based on the input-output relationship, the weight vectors for the LVQ-NN are adjusted accordingly.

3.3.3 Training the LVQ-NN algorithm

A training set consisting of Q training vector - target output pairs were attained during the investigation. The input training vector $x = (x_1, x_2, x_3, x_4, .., x_Q)$ where x represents the dynamic resistance vector and their corresponding weld quality classes were used as a training set to the LVQ-NN. All the weight vectors were first placed on random positions in the input space. The LVQ-NN training process is summarized as follows:

1. The weight vectors $W_{.j} = W_{1j}, W_{2j}, W_{3j}, ..$ were initialized for each epoch and the input vector $\mathbf{x} = \mathbf{s}^{(q)}$, one of the training vectors was selected.

2. For each cluster unit $j = 1, \ldots, M$ the Euclidean distance was computed as shown in equation (3.2).

$$d_j = \sum_{i \neq 1}^{N} (x_i - w_{ij}(k))^2. \tag{3.2}$$

3. The distances from each centroid were then calculated by determining the index j' such that $d_{j'}$ is a minimum.

4. In the final step the weight vectors were updated by moving the winner's neuron centroid closer to the input vector. Hence, for all cluster units j

within the specified neighbourhoods of j', the weight vectors are updated as shown in equation (3.3).

$$w_{ij}(k+1) = w_{ij}(k) + \alpha\left[x_i - w_{ij}(k)\right], \quad i = 1, \ldots, N. \tag{3.3}$$

The above updating rule moves the weight vectors for the winning neuron and those in its neighbourhood towards the input vector. The rate at which the weight vectors update depends on a α parameter (learning rate)

During training, the learning rate was decreased linearly, that is

$$\alpha(k) = \frac{\alpha(1)}{k} \tag{3.4}$$

where $k = 1, 2, \ldots$ was the iteration counter.

3.3.4 Testing the LVQ-NN algorithm

Once trained the LVQ-NN was then tested against a set of testing data which is generated from the experiment for validating the proposed model.

Hence the quality of the weld is estimated indirectly from the dynamic resistance curves as pointed out in [18, 25].

3.4 Design and implementation of ANFIS-based controller

This section outlines the procedure for designing, training, testing and implementing the ANFIS-based fuzzy logic controller. The ANFIS-based FLC is applied because of its ability to improve both the system performance and adaptability [37, 48–54].

3.5 Fuzzy logic controller design

A set of training data was presented to the ANFIS. Then, the membership functions, their number, and the rule base for the FLC were obtained from the ANFIS, and were used for tuning the fuzzy logic controller. The fuzzy logic controller works in a closed loop, adjusting the amount of current to compensate for the degradation in weld quality. Figure 3.7 shows the block diagram for the proposed fuzzy logic controller.

The Fuzzy logic controller design involves the following steps;

- Identification of the inputs, outputs and their ranges.
- Design of the fuzzy membership functions for each input and output by the use of ANFIS.
- Construction of the knowledge base that contains the fuzzy rules which are used for fuzzy reasoning. The knowledge base is constructed by ANFIS.

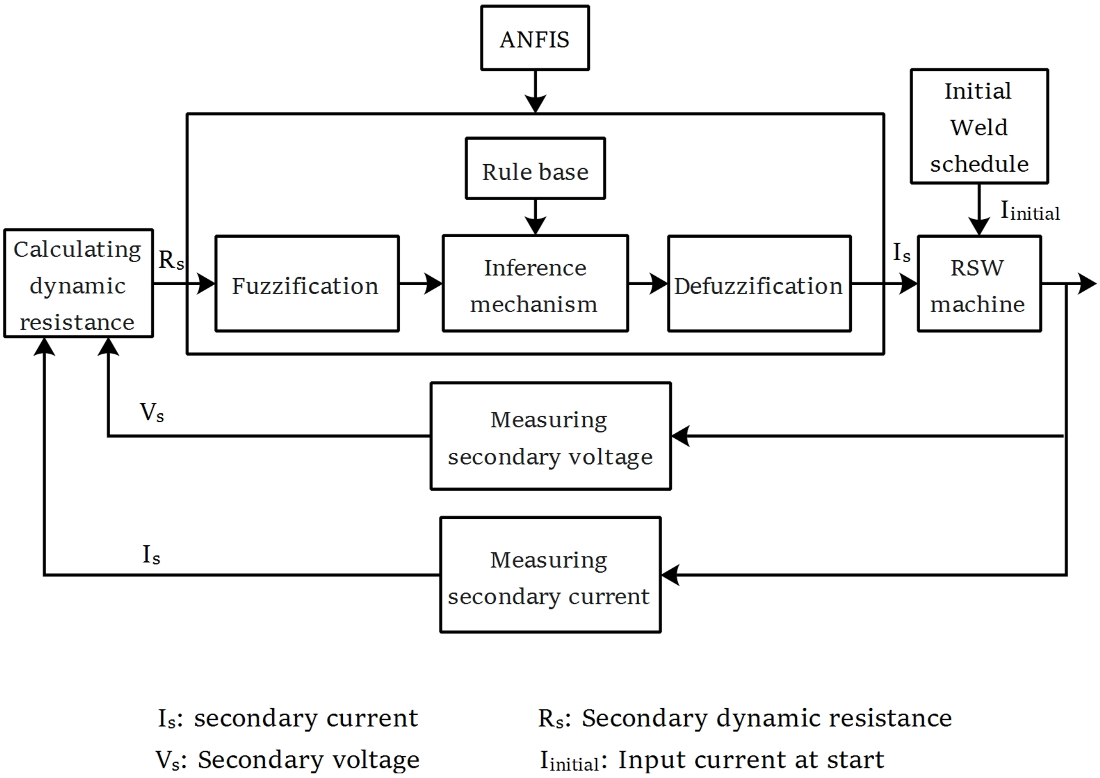


Figure 3.7: Proposed approach for adaptive control

- Mapping of the fuzzy logic controller's output to the corresponding crisp values by use of center of gravity defuzzification procedure.

3.5.1 Identification of inputs, outputs and their ranges

The inputs to the proposed controller are the vectors of dynamic resistance obtained from the RSW process. In order to reduce the dimensionality of the input dynamic resistance vector to the ANFIS, different features are selected in place of the whole vector, which include:

- Maximum value of the input dynamic resistance vector

- Minimum value of the input dynamic resistance vector
- Mean value of the input dynamic resistance vector
- Standard deviation value of the input dynamic resistance vector
- Range value of the input dynamic resistance vector
- Root mean square (RMS) value of the input dynamic resistance vector

The output of the FLC is the welding current which ranges from 0 kA to 10 kA. These values were arrived at from the experimental work.

3.5.2 Development of membership functions and the rule base

The ANFIS was presented with different input sets of training data, which constitutes the optimum welding conditions and the expected output so as to simulate a welding process. The results were used in the design of the input and output membership functions as well as in the generation of the rules for the Fuzzy Logic Controller.

The design of membership functions is achieved by use of ANFIS as follows:

- A set of training data, which constitutes the optimum grinding conditions and the expected output, is presented to the ANFIS. This set of data is generated from the experimental work.
- The ANFIS is generated by use of grid partitioning, which is a method for grouping data into clusters based on their similarity. The ANFIS is then

trained by use of hybrid learning rule. The hybrid learning rule combines the gradient method and the least squares estimate (LSE).

- The ANFIS is then tested against a set of testing data which is also generated from the experimental work.

- Different sets of data are presented to the ANFIS, and based on the input-output relationship of the ANFIS, the membership functions for the FLC are constructed.

- The rule base for the FLC is generated based on the execution of the ANFIS. This is because, ANFIS automatically generates its own rule base depending on its set of training data [50].

The main reason for the use of Takagi-Sugeno inference mechanism is the ability of the inference mechanism to model non-linear problems. In this type of inference mechanism, the output is a function of the inputs and is a fuzzy singleton [50]. Figure 3.8 is a screen shot of the ANFIS editor, showing a plot of the training errors after the training process. The ANFIS is generated with grid partitioning fuzzy inference mechanism, where each input is assigned nine membership functions, and then trained with 20 epochs (number of iterations for training) using hybrid learning rule.

3.5.3 Implementation of the ANFIS controller

The proposed ANFIS-based controller was implemented on the Lecco Annettoni resistance spot welding machine. For a RSW process, the welding power can

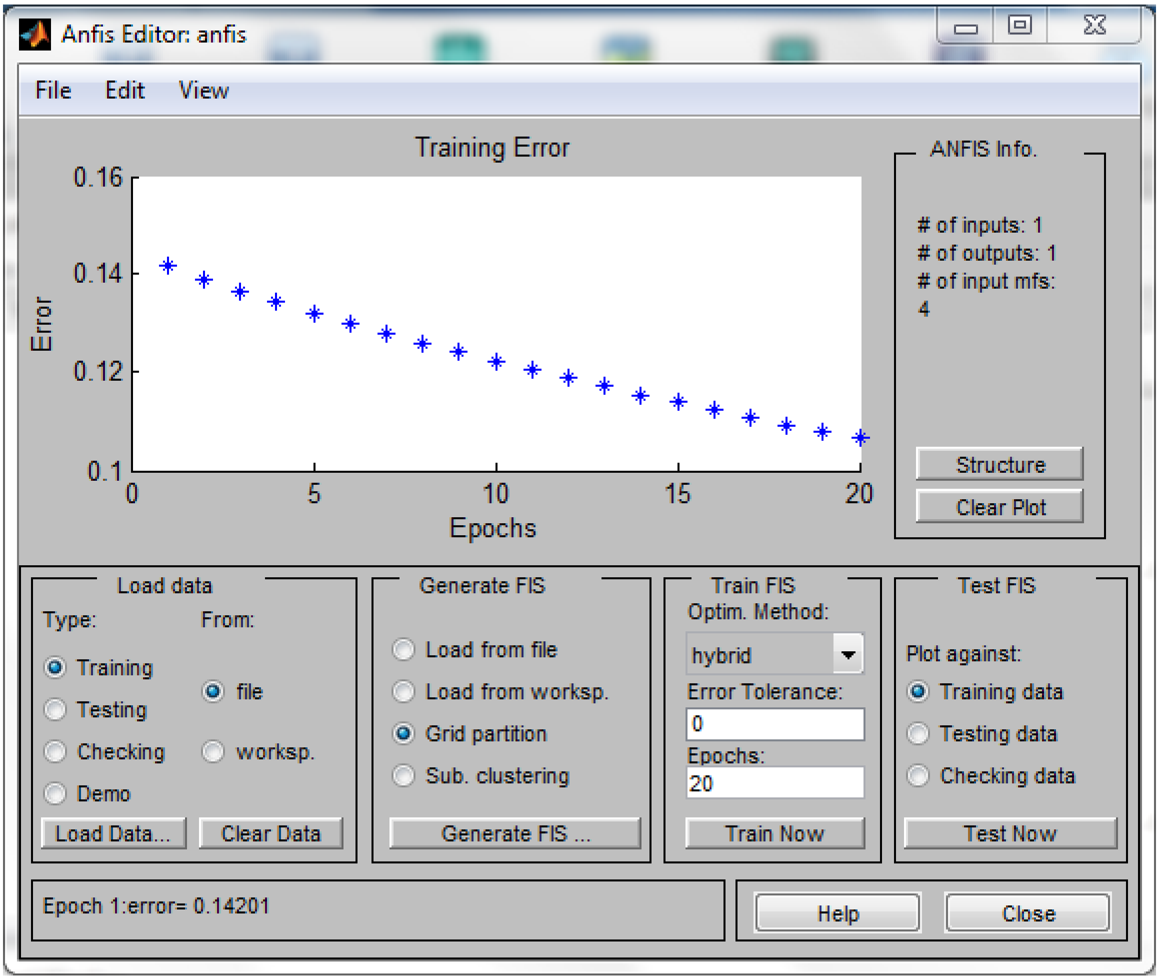


Figure 3.8: A screen shot of the ANFIS editor.

be controlled by varying the welding current. This is accomplished using phase controlled thyristors.

The desired control action for a RSW process is to obtain the welding current for each control cycle accurately in advance to prevent the formation of cold welds and expulsion welds.

All the control actions were conducted with a constant, predetermined welding force of 2.2KN. Figure 3.9 illustrates a schematic diagram of the experimental apparatus for implementation of the ANFIS-based controller.

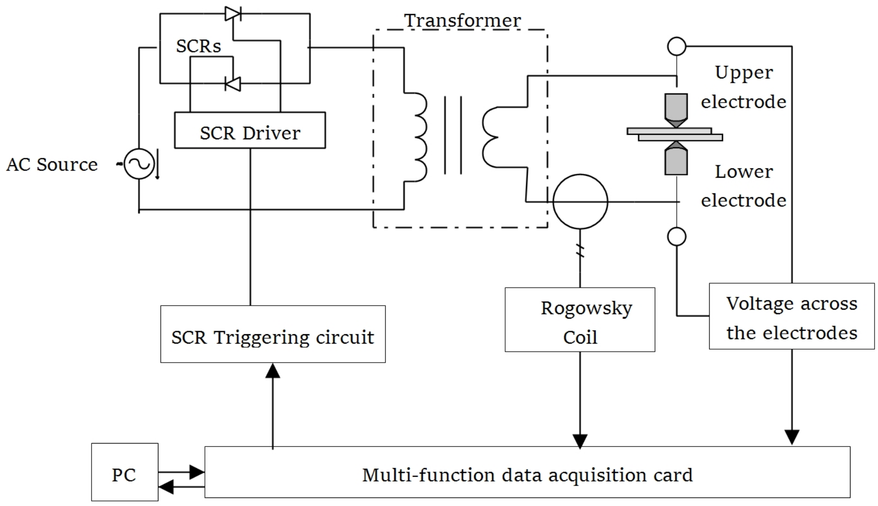


Figure 3.9: Schematic representation of experimental set-up for implementation of the ANFIS-based controller.

The proposed control action is used to generate an appropriate firing angle α of thyristors for each control cycle based on quality of weld nugget. Where the firing angle α is considered as the triggering time that defines a predetermined value of welding current. Figure 3.10 shows a photograph of the circuit of the RSW controller. The effectiveness of the proposed controller was then verified through experiments.

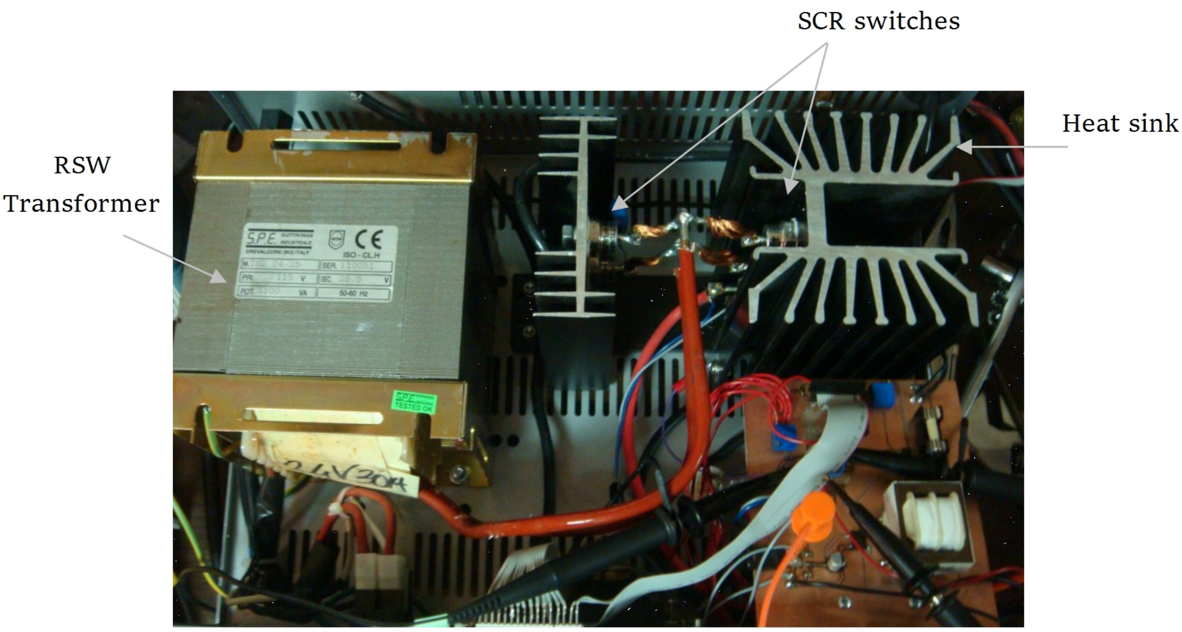


Figure 3.10: Experimental set-up for resistance spot welding.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Effect of welding current and welding time on the weld quality

In this work, the quality indicator used is the weld nugget diameter, which is one of the best-known and most-used quality indicators in industry and generally obtained by the peeling methods.

Destructive peel testing resulted in a weld zone that has been torn out of one of the metal sheets, the exposed weld area was measured. This measurement of weld size is typically used as an indication of weld quality, i.e. whether the weld is fit for its intended purpose [9, 10].

Table 4.1 shows the tabulated results on the effect of welding current and welding time on quality of the weld produced in terms of weld nugget diameter.

Typical graphs of the measured weld nugget diameter for different values of welding current and welding time are shown in Figure 4.1.

From the results shown in Figure 4.1, it is seen that the spot welds formed within

Table 4.1: Effect of welding parameters on the weld nugget diameter

	Weld nugget diameters (mm) for different welding times				
Welding current (kA)	160ms	180ms	200ms	220ms	240ms
0	N/A	N/A	N/A	N/A	N/A
1	N/A	N/A	N/A	N/A	1.95
2	N/A	N/A	N/A	N/A	2.21
3	N/A	N/A	N/A	2.80	3.60
4	N/A	N/A	N/A	3.00	3.70
5	N/A	N/A	2.50	3.60	4.20
6	2.50	2.50	3.00	3.80	4.40
7	2.60	3.00	3.80	4.30	4.50
8	2.90	3.70	4.00	4.50	5.31
9	3.60	3.90	4.40	5.00	5.76
10	4.00	4.50	5.00	5.50	5.78

a range of 160-200ms welding time sustained a gradual increase in weld nugget diameter as the welding current increases. Note that the spot welds corresponding to a welding time of 160ms and 180ms did not experience expulsion. The major problem with the above range of welding time is the formation of cold welds. On the other hand, for welding time greater than 200ms and welding current higher than 9kA, it can be seen that the weld nugget diameter increases in size at a faster rate, but experience expulsion.

