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TO STUDY THE QUALITY OF RESISTANCE SPOT WELDING JOINTS USING RANDOM VARIABLES METHOD

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Abstract- **Resistance spot welding is used to join two or more metal sheets together, and the technique is used widely in the automotive industry, for example. Furthermore, other metal-to-metal connections, such as wire-to -wire joints in the electronics industry, are accomplished by resistance spot welding. Application-specific measures, such as the diameter of the welding spot, define the quality of the joint. By using non-destructive methods to assure the quality of the welding spot, the need for destructive testing can be reduced, which leads to increasing profits. In this work, the reasons for variation in welding spot diameters were studied using computational methods, mainly Random variables methods. The features used in the study were extracted from histograms calculated from signal curves measured during the spot welding process. A new approach to modelling the quality of welding joints was developed and evaluated with a large sample test set. The configurations that resulted in failed welding spots proved to be of special importance for the modelling procedure.**

I. INTRODUCTION

Resistance spot welding is used to join two or more metal sheets together in, for example, the automotive industry. The fact that, in the all vehicle industry alone, more than 100 million spot welding joints are made daily tells something about the popularity of the method The quality of a joint is defined by the diameters of the welding spots. The diameters can be monitored by using, for instance, destructive or ultrasound testing. In destructive testing, the joint is torn apart and the diameters of the spots are inspected. In ultrasound testing and other analogous methods, the diameters are estimated by using additional sensors. These methods are, however, relatively expensive (destructive testing) or difficult to implement (methods) .

The goal of this paper is to study the relationships between the quality of resistance welding spots and signal curves measured during the welding event. If some indication of the quality of a joint could be gathered from the signal curves, the amount of destructive testing needed to assure the quality of the joint could be reduced. This, in turn, would lead to savings in material and production costs and more effective operation of the quality-assurance process.

The research on computational quality estimation techniques in the field has concentrated on improving quality by using neural networks, regression analysis and mathematical methods. The studies are made on the basis of different features extracted from the data. The variation of resistance over time (dynamic resistance pattern) has been an important explanatory variable in many studies. Artificial neural network and regression models were formulated based on the dynamic resistance pattern in, for example, the studies. Cho combined regression analysis with neural networks successfully and with very satisfying results. Studies with other input variables include approaches involving neural networks with tip force, the number of weld cycles, weld current and upslope current . Fuzzy algorithms combined with neural networks have also been applied in the field Histograms were used, together with fuzzy algorithms, to characterise welding signal curves in the work done in

This study introduces a new approach to defining the effects of different signal curves on the quality of welding joints by using easily understandable rules derived from Random variables methods. With the help of these results, the control algorithm of the spot welding machine could be developed further, so that it would use settings known to be typical of the desired welding curves. This will result in the desired welding spot diameter and guarantee higher quality. The methodology used in this study can be easily extended to many kinds of materials and welding processes.

II. DATA DESCRIPTION AND PRE-PROCESSING

The data used in this study comprise measurements from welding tests done at Voest Alpine, Austria. The data set contains observations from 192 experiments where two metal sheets were welded together using a resistance spot welding machine, The sheets were torn apart in a destructive test and the quality of the welding spot was defined based on its diameter

Apart from the diameter of the nugget from each welding spot, measurements were made of some general parameters of the material and the settings of the welding machine and the following signal curves: compression force between the metal objects, welding current and voltage. The signal curves were measured at intervals of 0.04 seconds during the welding. