Automotive Manufacturing: *Intelligent Resistance Welding*⋆

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1 Introduction

Resistance spot welding (RSW) is an important process in the automotive industry. The advantages of spot welding are many: an economical process, adaptable to a wide variety of materials (including low carbon steel, coated steels, stainless steel, aluminum, nickel, titanium, and copper alloys) and thicknesses, a process with short cycle times, and overall, a relatively robust process with some tolerance to fit-up variations. Although used in mass production for several decades, RSW poses several major problems, most notably, large variation in weld quality. Given the variation and uncertainty in weld quality (attributed to factors such as tip wear, sheet metal surface debris, and fluctuations in power supply), it is a common practice in industry to add a significant number of redundant welds to gain confidence in the structural integrity of the welded assembly [1]. In recent years, global competition for improved productivity and reduced non-value added activity, is forcing automotive OEMs and others to eliminate these redundant spot welds. The emphasis on reduction of the redundant welds significantly increases the need for monitoring of weld quality and minimizing weld process variability. Traditionally, destructive and nondestructive tests for weld quality evaluation are predominantly off-line or end-of-line processes. While this test information is useful and valuable for quality and process monitoring, it cannot be utilized in process control because of the significant delays that are associated with the off-line test analysis. In order to minimize the number of spot welds and still satisfy essential factors such as strength and surface integrity, weld quality has to be monitored and controlled in real-time. Advances over the last decade in the area of non-intrusive electronic sensors, signal processing algorithms, and computational intelligence, coupled with drastic reductions in computing and networking hardware costs, have now made it possible to develop non-intrusive intelligent resistance welding systems that overcome the above shortcomings.

The importance of weld quality monitoring and process variability reduction is further amplified by the recent changes in the materials used by automotive manufacturers. The demand for improved corrosion resistance has led the automotive industry to increasingly use zinc coated steel in auto body construction. One of the major concerns associated with welding coated steel is the mushrooming effect (the increase in the electrode diameter due to deposition of copper into the spot surface) resulting in reduced current density and undersized welds (cold welds). The most common approach to this problem is based on the use of simple unconditional incremental algorithms (steppers) for preprogrammed current scheduling. The main objective of the weld current steppers is to maintain weld nugget size within acceptable limits while at the same time minimizing electrode growth. Large current steps could lead to an increase in electrode tip growth due to the use of high current levels. This in turn requires even larger increases in current, thereby

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causing a runaway process of electrode growth. Under these conditions, weld size would deteriorate at a rapid rate. On the other hand, small increases in welding current result in a slow rate of electrode tip growth, which is advantageous in terms of electrode life, provided the small increases in current are sufficient to maintain adequate current density to produce the required weld nugget size. Since the direct measurement of the main process characteristics – weld quality and expulsion rate – is not feasible in an automotive plant environment one reasonable approach is to estimate these variables by virtual or soft (indirect) sensors. A soft sensor for indirect estimation of the weld quality can provide a real time approximate assessment of the weld nugget diameter. Another opportunity for soft sensing in weld process control is determined by the need to predict the impact of the current changes on the expulsion rate of the weld process. The combination of soft sensing with adequate control algorithms can have dramatic impact on reducing variability of the weld process and effectiveness of weld equipment. The final goal is to develop a control algorithm that can be applied in an automotive assembly plant environment with the final objective of improving the weld quality and consistency, in turn, improving overall manufacturing quality and productivity while reducing redundant welds.

In this chapter we discuss two specific topics: (1) Development of accurate in-process non-destructive evaluation (NDE) of nugget quality by using the dynamic resistance (or secondary voltage) profile during the welding process and (2) Design of closed-loop supervisory control algorithm for adapting the weld controller set points for weld quality enhancement and reduction of process variability.

We propose and demonstrate the performance of a Linear Vector Quantization (LVQ) network for on-line nugget quality classification in conjunction with an intelligent algorithm for adjusting the amount of current to compensate for the electrodes degradation. The algorithm works 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 state is identified by indirectly estimating two of the main process characteristics – weld quality and expulsion rate. A soft sensor for indirect estimation of the weld quality employing an LVQ type classifier is designed to provide a real time approximate assessment of the weld nugget diameter. Another soft sensing algorithm is applied to predict the impact of changes in current on the expulsion rate of the weld process in real time. By maintaining the expulsion rate just below a minimal acceptable level, robust process control performance and satisfactory weld quality are achieved. The Intelligent Constant Current Control for Resistance Spot Welding is implemented and validated on a Medium Frequency Direct Current (MFDC) Constant Current Weld Controller. Results demonstrate a substantial improvement of weld quality and reduction of process variability due to the proposed new control algorithm.

2 Resistance Spot Welding: Background

A schematic diagram for resistance spot welding is illustrated in Fig. 1. It consists of primary (high voltage, low current) and secondary circuits (low voltage, high current). The process employs a combination of pressure and heat to produce a weld between the sheet metal work pieces in the secondary circuit. Resistance

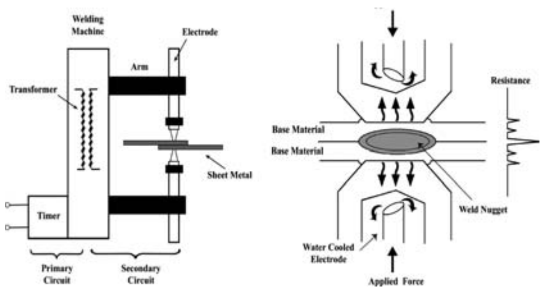

Fig. 1. Schematic diagram for resistance spot welding

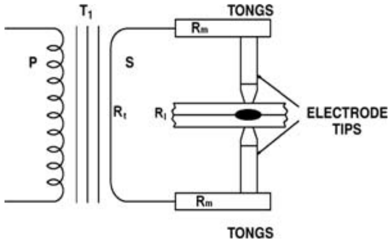

Fig. 2. Dynamic resistances in the secondary circuit

heating occurs as electrical welding current flows through the work pieces in the secondary circuit of a transformer. The transformer converts high-voltage, low current commercial power into suitable high current, low voltage welding power.