Hence, there is a tendency for the weld nugget diameter to increase in size with

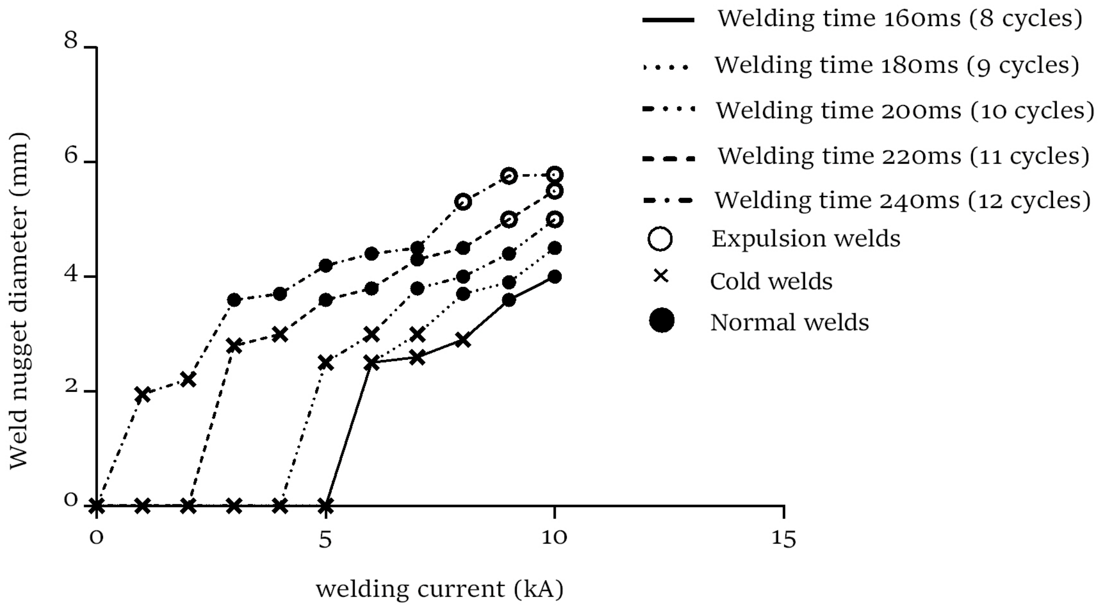


Figure 4.1: Effect of welding current and welding time on the weld nugget diameter

high current and longer welding time up to a point, beyond which it may either remain constant or experience expulsion.

ANOVA technique was employed to determine the percentage contribution of each RSW process parameter on quality characteristics against a stated level of confidence. The result of ANOVA for the welding outputs are presented in Table 4.2

In this analysis, the sum of squares and variance are calculated. F-test value is used to decide the significant factors affecting the RSW process and percentage contribution is calculated. The percentage contribution indicates the relative power of a factor to reduce variation. For a factor with a high percent contribution, a small variation will have a great influence on the performance. Furthermore, the con-

Table 4.2: Contribution of RSW process parameters on quality characteristics

Symbol	Factor	Degrees of freedom (DOF)	Sum of squares	Mean of squares	F	P	Contribution (%)
A	Welding current	2	51.2807	25.6403	133.13	0.007	88.65
B	Welding time	2	5.7801	2.8900	15.01	0.062	9.99
C	Welding force	2	0.3975	0.1988	1.03	0.492	0.687
Error		2	0.3852	0.1926			
Total		8	57.8435				

tribution of welding current and welding time to the weld nugget diameter shows that welding current is the major factor (88.65%). while the effect of welding force on weld quality is negligible. Hence for consistency of weld quality, the welding current must be controlled.

The focus should therefore be on controlling the welding current rather than the welding time and welding force for achieving acceptable weld quality.

4.2 Evaluation of dynamic resistance curves for various resistance spot welding quality

The dynamic resistance obtained as function of welding time gives a relative clear picture of the weld nugget formation and presents a significant correlation with several RSW quality indicators, this includes the quality of the weld nugget. Features extracted from the dynamic resistance data are used to characterize spot weld formed during RSW process.

From the experimental data obtained, it is seen that the spot welds formed under various welding conditions have a unique dynamic resistance curves. Figures 4.2-4.4 show dynamic resistance for various welding currents plotted against welding time, for a fixed welding force of 2200N. In these figures the initial drop in dynamic resistance within the first cycle of weld time, can be attributed to the electrode force flattening asperities slightly and bringing the sheets to be welded into contact [13]. It can also be seen that the dynamic resistance curves tend to increase almost immediately upon initiation of the current.

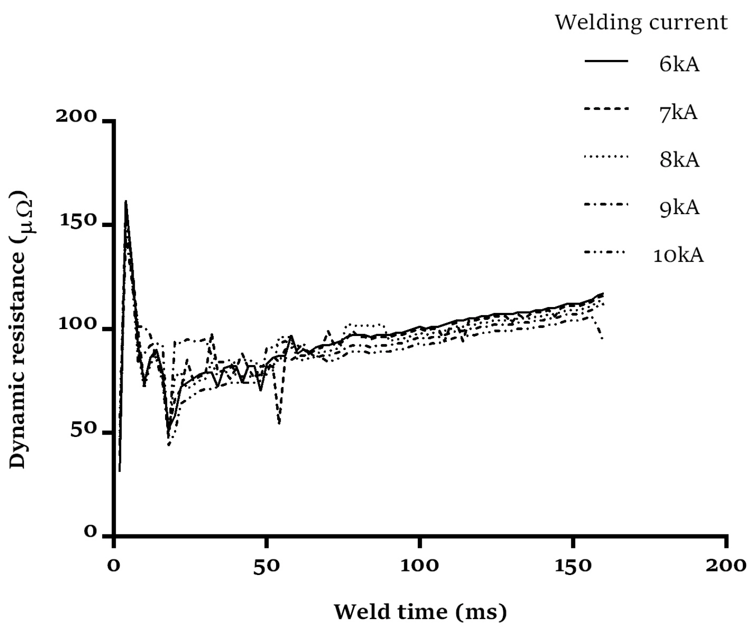


Figure 4.2: Dynamic resistance curves for cold welds

Figure 4.2 shows dynamic resistance curves for various welding currents and for a fixed welding time of 160ms (8 cycles). It is seen that initially the dynamic resistance decreases to a minimum value within the first cycle of weld time, then starts to increase steadily till the end of the weld period. This was invariably observed in cold welds.

