QUANTITATIVE ESTIMATION OF A RESISTANCE SPOT WELD QUALITY USING A SIMPLE MODEL

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Abstract. *The quality of a weld produced by a resistance spot welding process is an issue in various manufactures and areas due to the strong link between the weld quality and safety. In this paper it is proposed the use of a simple model based on physical properties of the process to obtain a quantitative estimation of a resistance spot weld, joining two metal sheets normally found in the automobile industry. The simple model parameter values are the features used in an artificial neural network in order to estimate the quantitative quality. It is based in the dynamic electrical resistance signal obtained in the secondary circuit of a welding machine. The model parameters are obtained by fitting the model curve against a real measured curve by means of an adapted Levenberg-Marquardt algorithm. Using data of about 150 measurements of the dynamic resistance over time from a resistance spot welding process, where each measured curve represents the resistance variation of a single weld during the welding process, the proposed approach were validated. For the analyzed process, the quantitative estimated value is the size of the weld diameter. The results obtained in the diameter estimation show a precision of +/- 0.6 mm and therefore can be considered a very good estimation due to the complexity of the analyzed process.*

Keywords: *non-destructive tests, quality estimation, resistance spot welding*

1. INTRODUCTION

The resistance spot welding process (RSW) is a non-linear process very commonly used in the industry and consists of the joining of two or more metal parts together in a localized area, based on the heat produced according to Joule's Law. High current is passed through the parts via the electrodes of a welding gun and since heat is produced mainly at the interface between the sheets due to electrical resistance, a molten pool is created in this location by the heating energy flowing in. After switching off the current, this molten material cools down and a solid weld nugget is produced.

The quality of a weld produced by a RSW is an issue in various manufactures and areas due to the strong link between the weld quality and safety. More than 100 million weld spots are produced daily only in the European vehicle industry (TWI), what give us an idea of the importance of the welding quality.

The research in the field has concentrated on estimating the quality of welding by using neural networks and regression analysis. In many studies the variation of resistance over time has been used since two quantities are accessible and can be measured during the RSW, the voltage and the current signals and the only material characteristic that can be extracted for each individual spot from the accessible voltage and current signals is the electrical resistance. Temporal and geometric features were taken from these resistance curves. Neural network and regression models have been generated based on the dynamic resistance pattern by, for example, (Aravinthan, 2001) and (Cho, 2002). Other variables were also studied as features and involved in neural networks like tip force, the number of weld cycles, the weld current and the upslope current (Ivezic, 1999).

In this paper it is proposed the use of a simple model of the electrical resistance variation during the RSW based on physical properties of the process to obtain a quantitative estimation of a resistance spot weld quality. It does not have the intention of being used for simulation ends and to cover all the details of the process, only to be used as feature generator in an artificial intelligence system in order to estimate the resistance spot weld quality.

The model parameters are obtained by fitting the model curve against a real measured curve by means of an adapted Levenberg-Marquardt algorithm. Using data of about 150 measurements of the dynamic resistance over time from a RSW of two metal sheets normally found in the automobile industry, where each measured curve represents the resistance variation of a single weld during the welding process, the proposed approach were validated. For the analyzed process, the diameter of the weld produced determines the quality of the weld and should be estimated. The results obtained in the diameter estimation show a precision of +/- 0.6 mm and therefore can be considered a good estimation due to the complexity of the analyzed process.

2. THE PHYSICAL-BASED MODEL

As mentioned, the only material characteristic that can be extracted for each individual spot from the accessible voltage and current signals is the electrical resistance. Considering the electrical resistance *R* as a combination of contact, bulk and electrode resistance values, affected by physical properties and laws, the changes in *R* will follow these properties and laws invariant to the control strategy. These assumptions are the basis of the physical-based model proposed. A sketch of the RSW arrangement presenting the electrical resistance components is shown in the Fig. 1.