The energy required to produce a given resistance weld is determined by several factors. Key among them is the weld area (heated volume), the peak temperature, the specific heat of the work pieces, and the heat loss through the surrounding metal and electrodes. An increase in magnitude of one or more of these factors requires a corresponding increase in energy to produce the weld. A typical spot welding operation is controlled by a weld schedule, whose time steps are controlled by a spot welding controller. The dynamic resistance technique involves monitoring the resistance in the secondary circuit during the welding process. It is least intrusive, very economical, and seems to provide reasonable and adequate information about the state of the weld process. The word dynamic comes from fact that the resistance changes during the welding cycle. While the electrical resistances of the transformer and the mechanical assembly, R_t and R_m, can be assumed to be reasonably constant during the welding process (see Fig. 2), the sheet metal stack resistance (R_l) varies with nugget formation.

Two of the commonly used types of resistance welding systems (welding machines) in automotive industry are alternating current (AC) type and Medium Frequency Direct Current (MFDC) type. The AC resistance welding machine is inexpensive and its electrodes wear out slowly. However, a disadvantage is that the current supplied to the weld can be controlled only within fairly loose time interval [2]. The major advantage of the MFDC type of welding system is that the current supplied to the weld can be controlled within relatively stringent limits. This is one of the reasons for the increasing share of the MFDC type systems in the automotive assembly plants. In this chapter we pay special attention to the MFDC weld controller, and more specifically to the MFDC controller that is combined with a Constant Current strategy (MFDC-CC). This type of RSW controller is employed to achieve a constant current in each millisecond within the weld but the current can be changed from weld to weld based on a supervisory control algorithm.

3 Online Nugget Quality Evaluation Using Linear Vector Quantization Network

The problem of real-time estimation of the weld quality from process data is one of the key objectives in current weld control systems. The most common techniques can be grouped into four major groups: Ultrasonic technique, Thermal Force technique, Displacement technique, and Dynamic Resistance technique. It should be noted here that some of these techniques tend to be too intrusive and/or expensive for wide-scale deployment (for example, the ultrasonic technique), and in that sense, not compatible for main-stream application in automotive resistance welding. Most of the methods offered in the literature to predict nugget diameter from the process data employ measurements such as voltage and force and are not suitable in an industrial environment for two major reasons: the input signals for prediction model are taken from intrusive sensors (which affect the performance or capability of the welding machine), and the methods often required very large training and testing datasets.

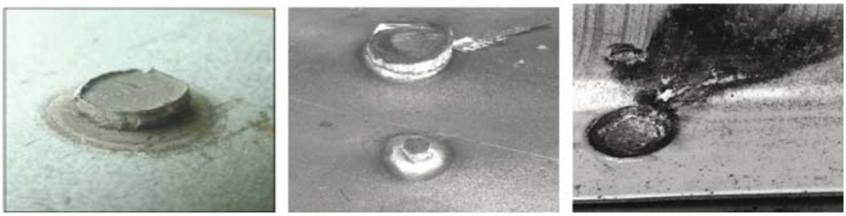

Fig. 3. Examples of normal, cold and expulsion welds [3]

This task can be alleviated if the weld controller is equipped with a voltage sensor in the secondary circuit, facilitating evaluation of dynamic resistance. Further simplification that significantly increases the feasibility of the mission of indirect estimation of weld quality follows from replacing the goal of quantifying the weld quality in terms of button size and integrity by the more modest objective of indirect estimation the class of the weld, e.g., satisfactory (acceptable, "normal" button size), unsatisfactory (under sized, "cold" welds), and defective ("expulsion") – Fig. 3. We consider normal the welds within the specifications, i.e., those that have nugget diameter more than the minimum acceptable limit and exhibit no expulsion. Those welds that do not meet the specification are characterized as cold welds. Additionally, we count as expulsion welds the welds that indicate ejection of molten metal – an undesirable event that has detrimental effect on weld nugget integrity (the loss of metal from the fusion zone can reduce the weld size and result in weld porosity), which may significantly reduce the strength and durability of the welded joints.

Given its non-intrusive nature, relatively low cost of implementation, and reasonable performance in many laboratory and industrial settings, we have adopted the dynamic resistance approach to monitor and control the process on-line. The measurements of voltage and current (at primary or secondary side) are used to calculate dynamic resistance.

Given its well-defined physical meaning and the ease of measurement, a number of studies on the problem of estimation of weld quality from the secondary dynamic resistance have been performed. Cho and Rhee [4] showed that the process variables, which were monitored in the primary circuit of the welding machine, can be used to obtain the variation of the dynamic resistance across electrodes. They introduced an artificial intelligence algorithm for estimation of the weld quality using the primary dynamic resistance. Cho and Rhee used uncoated steel welding (low carbon cold rolled steel) to verify their model but fall short from discussing the impact of coated steel (the material mainly used in the auto industry). Lee et al [5] proposed a quality assurance technique for resistance spot welding using a neuro-fuzzy inference system. They however used the displacement signal (something impractical in an automotive plant environment) as input to their model. Podrzaj et al [6] proposed an LVQ neural network system to detect expulsion. The results showed that the LVQ neural network was able to detect the expulsion in different materials. However, they identified the welding force signal as the most important signal for classification of the expulsion occurrence. Availability of force signal is limited to certain types of guns, and they are more expensive than other types of sensors. Park and Cho [7] used LVQ as well as a multi-layer perceptron neural network to classify the weld quality (strength and indentation) by using the force signal. All those studies targeted AC weld controller while the MFDC controller was not examined.

In order to overcome these shortcomings, in this section, we propose an algorithm for estimation of weld nugget quality through classification of button size based on a small number of patterns for cold, normal, and expulsion welds. Our approach uses an LVQ neural network for nugget quality classification that employs the easily accessible dynamic resistance profile as input. Our focus is on the Medium Frequency Direct Current Constant Current (MFDC-CC) controller. A more general LVQ based soft sensing algorithm considering also alternating current (AC) weld controllers is presented in [8]. The goal is to develop a method and algorithm for on-line classification between normal welds, cold welds, and expulsion welds that can be applicable for weld process control. It should be mentioned that LVQ classification of the weld status is performed after each weld, not during the welding time.