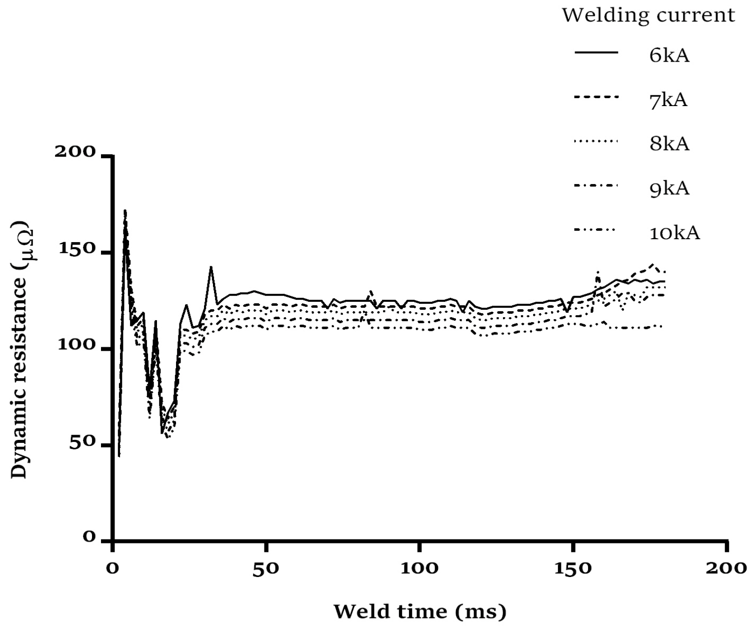


Figure 4.3: Dynamic resistance curves for normal welds

Figure 4.3 shows the dynamic resistance curves for a fixed welding time of 200ms (10 cycles), it seen that generally the rate of change of dynamic resistance is almost negligible as the welding current increases.

Figure 4.4 shows as the current increases, there is a sudden drop in the dynamic resistance level for a welding time of 240ms (12 cycles). The sudden drop in resistance was invariably observed in welds showing expulsion, and is believed to have resulted from the effective increase in contact area provided by the portion of the expelled metal trapped between the sheets. Increasing the weld current above the expulsion limit caused this sudden drop in contact resistance to occur earlier in the weld interval, as would be expected. Therefore, the expulsion can be marked by a sharp drop in the dynamic resistance.

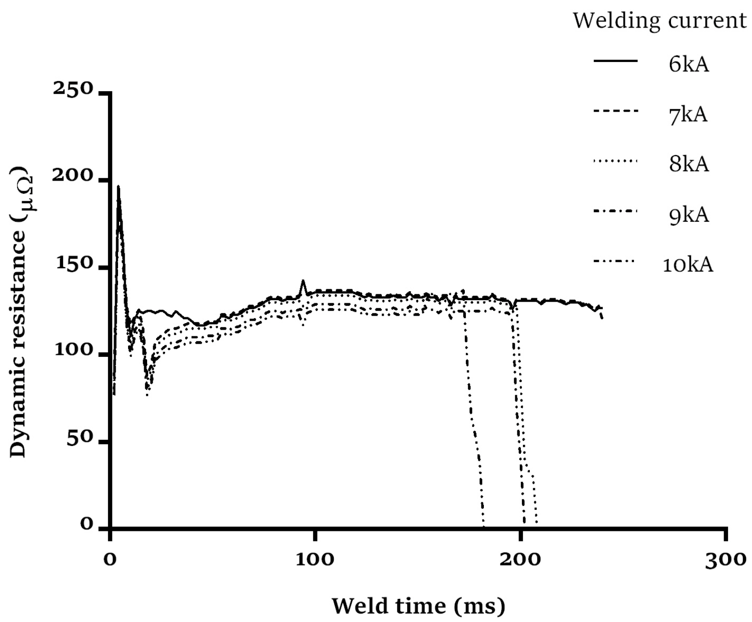


Figure 4.4: Dynamic resistance curves for expulsion welds

Hence, the dynamic resistance signal responds well to the variations of process conditions and provides plenty of quality information. The cold weld dynamic resistance profile tends to be lower than the other profiles, while the dynamic resistance curve for an expulsion weld, tends to have a sharp drop, especially towards the end.

4.2.1 On-line assessment of weld quality based on LVQ-NN model

The mapping of the measured dynamic resistance curves to their corresponding weld quality class is implemented by the LVQ-NN method, which is an unsupervised learning method for a neural network that is composed of an input layer, an output layer and a competitive layer.

The dynamic resistance curves obtained as a function of welding time from the experiment are classified according to an appropriate class of the three welding quality classes which are cold welds, normal welds and expulsion welds.

In all tests, the classification of nugget quality is based on their corresponding dynamic resistance curve obtained as function of welding time. Table 4.3 gives a summary of the classification of the measured dynamic resistance using the proposed LVQ-NN model.

Table 4.3: Evaluation of the LVQ algorithm

Weld quality class	No. of samples	Correctly classified	Misclassified			Total misclassified welds in %
			Cold	Normal	Expulsion	
Cold	12	10	N/A	2	0	17
Normal	22	18	3	N/A	1	18
Expulsion	16	13	0	3	N/A	19

The judgment results when cold welds were evaluated as normal welds was 2 out of 12 specimens (17% misjudgment ratio) and when normal welds were evaluated as either cold welds or expulsion welds were 3 and 1 respectively out of 22 specimens (18% misjudgment ratio). Finally, the judgment results when expulsion welds were evaluated as normal welds was 3 out of 16 specimens (19% misjudgment ratio). Hence 82% of the total number of specimens were successfully inferred within a range of 18% error.

4.3 Evaluation of weld quality control model based on ANFIS

The developed ANFIS-based controller is analyzed in this section. The effectiveness of the controller was tested by comparing the results of the ANFIS-based control system with those of the conventional control system.