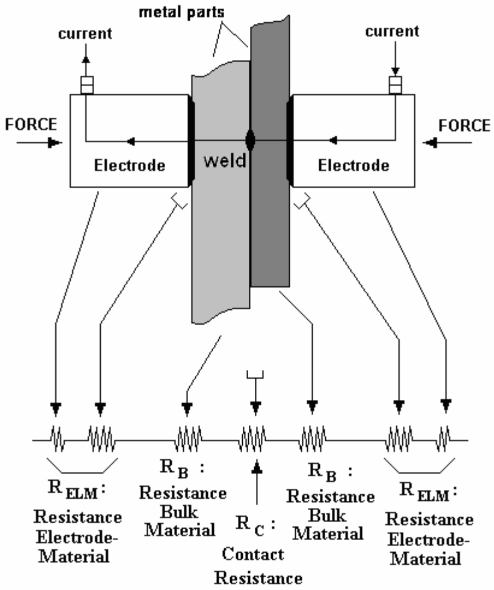

Fig. 1. RSW sketch and electrical resistance components

Assuming symmetry of the arrangement, *R(t)* is defined as:

$$R(t) = 2.R_B(t) + R_C(t) + 2.R_{ELM}(t) \tag{1}$$

The electrical resistance *R* is the sum of the electrical resistance of the bulk material (R_B) in addition to the electrical resistance of the interface between the sheets (contact resistance R_C) and in addition to the electrical resistance of the interface between the sheet and the electrode plus the electrical resistance of the electrode itself (R_{ELM}). These components will be analyzed and discussed individually.

2.1. Temperature vs. time

Important information in the RSW is the heat produced. This heat causes the increase of the temperature that is the basis of a resistance spot welding process. The electrical resistance is dependent on the temperature and this is the first parameter to be defined.

The heat produced by the circulating current and the restructuring of the sheet's material has a behavior that is approximated by an exponential behavior. The weld temperature T increases approaching asymptotically the melting temperature. The items that influence how fast *T* increases are mainly the material used, the current and the force applied in the system.

In this model a different temperature profile for the interface between the sheets, bulk material and electrode plus the electrical resistance of the interface between electrode and sheets is considered.

The temperature *T* of the interface between the sheets can be characterized by equation (2):

$$T = T_o + (T_{melt} - T_o)(1 - e^{-tIK_t}) \tag{2}$$

where:

T – Estimated Temperature of the interface between the sheets;
T_0 – Initial Temperature;
T_{melt} – Melting Temperature (influences: material);
I – Current (influences: controller);
K_T – Temperature Factor (influences: material, force);
t – time.

The temperature of the interface between electrode and sheets that will be called T_{ELM} will be now defined. The initial temperature at this point will be considered the same as in the interface between the sheets. This temperature in a normal process tends to the temperature T.

The temperature flows from the interface between the sheets to the interface between electrode and sheets. This does not occur instantaneously and there is loss of energy in this way. There is also a cooling system coupled to the electrodes that should be taken in consideration. To reflect these factors, a variable called L_E was introduced. The final equation for T_{ELM} is:

$$T_{ELM} = T_o + (T - T_o)(1 - e^{-tL_e K_t}) \tag{3}$$

where:
T_{ELM} – Estimated Temperature of the interface between electrode and sheets;
T – Estimated Temperature of the interface between the sheets;
T_0 – Initial Temperature;
K_T – Temperature Factor (influences: material, force);
L_E – Loss of energy Factor (influences: material, process, electrode cooling);
t – time.

The temperature of the bulk material was also defined separately and called T_B. Since this is the temperature between the two interfaces, it was defined as the average between T and T_{ELM}. The final equation for T_B is:

$$T_B = \frac{T + T_{ELM}}{2} \tag{4}$$

where:
T_B – Estimated Temperature of the bulk material;
T_{ELM} – Estimated Temperature of the interface between electrode and sheets;
T – Estimated Temperature of the interface between the sheets.