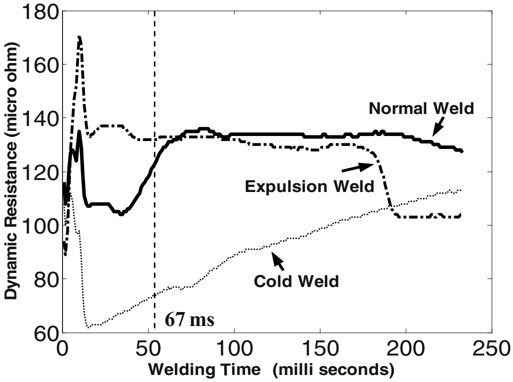

Fig. 4. Dynamic resistance profiles for cold, expulsion and normal welds for MFDC with constant current control

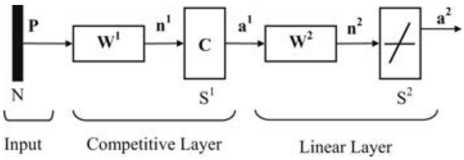

Fig. 5. Learning vector quantization (LVQ) neural network architecture

Figure 4 shows prototypical dynamic resistance profiles for three types of welds; cold, normal, and expulsion, for MFDC–CC controller. It can be seen that these profiles are not easily distinguishable. The cold weld dynamic resistance profile tends to be lower than the other profiles, while the expulsion weld dynamic resistance profile tends to have a sharp drop especially towards the end. In order to classify them we apply an LVQ neural net classifier.

Learning vector quantization (LVQ) [9] is a method for training competitive layers of a neural network in a "supervised" manner. It consists of three layers: an input layer, a competitive layer, and an output layer (Fig. 5). The "classes" that the competitive layer finds are dependent only on the distance between input vectors. If two input vectors are very similar, the competitive layer assigns them to the same class. LVQ shows good performance for complex classification problems because of its fast learning nature, reliability, and convenience of use. It particularly performs well with small training sets. This property is significantly important for industrial application, where training data is very limited; take considerable time, cost, or even impractical to get more data.

The network parameters are as follows: $\mathbf{P}$ is the N dimensional input vector, $\mathbf{W}^i$ is the weight matrix for the ith layer, S^i number of neurons in the ith layer, $\mathbf{n}^i$ the net input vector of the ith layer, and $\mathbf{a}^i$ the output of the ith layer. The first (competitive) layer is used to find the prototype vector $\mathbf{W}^1{}_s$ (i.e., a row of the weight matrix $\mathbf{W}^1$) that points in the direction closest to the input vector, i.e.,

$$\mathrm{Min}_i \left\|\mathbf{P} - \mathbf{W}_i^1\right\|^2 \ \forall i, \text{ where } i \in (1, 2 \ldots S^1)$$

The neurons that possess the least distance between vector weight matrix and input vector are assigned a value of one and the other neurons are assigned a value of zero. Finally, the output layer (linear layer) joins the subclasses ($\mathbf{S}^1$) from the competitive layer and $\mathbf{W}^2$ weight matrix into target classes ($\mathbf{S}^2$) through a linear transfer function. Matrix $\mathbf{W}^2$ defines a linear combiner and remains constant while the elements of $\mathbf{W}^1$ change during the training process. The weights of the winning neuron (a row of the input weight matrix) are adjusted using the Kohonen learning rule [20]. For example, supposing that the ith neuron wins the competition, the elements of the ith row of the input weight matrix are adjusted as shown below:

$$\mathrm{w}^1(\mathrm{i}) = \mathrm{w}^1(\mathrm{i}-1) + \rho(\mathrm{P}(\mathrm{i}) - \mathrm{w}^1(\mathrm{i}-1)),$$

where $\mathbf{P}(\mathrm{i})$ is the input vector of the ith iteration and ρ is the learning rate.

If just the Kohonen learning rule is employed, the neural network is called LVQ1. LVQ2 is an improved version of LVQ1, with the main difference being that in the latter case, the prototype vectors of two neurons are updated if the input vector $\mathbf{P}(\mathrm{i})$ is classified incorrectly. The weights of the neuron that wrongly won the competition are also updated as follows:

$$\mathrm{w}^1(\mathrm{i}) = \mathrm{w}^1(\mathrm{i}-1) - \rho(\mathrm{P}(\mathrm{i}) - \mathrm{w}^1(\mathrm{i}-1))$$

The LVQ2 was applied to estimate weld quality by classifying the dynamic resistance vectors corresponding to cold, normal an expulsion welds. The inputs to the network were the vectors of dynamic resistance sampled at 1 ms sampling rate.

An experiment was conducted with an MFDC welding machine with capacity of 180 kVA, 680 lb welding force provided by a servo gun, HWPAL25 electrode type with 6.4 mm face diameter, 233 ms welding time, 11.5 kA initial input secondary current, and an incremental stepper of 1 A per weld. The nugget diameter was measured for a total of 550 welds: 411 were found to be good welds, 22 were cold welds, and 117 welds with expulsion. In this experiment, LVQ2 network was trained on three, six, and five patterns for cold, normal, and expulsion welds, respectively. Twelve hidden neurons were used with a learning rate $\rho = 0.01$.

The performance of the LVQ-based on-line nugget quality classification algorithm was evaluated in terms of type 1 (α) and type 2 errors (β) for cold, normal, and expulsion welds. Type 1 error (α) (known as false alarm rate) defines the probability of "rejecting" the null hypothesis, while it is true. For example, if the null hypothesis defined the weld as expulsion weld, Type 1 error (α) defines the probability that the weld is misclassified as normal or cold weld, while it really is an expulsion weld. Type 2 error (β) defines the probability of not rejecting the null hypothesis, while it is false. It is important to note that that there is a trade off between Type 1 error and Type 2 error. If the model is too sensitive (i.e., type 2 error is very low), it is normal to have a larger number of false alarms (i.e., type 1 error will be high). Tables 1–3 report type 1 errors (α) and type 2 errors (β) for cold, normal, and expulsion welds when using the entire discretized dynamic resistance profile as an input vector to the LVQ neural network. It can be seen that the percent of false alarms are lowest for the cold weld case at 0, 11% for normal welds, and 40% for expulsion welds. As for type 2 errors, they are once again lowest for cold welds at 4, 6% for expulsion welds, and 34% for normal welds.