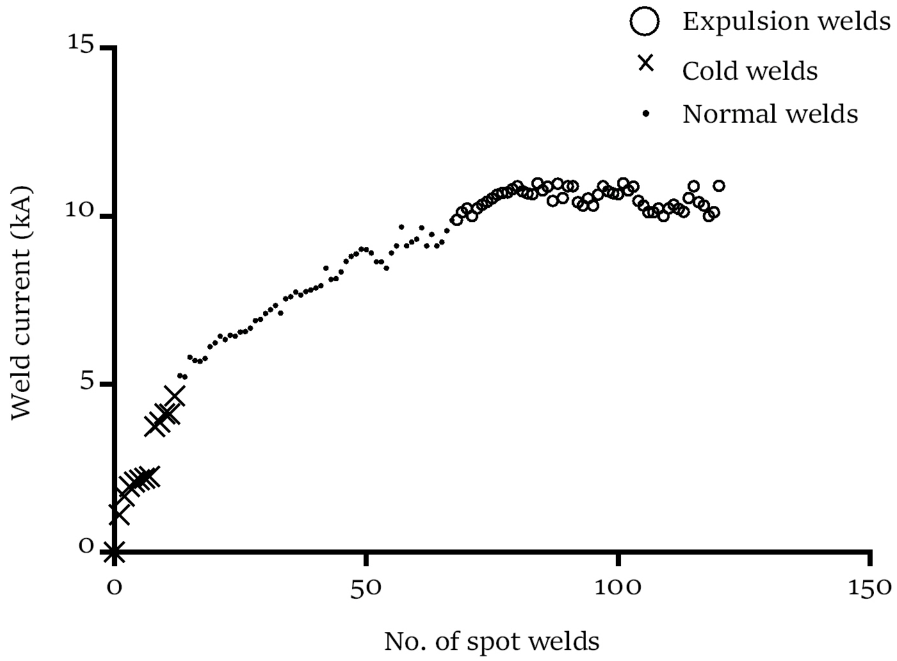


Figure 4.5: Weld quality based on conventional control model

Figure 4.5 shows the variation of weld quality for the conventional control system. The weld secondary current was set to a constant value at the beginning of the test, and then an increment of 1 kA per weld was used as a stepper. It can be seen that there were a couple of cold welds at the beginning of the test, followed by a couple of normal welds, and then expulsion welds were dominant until the end of the test.

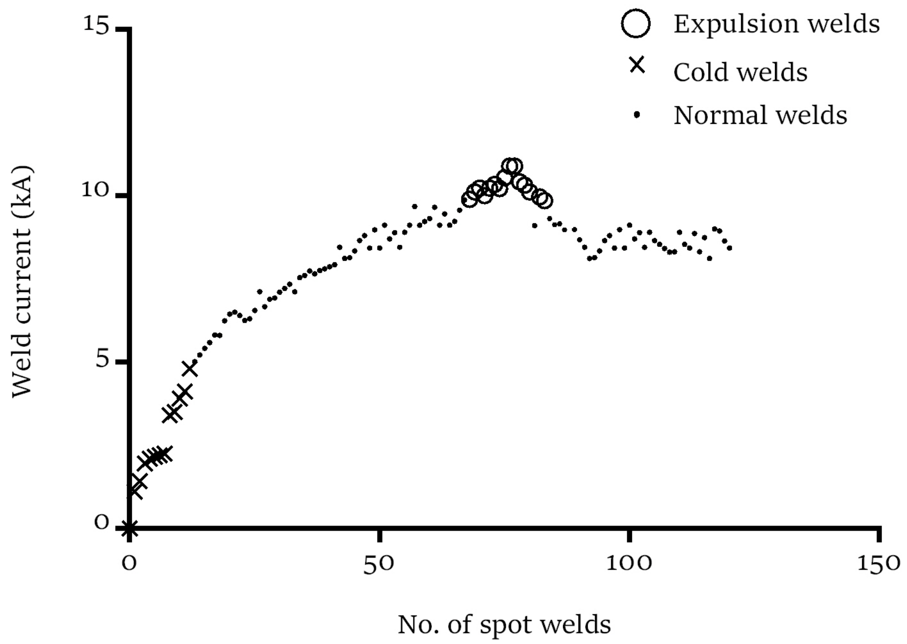


Figure 4.6: Weld quality based on the proposed ANFIS model

From Figure 4.6 it can be seen that the secondary current in the ANFIS-based control system was responding to the weld status; in case of expulsion welds, the secondary current was decreased, and in case of cold welds, the secondary current was increased. Thus, the ANFIS-based control scheme was able to adapt the secondary current level according to the weld state as shown in Table 4.4

Table 4.4: General rules for the ANFIS controller

Weld quality class	welding state	Action
Cold welds (C)	Poor welding	Increase welding current
Normal welds (N)	Good welding	No action
Expulsion welds (E)	Excessive welding	Decrease welding current

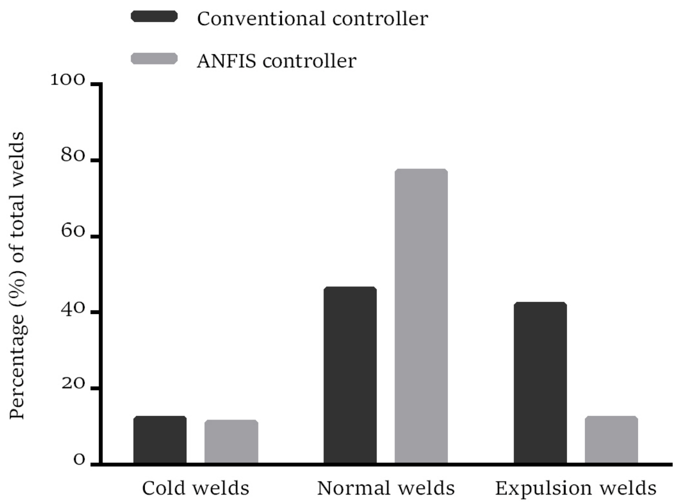


Figure 4.7: Comparison between ANFIS and conventional control models

The results obtained when applying the ANFIS-based controller trained using very limited data collected during the stabilization process are summarized in Figure 4.7. It can be seen that using the conventional controller, from the total number of spot welds, 12% were cold welds, 46% were normal welds and 42% were expulsion welds. while for the ANFIS-based controller the total cold welds produced were 11%, 77% normal welds and 12% expulsion welds. Hence, the proposed control algorithm based on ANFIS demonstrated robust performance reducing the number of expulsion welds by 30% compared to the conventional controller, while increasing the number of normal welds by 31%. Which is far better than the conventional controller.