2.2. Electrical resistance of the bulk material (R_B) vs. time

The variation of R_B will now be defined. The electrical resistance of a material depends on the electrical resistivity of a material (ρ). The electrical resistivity of a material (ρ) depends on the temperature and consequently the electrical resistance will change with it too. This change follows a temperature coefficient of resistance (α) that is characteristic for each material. The area and length will also change with the temperature by expansion of the material but this effect in the resistance compared with the one caused by the change in the resistivity can be neglected.

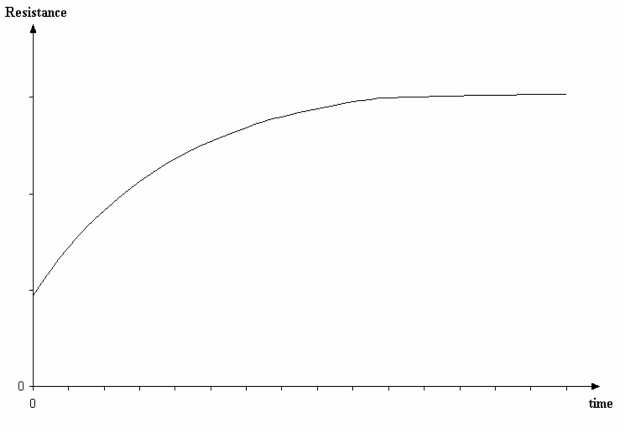

Fig. 2. Resistance of the bulk material vs. time

The electrical resistance of the bulk material can be then characterized by equation (5):

$$R_B(t) = R_{0B} * [1 + (alpha * T_B)] \tag{5}$$

where:
R_B – Electrical Resistance of the bulk material;
R_{0B} – Initial electrical resistance of the bulk material (influences: material, dimensions);
Alpha – Temperature coefficient of resistance (influence: material);
T_B – Estimated weld temperature for the bulk material.

The resistance of the bulk material has in the time, using equation (5), the behavior shown in the Fig. 2.

2.3. Electrical resistance of the electrode and of the interface between electrode and sheets (R_{ELM}) vs. time

Another electrical resistance component is the electrical resistance of the electrode and the electrical resistance of the interface between electrode and sheets. These resistances will be considered as one resistance called R_{ELM}. In a first moment of the welding process the electrode will have certain contact area with the sheets.

When the material is softening due to increase of the temperature, the electrodes will fit better and maybe also sink in the sheets and the contact area will increase. In this way the resistance between the electrodes and the sheets will be reduced since the current has a bigger surface to flow. This sinking in is also directly related to the force applied in the electrodes. The electrical resistance R_{ELM} will be characterized by equation (6):

$$R_{ELM} = R_{0ELM} * e^{[-(t*K_{ELM}*T_{ELM})^2]} \tag{6}$$

where:
R_{ELM} – Electrical Resistance of the electrode and interface between electrode and sheets;
R_{0ELM} – Initial electrical resistance of R_{ELM} (influences: electrode type and diameter, material, force);
K_{ELM} – Electrode-Material factor (influence: electrode and sheets material, force);
t – Welding time;
T_{ELM} – Estimated weld temperature in the interface between electrode and sheets.

The R_{ELM} has in the time, using equation 6, the behavior shown in the Fig. 3.