Table 1. Type 1 and 2 errors for classification of cold welds when using the entire dynamic resistance profile as input to the LVQ neural network

H_0: Weld is cold	True state of H_0	
statistical decision	H_0 is true	H_0 is false
Reject H_0	$\alpha = 0.00$	$1-\alpha = 1.00$
Don't reject H_0	$1-\beta = 0.96$	$\beta = 0.04$

Table 2. Type 1 and 2 errors for normal welds classification when using the entire dynamic resistance profile as input to the LVQ neural network

H_0: Weld is normal	True state of H_0	
statistical decision	H_0 is true	H_0 is false
Reject H_0	$\alpha = 0.11$	$1-\alpha = 0.89$
Don't reject H_0	$1-\beta = 0.66$	$\beta = 0.34$

Table 3. Type 1 and 2 errors for expulsion welds classification when using the entire dynamic resistance profile as input to the LVQ neural network

H_o: Weld is expulsion statistical decision	True state of H_0	
	H_0 is true	H_0 is false
Reject H_0	$\alpha = 0.40$	$1 - \alpha = 0.60$
Don't reject H_0	$1 - \beta = 0.94$	$\beta = 0.06$

Table 4. Power of the test $(1 - \beta)$ for different features inputs to the LVQ neural network

Feature	Cold welds (%)	Normal welds (%)	Expulsion welds (%)
Maximum	99.8	78.6	83.0
Minimum	94.6	13.0	100.0
Mean	98.3	13.7	100.0
Standard deviation	74.9	60.3	72.2
Range	100.0	38.2	75.0
Root mean square (RMS)	92.1	14.5	100.0
Slope 1	53.6	80.2	79.2
Slope 2	67.7	100.0	30.7
Slope 3	73.9	90.1	45.8
Slope 4	100.0	37.4	99.8
Bin 1	83.6	31.3	76.2
Bin 2	90.7	16.0	88.7
Bin 3	89.6	14.5	100.0
Bin 4	92.1	100.0	14.4
Bin 5	98.1	20.6	98.6

In order to reduce the dimensionality of the LVQ neural network input vector (dynamic resistance profile), different features were tested as possible candidates to replace the dynamic resistance profile vector as input, i.e., reducing the input of the LVQ network to a feature vector (the first ten models have a single feature input while the last one has a 5-feature input vector):

- Maximum value of the dynamic resistance profile
- Minimum value of the dynamic resistance profile
- Mean value of the dynamic resistance profile
- Standard deviation value of the dynamic resistance profile
- Range value of the dynamic resistance profile
- Root mean square (RMS) value of the dynamic resistance profile
- First region slope (S1) value of the dynamic resistance profile
- Second region slope (S2) value of the dynamic resistance profile
- Third region slope (S3) value of the dynamic resistance profile
- Fourth region slope (S4) value of the dynamic resistance profile
- Binned RMS of dynamic resistance profile: dynamic resistance vector is divided into five bins and RMS values are calculated for each bin

The criteria for features selection was based on power of the test (i.e., $1 - \beta$) for the cold, normal, and expulsion welds as shown in Table 4. The feature that demonstrates the highest classification performance for the three types of welds was chosen as input for the LVQ network (the first row in Table 4). In order to simplify features selection, we assume that interactions among features are negligible.

In our work, we just employed the most promising feature identified by power of the test criteria, the maximum value of the dynamic resistance vector, as input for LVQ neural network. Tables 5–7 show the type 1 and 2 error results from the network when employing just this feature. It can be seen that both types

Table 5. Type 1 and 2 errors for cold welds classification when using the maximum of dynamic resistance profile as a single input to the LVQ neural network

H_0: Weld is cold statistical decision	True state of H_0	
	H_0 is true	H_0 is false
Reject H_0	$\alpha = 0.00$	$1 - \alpha = 1.00$
Don't reject H_0	$1 - \beta = 0.88$	$\beta = 0.12$

Table 6. Type 1 and 2 errors for normal welds classification when using maximum of dynamic resistance profile as a single input to the LVQ neural network

H_0: Weld is normal statistical decision	True state of H_0	
	H_0 is true	H_0 is false
Reject H_0	$\alpha = 0.29$	$1 - \alpha = 0.71$
Don't reject H_0	$1 - \beta = 0.81$	$\beta = 0.19$

Table 7. Type 1 and 2 errors for expulsion welds classification when using maximum of dynamic resistance profile as a single input to the LVQ neural network

H_0: Weld is expulsion statistical decision	True state of H_0	
	H_0 is true	H_0 is false
Reject H_0	$\alpha = 0.23$	$1 - \alpha = 0.77$
Don't reject H_0	$1 - \beta = 0.87$	$\beta = 0.13$

of errors are reduced by using the maximum resistance feature instead of the entire vector of resistance for normal and expulsion welds. On the other hand, for cold welds, the type 2 error degrades.

LVQ network shows good performance for complex classification problems because of its fast learning nature, reliability, and convenience of use. It particularly performs well with small training sets. This property is especially important for automotive manufacturing applications, where the process of obtaining large training data sets may require considerable time and cost. Overall, the results are very promising for developing practical on-line quality monitoring systems for resistance spot-welding machines and complete automation of the welding process.

4 Intelligent Constant Current Control Algorithm

Most of the conventional weld control systems are based on the concept of "stepper" type preprogrammed scheduling of the primary current. A basis for setting up a current stepper can be developed by determining the pattern of electrode growth obtained in a particular welding cell. Different approaches are used for setting up a weld current stepper, including subjective methods, fixed increments, constant current density, gradient following, and iterative approaches. In a subjective or "best guess" approach, current steps are based on maintaining a slight red glow at the electrode/sheet interface and/or regularly adjusting the current to a level just below the splash or expulsion level. This approach has been found to give significant improvements in electrode life. While acceptable results can be achieved by this means, an extreme skill is required in determining the point at which current is to be increased.

In a fixed (preprogrammed scheduling) increment approach, a current stepper can be based on increasing either the heat control (i.e., phase shift control) or the actual welding current, in fixed increments after performing a predetermined number of welds. Generally, the increment of phase shift can be set between 1 and 5%. It was concluded [10] that a stepper function based on a fixed increment of the heat control or phase shift control was not a viable means of extending electrode life in many instances.

Multiple alternative approaches for adjusting the stepper algorithms based on different criteria have been reported (constant current density [10], gradient following approach [11], fuzzy controlled adaptation of delivered power [12], dynamic resistance profile estimation [13], prediction of weld strength [14], etc.) but have not found strong acceptance in automotive industry for various reasons (sensitivity to the coating type, undesirable rapid growth of electrode diameter, assumption of intrusive (electrode displacement) sensors, lack of robustness with respect to expulsions, etc.