4.4 Summary

In this chapter, the results obtained from the experiment demonstrated the relationship between the welding current and welding time on the weld quality. The developed online weld quality monitoring system satisfactorily predicted the weld quality, based on the weld's dynamic resistance curve. Experimental results show that the performance of the proposed controller is superior to that of a conventional controller, as commonly used in actual RSW applications.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

In this study, a model for weld quality monitoring and control to predict quality of the weld nugget in a RSW process was developed and validated through the experimental work. Firstly, the effects of welding current, as well as welding time on the weld quality were investigated. Secondly, an on-line quality assessment and control model based on LVQ-NN system and ANFIS model were developed.

Based on the experimental results it is confirmed that the welding current seems to be giving the most significant contribution of 88.65%. This is followed by welding time with 9.99% contribution to improve on the weld quality in relation to nugget diameter, if simultaneously considered.

The results from applying the LVQ-NN trained using the dynamic resistance data collected during the stabilization process are very promising, 82% of the total number of specimens were successfully inferred within a range of 18% error.

The proposed control algorithm based on ANFIS demonstrates robust performance reducing the number of expulsion welds by 30% compared to the conventional controller, while increasing the number of normal welds by 31%. It can be concluded that the ANFIS based controller is capable of successfully varying the welding current according to weld's state and to maintain a robust performance.

5.2 Recommendations

Though the proposed system has been experimentally validated in the laboratory, the robustness of the system has not been verified in the harsh environment of the production line. Extra work should be performed in both the hardware and software design before the proposed system can be implemented in practice, as, for example, in developing a unified control system to handle the control and quality monitoring simultaneously. In addition, a better filter algorithm should be developed to further improve the performance of the system, especially when the working environment changes from the laboratory to the real production line.

In this work, the experiments were conducted on welds made of steel of a limited size. Whether the proposed model can be extended to other materials, such as stainless steel, zinc, aluminum, etc., need to be investigated in the future. As a result, a more sophisticated mode of combining the parameters of material characteristics or other effective information may also be obtained.

REFERENCES

[1] *Ruukki, Resistance welding manual.* http://www.ruukki.com/ /media/Files/Steel-products/Cold-rolledmetal-colour-coated-instructions/Ruukki-Resistance-welding-manual.ashx, 2009.

[2] MATLAB, *version 7.10.0 (R2010a).* Natick, Massachusetts: The MathWorks Inc., 2010.

[3] El-Banna M., *Dynamic resistance based intelligent resistance welding.* Ph.D. Thesis, Wayne State University, 2006.

[4] Li W., Cerjanec D. and Grzadzinski G., "A comparative study of single-phase ac and multiphase dc resistance spot welding," *Journal of Manufacturing Science and Engineering*, vol. 127, no. 8, pp. 583–589, 2005.

[5] Zhao X., "Design of current controller for single phase ac resistance spot welding(rsw) machine using fourier learning scheme," mechanical engineering, Hong Kong University of Science and Technology, 2007.

[6] Zhou K., "Development of an online quality control system for resistance spot welding," M.Sc. Thesis, The Hong Kong University of Science and Technology, 2012.

[7] Zhang H., "Expulsion and its influence on weld quality," *Welding Research Supplement*, vol. 2, pp. 373–380, 1999.

[8] Zhang H. and Senkara J., *Resistance welding: fundamentals and applications*. CRC Press, 2006.

[9] Chao Y. J., "Failure mode of spot welds: Interfacial versus pullout," *Science and Technology of Welding and Joining*, vol. 8, no. 2, pp. 133–137, 2003.

[10] Chao Y. J., "Ultimate strength and failure mechanism of resistance spot weld subjected to tensile, shear, or combined tensile/shear loads," *Journal of Engineering Materials and Technology, Transactions of the ASME*, vol. 125, pp. 125–132, 2003.

[11] Jou M., "Real time monitoring weld quality of resistance spot welding for the fabrication of sheet metal assemblies," *Journal of Materials Processing Technology*, vol. 132, pp. 102–113, 2003.

[12] Jou M., Li C., and Messler R., "Controlling resistance spot welding using neural network and fuzzy logic," *Science and Technology of Welding and Joining*, vol. 3, no. 1, pp. 42–50, 1998.

[13] Gedeon S. A., Sorensen C. D., Ulrich K. T. and Eager T. W., "Measurement of dynamic electrical and mechanical properties of resistance spot welds," *Welding Research Supplement*, pp. 387–385, 1987.

[14] Klopcic B., Dolinar D. and Ctumberger G., "Advanced control of a resistance spot welding system," *Power Electronics, IEEE Transactions*, vol. 23, no. 1, pp. 144–152, 2008.

[15] Doyum B., "Ultrasonic examination of resistance spot welds," *Non Destructive Testing (NDT)*, vol. 8, 2003.

[16] Tusek J. and Blatnik T., "Ultrasonic detection of lack of fusion in spot welds," *Insight*, vol. 44, no. 11, pp. 684–688, 2002.

[17] Stiebel A., "Thermal force feedback system," 1990.

[18] Podrzaj P., Polajnar I., Diaci J. and Kariz Z., "Expulsion detection system for resistance spot welding based on a neural network," *Measurement Science & Technology*, vol. 15, pp. 592–598, 2004.

[19] Kannatey A. E. and Chien C. S., "Investigation of monitoring systems for resistance spot welding," *Welding Journal*, 2002.

[20] Xiaoyun Z., Zhang Y. and Chen G., "Weld quality inspection based on online measured indentation from servo encoder in resistance spot welding," in *Instrumentation and Measurement Technology Conference, 2006. IMTC 2006. Proceedings of the IEEE*, pp. 1353–1356, April 2006.