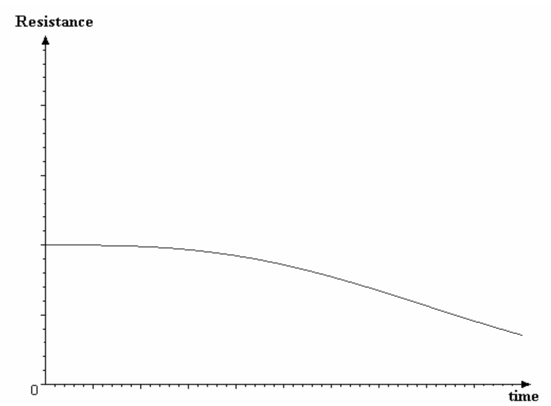

Fig. 3. R_{ELM} vs. time

2.4. Electrical resistance of the interface between the sheets (R_C) vs. time

The electrical resistance of the interface between the sheets is called contact resistance R_C. R_C is mostly responsible for the heat produced and necessary for the welding process. In the beginning this resistance is relatively high and will decrease due to the fitting of the surface of the two sheets by material softening. This is basically influenced by the force applied in the electrodes and the surface of the material used. After this, R_C will continue to slowly decrease until certain value is reached. This will happen because the temperature will increase, the sheets will become soft and consequently will fit better to each other.

After the start of the melting, this resistance tends to a small increase due the electrical resistance in the liquids is normally higher than in the solids. A logistic function is used to reflect this characteristic. A parameter called L_{COEF} controls the change of the logistic function from 0 to 1. Another parameter, the called K_{MELT}, is responsible to define the temperature point after that the changes in the material properties are going to be considered. A third parameter called K_{RHO} reflects the changes in the material resistivity when changing state from solid to liquid.

The electrical resistance R_C can then be characterized by equation (7):

$$R_C = R_{0C} * [1-(K_{C-soft} * (1-e^{-t*K_C*T}))] + [1/(1+e^{(-L_{COEF}*(T-(K_{MELT}*T_{MELT})))})] / K_{RHO} \quad (7)$$

where:
R_C – Electrical Resistance of the interface between the sheets;
R_{0C} – Initial electrical resistance of R_C (influences: material, force);
$K_{C\text{-}Soft}$ – Material Softening factor (influence: material);
K_C – Factor for the contact resistance between the sheets (influence: sheets material, force);
L_{COEF} – Logistic function coefficient;
K_{MELT} – Factor for the temperature where the material properties varies;
K_{RHO} – Factor for the changes in the material properties.
t – Welding time;
T – Estimated weld temperature in the interface between the sheets.

R_C has in the time, using equation 7, the behavior shown in the figure 4.

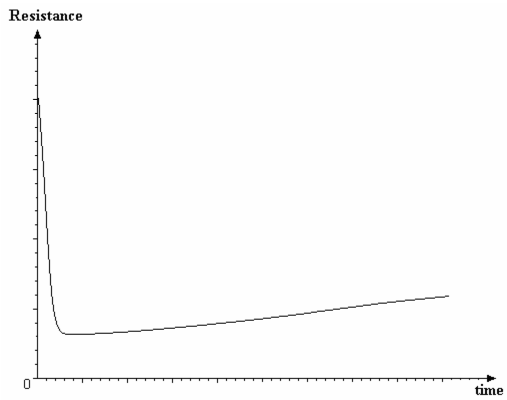

Fig. 4. R_C vs. time

After defining all the partial resistances, the electrical resistance of the whole process can be calculated using (1). Using values close to the reality in the partial equations to the parameters α, T_{melt}, T_0 and K_T and with reasonable parameter values for R_{0C}, R_{0B}, R_{0ELM} and with guesses for L_E, K_C, $K_{C\text{-}Soft}$, L_{COEF}, K_{MELT}, K_{RHO}, and K_{ELM}, the curve shown in the Fig. 5 was obtained. This curve presents almost the same behavior as the called "classic resistance profile" for a good welding (Bhattacharya and Andrew, 1974).

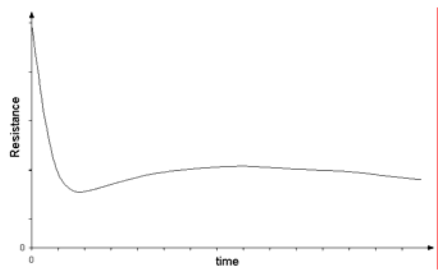

Figure 5. Electrical resistance R vs. time

3. MODEL PARAMETER ESTIMATION

A fitting algorithm is needed for determining the physical-based model parameter values. Due to the non-linear dependence on the parameters, model parameters cannot be estimated using simple matrix techniques. Instead, an iterative approach is required. The Levenberg-Marquardt method (LV) is a standard iterative method for non-linear curve fitting. It is useful for finding solutions to complex fitting problems (Press et al., 1996). Since the LV method is an iterative non-linear process it can get stuck in a local minimum, depending on the parameter starting values. For this reason, the final result may depend on the initial parameter guess. This characteristic causes the LV method sometimes to be unstable depending on the initial guess, number of variables and order of the involved equations.