In this section, we present an intelligent control algorithm that addresses the problem of constant current weld control of coated steels in the presence of significant electrode degradation [15]. The algorithm is implemented 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 welding process. Since the direct measurement of the main process characteristics – weld quality and expulsion rate – is not feasible in an industrial environment, these variables are estimated by soft (indirect) sensors.

A soft sensor for indirect estimation of the weld quality employing an LVQ type classifier that was described in the previous section provides a real time approximate assessment of the weld nugget diameter. Another soft sensing algorithm that is based on continuous monitoring of the secondary resistance is applied to predict the instantaneous impact of the current changes on the expulsion rate of the weld process. The reason for using the second soft sensor is to monitor the expulsion during the actual welding time (i.e., in each millisecond) so if expulsion is detected during the welding process, current should be turned off or reduced for the remaining welding time. Therefore, the second soft sensor complements the LVQ based soft sensor that was introduced in Sect. 3 with a real time estimation of potential expulsion conditions, while the LVQ soft sensor provides estimation of weld quality only after the completion of the weld process.

The main objective of the rule set of the fuzzy logic control algorithm is to describe a nonlinear control strategy that adjusts the secondary current to maintain the expulsion rate just below a minimal acceptable level guaranteeing satisfactory weld quality with robust process control performance, and minimize the electrode degradation. The fuzziness of the rules predicates reflects the uncertainty of the indirectly estimated weld quality and expulsion rate variables. The Intelligent Constant Current Control algorithm was implemented and validated on a Medium Frequency Direct Current Constant Current (MFDC-CC) Weld Controller. Results demonstrate a substantial improvement of weld quality and reduction of process variability due to the proposed new control algorithm.

The fuzzy logic control algorithm is implemented in a supervisory control mode (Fig. 5) – it replaces the conventional "stepper" type constant current weld control algorithm. The primary current remains unchanged during the weld process but the primary current level for each weld is continuously adjusted based on the estimated state of the weld process during the last p welds (parameter p represents the size of a moving process window). The adjustment of the primary current results in a consequent adjustment of the secondary current. Two of the main process characteristics that are used as inputs to the fuzzy logic controller – the expulsion rate and the size of the weld nugget – are not directly measured but are derived from the secondary resistance profiles of the last p welds. The dynamic resistance is calculated from the measured secondary voltage and the calculated secondary current (Fig. 6).

On the other hand, in order to get the optimum strength for the weld, the input parameters (current, time, force) need to be targeted just below the expulsion level.

The nugget quality estimation algorithm is used to determine the number of normal welds produced during the last process window of p welds based on a LVQ neural network that was discussed in detail in the previous section. We consider the full size input vector, i.e., $\mathbf{P}$ is a vector of dimension 167 (i.e., $N = 167$), which is equal to the number of millisecond samples in one weld after the pre-heat and cooling phase. The reason for using the vector of dynamic resistance profile rather than a single feature input (the maximum of the profile) is to guarantee robustness of the proposed control algorithm. While an LVQ classifier with a single feature input can be applied for process monitoring for the purpose of supervisory control we consider the full size input vector classifier that contains complete information of the welding process. The number of hidden neurons in the LVQ neural network is 12 while the number of output neurons is three corresponding to the three categories of welding status; cold, normal, and expulsion. Consequently, the weight matrices $\mathbf{W}^1$ and $\mathbf{W}^2$ are of size (167×12) and (12×3), respectively.

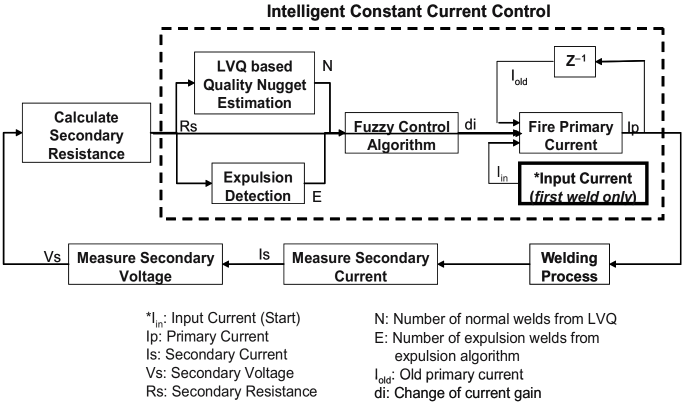

Fig. 6. Intelligent constant current control

The LVQ model (Fig. 5) was trained on three, six, and five patterns of the secondary resistance vectors for cold, normal, and expulsion welds, respectively. Twelve hidden neurons were trained with a learning rate of 0.01.

Since the number of expulsions over time (expulsion rate) plays very significant role in the proposed control algorithm, we complement the estimation of the expulsion welds with an alternative algorithm for indirect estimation of the expulsion rate. Expulsion is estimated indirectly from the resistance profile. The main indicator for expulsion, as pointed out in [6, 16, 17], is the instantaneous drop in the resistance (Fig. 4). In this chapter we use a modified version of the expulsion algorithm from reference [18].

Lets R(k) denote the dynamic resistance value at the current millisecond cycle (the MFDC weld process takes 233 ms), and R(k − 1) and R(k − 2) the two previous resistance values. The soft sensing expulsion algorithm continuously checks for a resistance drop with respect to a dynamically defined expulsion threshold $E_{level}(k)$ (after the cooling period, i.e., in our experiment after 67 ms) that is represented by the following condition for the resistance:

If $\mathrm{Max}\{R(k-2), R(k-1), R(k)\} > \mathrm{Max}\{R(k-1), R(k)\}$
Then $E_{level}(k) = \frac{Max\{R(k-2),R(k-1),R(k)\}-Max\{R(k-1),R(k)\}}{Max\{R(k-1),R(k)\}} * 100$
Else
$E_{level}(k) = 0$
To determine if there is an expulsion in the examined weld, the following conditions are checked against $E_{level}(k)$:
If $E_{level}(k) \geq A$
Or
If $\{E_{level}(67) + \ldots + E_{level}(k)\} \geq B$,

where A and B are threshold parameters for expulsion detection (in our experiment A = 3, and B = 14).