[21] Xianfeng W., GuoXiang M., Qian Y., Wenhua X. and Zhengjin F., "Real-time quality estimation of resistance spot welding based on electrode displacement characteristics and hmm," in *Natural Computation, 2009. ICNC '09. Fifth International Conference on*, vol. 3, pp. 634–638, Aug 2009.

[22] Patange S., Anjaneyulu T. and Reddy G., "Microprocessor-based resistance-welding monitor," *Welding Journal*, vol. 64, pp. 33–38, 1985.

[23] Klopcic B. and Dolinar D. and Stumberger G., "Advanced control of a resistance spot welding system," *Power Electronics, IEEE Transactions on*, vol. 23, pp. 144–152, Jan 2008.

[24] Kang Z. and Lilong C., "A nonlinear current control method for resistance spot welding," *Mechatronics, IEEE/ASME Transactions on*, vol. 19, pp. 559–569, April 2014.

[25] Cho Y. and Rhee S., "New technology for measuring dynamic resistance and estimating strength in resistance spot welding," *Measurement Science & Technology*, vol. 11, pp. 1173–1178, 2000.

[26] Wang S. C. and Wei P. S., "Modeling dynamic electrical resistance during resistance spot welding," *Journal of Heat Transfer-Transactions of the ASME*, vol. 123, pp. 576–585, 2001.

[27] Lee S. R., Choo Y. J., Lee T. Y., Kim M. H., and Choi S. K.,, "A quality assurance technique for resistance spot welding using a neuro-fuzzy algorithm," *Journal of Manufacturing Systems*, vol. 20, pp. 320–328, 2001.

[28] Hongjie Z. and Yanyan H., "Quality estimation of the resistance spot welding based on genetic k-means cluster analysis," in *Control, Automation and Systems Engineering (CASE), 2011 International Conference on*, pp. 1–4, July 2011.

[29] Liang G. and Cheng-liang L., "Electrode displacement patterns inferred as the optimal control criteria during the resistance spot welding process," *IEEE International Conference on Robotics and Automation, Shanghai International Conference Center*, pp. 148–152, 2011.

[30] Park Y. and Cho H., "Quality evaluation by classification of electrode force patterns in the resistance spot welding process using neural networks," *Pro-*

ceedings of the Institution of Mechanical Engineers, Part B (Journal of Engineering Manufacture), vol. 218, p. 1513, 2004.

[31] Kohonen T., "Improved versions of learning vector quantization. in: Neural networks," *1990 IJCNN international joint conference on, IEEE Journal,*, pp. 545–550, 1990.

[32] Kohonen T., *Self-organizing maps.* Springer-Verlag New York, Inc., 1997.

[33] Xingqiao C., Kenji A., "Fuzzy adaptive process control of resistance spot welding with a current reference model," *Proceedings of the 1997 IEEE International Conference on Intelligent Processing Systems*, 1997.

[34] Kang Z. and Lilong C., "Online measuring power factor in ac resistance spot welding," *Industrial Electronics, IEEE Transactions on*, vol. 61, pp. 575–582, Jan 2014.

[35] Robert B., "An overview of nonlinear identi cation and control with fuzzy systems.," *in Intelligent control systems using computational intelligence technique.*, 2005.

[36] Jos C. P., Neil R. E., Curt L. W., *Neural and Adaptive Systems: Fundamentals through Simulations.* Wiley., 1999.

[37] Jang J.S., Sun C.T., Mizutani E., *Neuro-Fuzzy and Soft Computing A computational approach to learning and machine intelligence.* Prentice-Hall, Inc., Upper Saddle River, New Jersey, 1997.

[38] Timothy J. Ross, *Fuzzy logic with engineering applications.* John Wiley and Sons Ltd., 2004.

[39] Claudio M., "Introduction to fuzzy logic.," *Facta Universitatis (NIS)*, 2000.

[40] Zadeh L. A., "Fuzzy sets, information and control," vol. 8, pp. 338–353, 1965.

[41] Guanrong C., *Introduction to fuzzy sets, fuzzy logic, and fuzzzy control systems.* CRC Press, 2001.

[42] Edward T., Tanya L. and Mo J., "Introduction to fuzzy logic control with application to mobile robotics.," *NASA Center for Autonomous Control Engineering Department of Electrical and Computer Engineering University of New Mexico.*, 2009.

[43] Xiaolin Z., Hongwei Z., Yiming Q., Li W., "Grinding process fuzzy control system design and application based on matlab," *IEEE*, vol. 1, pp. 311–315, 2008.

[44] Hellmann M., *Fuzzy Logic Introduction.* PhD thesis, Universite de Rennes, 2005.

[45] Takagi T., Sugeno M., "Fuzzy identification of systems and its applications to modeling and control.," *IEEE Trans. on System, Man and Cybernetics.*, vol. 4, no. 9, pp. 116–132, 1985.

[46] Podrzaj P., Polajnar I., Diaci J. and Kariz Z. *Science and Technology of Welding and Joining*, vol. 13, pp. 215–224, 2008.

[47] Gould J. E., "An examination of nugget development during spot welding, using both experimental and analytical techniques," *Welding Journal*, vol. 66, pp. 1s–10s, 1987.

[48] Lee C. C., "Fuzzy logic in control systems: Fuzzy logic controller-part i.," *IEEE Transactions, System, Man, Cybernetics.*, vol. 20, pp. 404–418, 1990.

[49] Graham C. G., *Adaptive filtering prediction and control.* Prentice-Hall (Englewood Cliffs, N.J), 1984.

[50] Takagi T. and Sugeno M., "Derivation of fuzzy control rules from human operators control actions.," *in In Procedings, IFAC Symposium: Fuzzy Information, Knowledge Representation and Decision Analysis.*, vol. 1, 1983.

[51] Ruano A. E., "An overview of nonlinear identification and control with fuzzy systems.," *Intelligent control systems using computational intelligence techniques*, 2005.

[52] Roger J. S. R., "Fuzzy modeling using generalized neural networks and kalman filter algorithm.," *in In Proceedings of the Ninth National Coference on Artificial Intelligence*, 1991.

[53] Paul J. W., *The roots of backpropagation: from ordered derivatives to neural networks.* John Wiley and Sons Inc., 1994.

[54] Piero P. B., *Adaptive neural fuzzy inference systems (ANFIS): Analysis and applications.* Lecture notes, 2000.