A challenge in this method is to find the condition for stopping iterations. It is not uncommon to find the parameters wandering around the minimum in a flat valley of complicated topology and maybe this minimum is not the sought one due this complex topology. In this investigation the stopping and search method for the iterations was modified according with the model characteristics. A precision value, an increase (multiplication) factor, a decrease (division) factor and the chi-square value are the basis for the stopping condition. As said before, the result of the method depends on the initial guess.

Figure 6 shows the result of the fitting algorithm applied to fit the curve produced by the variation of the proposed simple model parameters against a real resistance curve acquired from a real RSW.

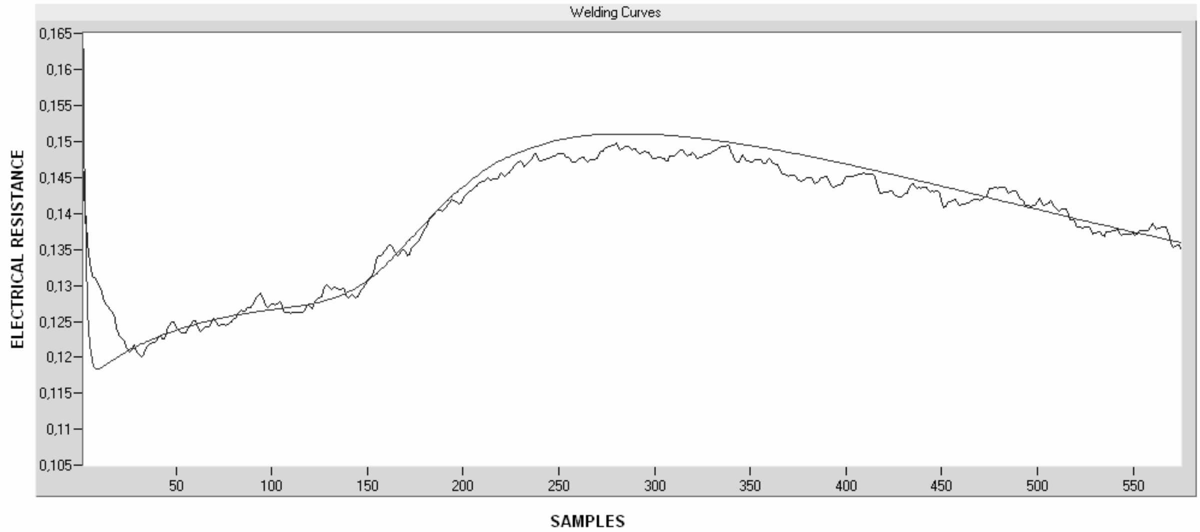

Figure 6. Real resistance curve (noise curve) and model fitted curve vs. time

4. DESCRIPTION OF THE ASSESSED DATA

The data used to assess the method was obtained from a RSW of the company Harms&Wende (HWH). In the referred process, a sheet of zinc coated material DC07 with a thickness of 1[mm] and a sheet of steel ST14 with a thickness of 1,5[mm] are welded. The electrodes have a diameter of 5[mm] and there is a cooling system in the electrodes in the way that their temperature is tried to be kept about 16°C. The welding settings for the welding time, force and current are respectively 300[ms], 3000[N] and 8 [kA].