In order to enhance the indirect estimation of the weld status, another soft sensing algorithm (LVQ based quality nugget estimation block in Fig. 6) based on quality nugget estimation is introduced. Quality nugget estimation employing an LVQ classifier is designed to provide a real time approximation of the weld nugget status. The primary current for the next window of p welds is calculated by using a fuzzy control algorithm relating the number of expulsion welds and number of normal welds.

Let "E" denote the number of expulsion welds detected from the expulsion algorithm, "N" the number of normal welds detected from LVQ neural network, for the last window of p welds, and dI be the change of current that is inferred by the algorithm. We define the mechanism for adjusting the current gain based on

Table 8. Fuzzy logic controller rule-base

	Rule
1	If "E" is *low* AND "N" is *low* THEN $dI = \mathrm{P_a}$
2	If "E" is *medium* AND "N" is *low* THEN $dI = \mathrm{N_g}/2$
3	If "E" is *high* AND "N" is *low* THEN $dI = \mathrm{N_g}$
4	If "E" is *low* AND "N" is *medium* THEN $dI = \mathrm{P_a}/2$
5	If "E" is *medium* AND "N" is *medium* THEN $dI = \mathrm{N_g}/4$
6	If "E" is *high* AND "N" is *medium* THEN $dI = \mathrm{N_g}/2$
7	If "E" is *low* AND "N" is *high* THEN $dI = \mathrm{P_a}/4$
8	If "E" is *medium* AND "N" is *high* THEN $dI = \mathrm{N_g}/8$
9	If "E" is *high* AND "N" is *high* THEN $dI = \mathrm{N_g}/4$

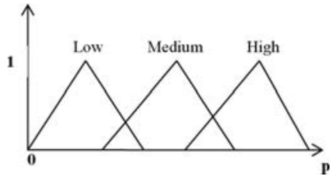

Fig. 7. Membership functions of the number of expulsion welds and the number of normal welds in a process window of the last p welds (p is a fixed parameter). Parameter p defines a universe $[0,\ p]$ of the all possible expulsion and normal welds within that moving window

the number of expulsion and normal welds in the last window of p welds through a set of rules with fuzzy predicates (Table 8).

In the rules of the fuzzy logic controller *low, medium*, and *high* are fuzzy subsets defined on the $[0,\ p]$ universe for the number of expulsions "E," and the number of normal welds "N" (Fig. 7). $\mathrm{N_g} < 0$ and $\mathrm{P_a} > 0$ are constants (fuzzy singletons) defining control changes of the current.

The first three fuzzy rules deal with the case where the number of normal welds "N" in the last window is low. Based on the number of detected expulsions, three alternative strategies for changing current level are considered:

- If the number of expulsions is *low*, it is reasonable to think that the state of the welds is close to the cold welds status. Hence, it is necessary to increase gradually the amount of current, i.e., the current is changed by. $dI = \mathrm{Pa}$.
- If the number of detected expulsions is *medium* or *high*, it is reasonable to think that the state of the welds is close to the expulsion state. Hence, it is necessary to decrease the amount of current. This is performed selectively, based on the number of expulsions (*high* vs. *medium*), resulting in negative changes of the current $dI = \mathrm{Ng}$ vs. $dI = \mathrm{Ng}/2$.

When the number of normal welds N in the process window is *medium*, the strategies for adjusting the current level are as follows (rules 4–6):

- When we have low expulsion detection rate, the weld state is likely approaching a cold weld. Therefore, the level of current should be increased. This is done by increasing the current level, i.e., $dI = \mathrm{Pa}/2$. Note that the amount of increase when the number of normal welds "N" is *medium* ($dI = \mathrm{Pa}/2$) is less than in the case when that number "N" is *low* ($dI = \mathrm{Pa}$).
- The next case deals with medium expulsion rate, i.e., the weld state is close to the expulsion status. This requires a gradual reduction of the current dI. Note that the amount of decrease when "N" is *medium* ($dI = \mathrm{Ng}/4$) is also less than the case when the "N" is *low* ($dI = \mathrm{Ng}/2$).
- The last case appears when the expulsion rate is *high*. Since this is an undesirable state, the level of current should be lowered dramatically to minimize the number of expulsions. This is also done by modifying the secondary current $dI = \mathrm{Ng}/2$ when "N" is *medium* and $dI = \mathrm{Ng}$ when "N" is *low*.

The last three fuzzy rules (7–9) consider high level of normal welds, i.e., satisfactory weld quality. Their corresponding control strategies are:

- If we have low expulsion detection, the state of the welds will be approaching a cold weld status. Therefore, current level should be increased to prevent potential cold welds. This is done by a minor positive change of the current to $dI = \mathrm{P_a}/4$.
- If we have medium expulsion detection, it is reasonable to consider that the state of the welds is close to the expulsion welds status. Therefore the current level should be decreased gradually to $dI = \mathrm{Ng}/8$).
- In the last case, when the expulsion detection is high, the level of the current should be decreased. The corresponding change of the current is slightly negative ($dI = \mathrm{Ng}/4$), i.e., significantly less than in the cases when "N" is *medium* ($dI = \mathrm{Ng}/2$) or when "N" is *low* ($dI = \mathrm{Ng}$).

Applying the Simplified Fuzzy Reasoning algorithm [19], we obtain an analytical expression for the change of the current *dI* depending on the rates of expulsion welds "E" and normal welds "N" as follows:

$$dI = \frac{\sum\limits_{\forall i}\sum\limits_{\forall j}\mu_i(x)\nu_j(y)\Delta_{i,j}}{\sum\limits_{\forall i}\sum\limits_{\forall j}\mu_i(x)\nu_j(y)}$$

where:

μ_{i}: membership function of the linguistic value of the expulsion welds {*low, medium, high*}
ν_{j}: membership function of the linguistic value of the normal welds {*low, medium, high*}
x: number of expulsion welds in the process window detected by the expulsion algorithm
y: number of normal welds in the process window detected by the LVQ soft sensing algorithm
$\mu_{\mathrm{i}}(\mathrm{x})$: firing level for the expulsion membership function
$\nu_{\mathrm{j(y)}}$: firing level for the normal membership function
$\Delta_{i,j}$: amount of increment/decrement when the linguistic value of expulsion welds is "i" and the linguistic value of normal welds is "j" (for example, if the linguistic value of the expulsion welds is *high* and the linguistic value of the normal welds is *low* then $\Delta_{high,low} = Ng$, where Ng negative value determines the change of the current *dI*); see Table 8.

Triangular shape membership functions μ_{i}, ν_{j} are used in the fuzzy control algorithm (Fig. 7) to define the linguistic values of the numbers of expulsion and normal welds in the process window. These membership functions depend on the scalar parameters a, b, c as given by:

$$\mu_i, \nu_j(x, y; a, b, c) = \left\{\begin{matrix} 0, & x \le a \\ \frac{x-a}{b-a} & a \le x \le b \\ \frac{c-x}{c-b} & b \le x \le c \\ 0, & c \le x \end{matrix}\right\}$$

The new target current ($\mathrm{I_{new}}$) for the next window of p welds will be:

$$\mathrm{I_{new}} = \mathrm{I_{old}} + dI\mathrm{I_{old}}$$

where $\mathrm{I_{old}}$ is the current in the previous window of p welds and *dI* is the change of the current that is calculated from the fuzzy control algorithm.

Proposed Intelligent Constant Current Control algorithm was implemented in Matlab/Simulink and was experimentally tested in a supervisory control mode in conjunction with an MFDC Constant Current Controller. Four sets of experiments were performed as follows. The first group of tests (with/without sealer) was performed using the Intelligent Constant Current Controller. The second group (with/without sealer) was carried out by using a conventional stepper. The role of the sealer in this test is to simulate a typical set of disturbances that are common for automotive weld processes. Sealer is commonly used to examine the performance of weld controllers and their capability to control process variability.

Each group of tests consists of sixty coupons, i.e., 360 welds (for each test without sealer), and ten coupons, i.e., 60 welds (for each test with sealer) with two metal stacks for each coupon are used for each test. Both tests involved welding 2.00 mm gage hot tip galvanized HSLA steel with 0.85 mm gage electrogalvanized HSLA steel. Thirty six coupons (216 welds) without a sealer between sheet metals and ten coupons (60 welds) with a sealer for each group of tests were examined. Cold and expulsion welds were checked visually in each coupon.

The length of the moving window in the Intelligent Constant Current Controller algorithm was $p = 10$, i.e., the soft sensing of expulsion and normal welds was performed on a sequence of ten consecutive welds. The negative and positive consequent singleton values in the rule-base of the fuzzy control algorithm were set at Ng $= -0.09$ and Pa $= +0.07$.

In the stepper mode test, an increment of one ampere per weld was used as a stepper for this test. The initial input current was set at 11.2 kA for all tests, with no stabilization process to simulate the actual welding setup conditions in the plant after tip dressing.

4.1 Intelligent Constant Current Control and Stepper Based Control without Sealer

Figure 8 shows the weld secondary current generated by the Intelligent Constant Current Control algorithm without sealer. It can be seen that at the beginning of the welding process, there were a couple of cold welds, so the fuzzy control scheme increased the current gradually until expulsion began to occur. When expulsion was identified by the soft sensing algorithm, the fuzzy control algorithm began to decrease the current level until expulsion was eliminated and normal welds were estimated again. After that it continued to increase the current until expulsion occurred again and so on.

It can be concluded from the test above that the secondary current in the intelligent control scheme 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 fuzzy control scheme was able to adapt the secondary current level to weld state estimated by the soft sensing algorithms.

Figure 9 shows the secondary current in the case of conventional stepper mode. The weld primary current was set to a constant value at the beginning of the test, and then an increment of one ampere per weld was used as a stepper to compensate for the increase in electrodes diameter (mushrooming of the electrode); observed nonlinearity of the secondary current is a result of the transformer nonlinearities. It can be seen that there were several cold welds at the beginning of the test, followed by some of normal welds, and then expulsion welds were dominant until the end of the test.

Evidently, the secondary current in the stepper mode was too aggressive towards the end of the welding process, resulting in many expulsion welds. On the other hand, at the beginning, the secondary current was not enough, resulting in cold welds. The stepper mode does not really adapt the current to the actual weld state at the beginning or at the end of the welding process.

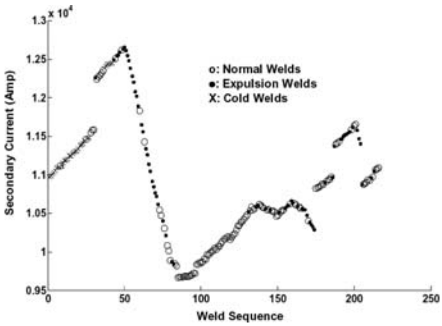

Fig. 8. Secondary current using the intelligent constant current fuzzy control algorithm

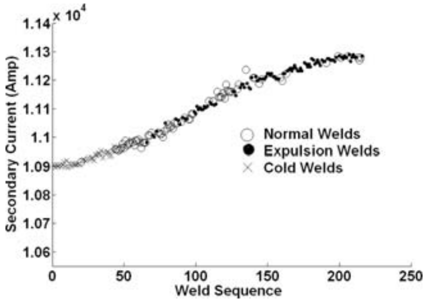

Fig. 9. Secondary current for the stepper based algorithm without sealer

Table 9. Number of expulsion welds for the fuzzy control algorithm and the conventional stepper mode without sealer

Number of expulsion welds using fuzzy controller	Number of expulsion welds using stepper mode
$68/216 = 31.5\%$	$98/216 = 45.4\%$

Table 10. Number of cold welds for the fuzzy control algorithm and the conventional stepper mode without sealer

Number of cold welds using fuzzy controller	Number of cold welds using stepper mode
$31/216 = 14.4\%$	$44/216 = 20.4\%$

Tables 9 and 10 show the number of expulsion and cold welds for the Intelligent Constant Current Control algorithm versus the conventional stepper mode implementation. As expected, the number of expulsion welds in the stepper mode ($98/216 = 45.4\%$) is higher than the number of expulsion welds in the fuzzy control scheme ($68/216 = 31.5\%$). It can also be seen that the number of cold welds in the fuzzy control scheme test ($31/216 = 14.4\%$) was less than the number of cold welds in the stepper mode ($44/216 = 20.4\%$).