The voltage and current signals were measured and recorded during each welding test and from them the resistance curves were derived. During the tests some conditions of the process were changed like the level of the applied current and the applied force and also a worn electrode was used in some tests in order to simulate real variations that can occur during the welding production. Using a destructive test, the diameter in millimeters of each weld produced was measured and this is the quality parameter for this process, the weld spot diameter. Values bigger than 5 [mm] should be achieved to indicate a weld with a good quality. About 150 experiments were made and used for an offline training of a neural network. After trained, the neural network can be used online to estimate the quality of the new acquired data.

5. RESULTS

Using seven of the adjustable parameter values (R_{0C}, R_{0ELM}, K_C, $K_{C\text{-}Soft}$, K_{MELT}, K_{RHO}, and K_{ELM}) as input data for the neural network, different topologies of neural network were trained and validated with the available data which had to estimate the welding spot diameter (in mm) at its single output neuron. For the neural network training we used 99 experiments and for the validation 51 experiments. In both, training data and validation data, we tried to include data recorded in all simulated process conditions. The best topology found was: 7 input neurons, 12 neurons in the hidden layer and 1 output neuron. The result using such topology is shown in the fig. 7.

The quality expected for the welded joints in the analyzed process is to be bigger than 5 [mm] but welding spots with diameter bigger than 4 [mm] are also considered good welding spots. The value 0.6 was selected as a tolerance value for the presented approach. Therefore in this case the estimated value should be bigger than 4.6 [mm] to guarantee a good quality weld joint, which is a very reasonable value since the company works in the set point 5 [mm].

In the fig. 7 it is possible to see that the Mean Square Error (MSE) obtained was 0.08148 for the validation data, which is a very reasonable value. The recognition rate was 98% for the validation data. It is possible to check in the validation result that only one welding test had the estimated quality value out of the tolerance range and this was not far away of this range showing a good estimation using the simple physical-based model parameters as input data to the neural network.

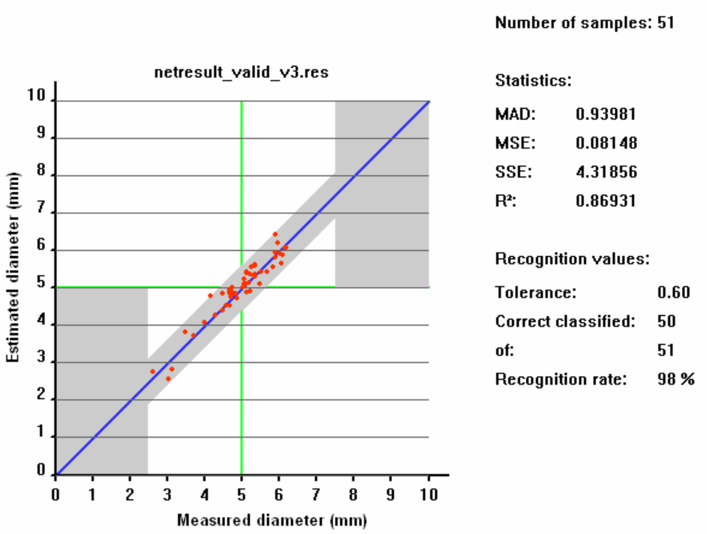

Figure 7. Estimated Value x Measured Value for the validation data

6. CONCLUSION

The work presented shows that since in a very complex process affected by non-deterministic parameters like the resistance spot welding process, a simple model describing the behavior of an observable magnitude of the welding process based on physical properties of the process may be sufficient to obtain a correlation between the final quality parameter, in this case, the weld spot diameter, and the model parameters that are used as features.

It was possible to confirm the success of the proposed approach by testing different neural network topologies, combination and sequences of adjustable model parameters, and obtaining a precision of +/- 0.6 mm for the estimating the diameter of the resistance spot welding which can be considered a very good estimation due to the complexity of the analyzed process. The most crucial point with non-linear models is the parameter estimation. Major improvements are possible by further investigating robust parameter estimation and linearization methods.

7. ACKNOWLEDGEMENTS

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