4.2 Intelligent Constant Current Control and Stepper Based Control with Sealer

It is a common practice in the automotive industry to intentionally introduce sealer material between the two sheet metals to be welded. The purpose of this sealer is to prevent water from collecting between the sheets and in turn reduce any potential corrosion of the inner surface of sheet metals. However, the sealer creates problems for the spot welding process. In particular, the sealer increases the resistance significantly between the two sheet metals to be welded. When the welding process starts, high current will be fired, which is faced by high resistance (because of the sealer) in the desired spot to be welded, that prevents the current from flowing in that direction. The other alternative direction for this current is to flow in the direction of less resistance; this is what is known as shunting effect. Shunting effect produces cold welds, or at least small welds, which will cause a serious problem to the structure.

Figure 10 shows the spot secondary current for the Intelligent Constant Current Control algorithm with sealer. It demonstrates a performance similar to the case with no sealer – increasing/decreasing of the current level to adapt to the estimated cold/expulsion welds.

Figure 11 shows the spot stepper mode secondary current in the presence of sealer. The weld secondary current was set to a constant value at the beginning of the test with subsequent increments of one ampere per weld. It can be seen that the cold welds were dominant until just before the end of the test. There were a

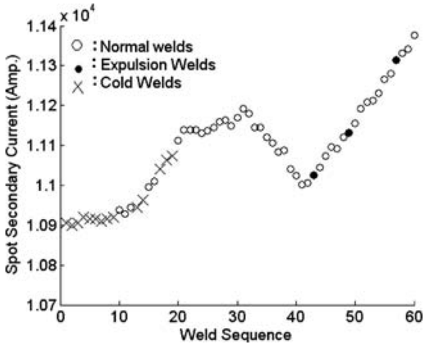

Fig. 10. Spot secondary current for the fuzzy control algorithm with sealer

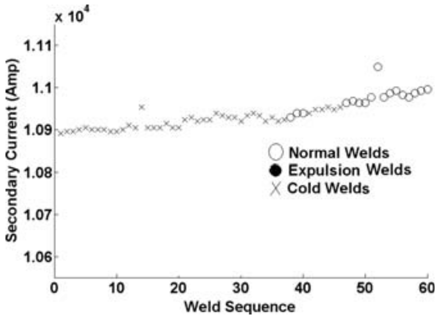

Fig. 11. Spot secondary current for the stepper mode with sealer

Table 11. Number of expulsion welds for the fuzzy control scheme, the stepper, and the no stepper modes with sealer

Number of expulsion welds using fuzzy controller	Number of expulsion welds using stepper mode
$3/60 = 5\%$	$0/60 = 0.0\%$

Table 12. Number of cold welds for the fuzzy control algorithm, the stepper, and the no stepper modes with sealer

Number of cold welds using fuzzy controller	Number of cold welds using stepper model
$14/60 = 23.3\%$	$43/60 = 71.7\%$

couple of normal welds towards the end of the test. No expulsion welds occurred in this test. Apparently, the secondary current was not enough to produce cold welds. Using stepper mode does not adapt the secondary current according to the weld status.

Tables 11 and 12 compare the number of expulsion and cold welds for the Intelligent Constant Current Control algorithm and the conventional stepper mode implementation in the case of welding with sealer. The number of expulsion welds in the fuzzy control scheme test ($3/60 = 5\%$) is slightly higher than the number of expulsion welds in the stepper mode test ($0/60 = 0.0\%$). However, the number of cold welds in the case of application of the fuzzy control algorithm ($14/60 = 23.3\%$) is much less than the number of cold welds in the conventional stepper mode test ($43/60 = 71.7\%$).

5 Conclusions

The problem of real time estimation of the weld quality from the process data is one of the major issues in the weld quality process improvement. This is particularly the case for resistance spot welding. Most of the models offered in the literature to predict nugget diameter from the process data employ measurements such as ultrasonics, displacement, and thermal force and are not suitable in an industrial environment for two major reasons: the input signals for prediction model are taken from intrusive sensors (which will affect the performance or capability of the welding cell), and, the methods often required very large training and testing datasets.

In order to overcome these shortcomings, we proposed a Linear Vector Quantization (LVQ) neural network for nugget quality classification that employs the easily accessible dynamic resistance profile as input. Instead of estimating the actual weld nugget size the algorithm provides an on-line estimate of the weld quality by classifying the vectors of dynamic resistance profiles into three classes corresponding to normal, cold, and expulsion welds. We also demonstrated that the algorithm can be successfully applied when the dynamic resistance profile vector is replaced by a limited feature set. Based on the results from LVQ, a control algorithm called the Intelligent Constant Current Control for Resistance Spot Welding was proposed for adapting the weld current level to compensate for electrode degradation in resistance spot welding. The algorithm employs 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. A soft sensor for indirect estimation of the weld quality employing an LVQ type classifier was implemented in conjunction with the intelligent control algorithm to provide a real time approximate assessment of the weld nugget status. Another soft sensing algorithm was applied to predict the impact of the current changes on the expulsion rate of the weld process. By maintaining the expulsion rate just below a minimal acceptable level, robust process control performance and satisfactory weld quality were achieved. The Intelligent Constant Current Control for Resistance Spot Welding was implemented and experimentally validated on a Medium Frequency Direct Current (MFDC) Constant Current Weld Controller.

Results were verified by benchmarking the proposed algorithm against the conventional stepper mode constant current control. In the case when there was no sealer between sheet metal, it was found that the proposed intelligent control approach reduced the relative number of expulsion welds and the relative number of cold welds by 31% (from absolute 45.4–31.5%) and 29% (from absolute 20.4–14.4%) respectively, when compared to the stepper mode approach.

In the case when there was a sealer type disturbance, the proposed control algorithm once again demonstrated robust performance by reducing the relative number of cold welds by 67% compared to the stepper mode algorithm (from absolute 71.7–23.3%), while increasing the absolute number of expulsion welds by only 5%.

Our Intelligent Constant Current Control Algorithm is capable of successfully adapting the secondary current level according to weld state and to maintain a robust performance.

Our focus in this chapter was on the Medium Frequency Direct Current (MFDC) weld controllers. An alternative version of the Intelligent Constant Current Control Algorithm that is applicable to the problem of alternating current (AC) weld control in conjunction with the Constant Heat Control Algorithm [8] is under development.

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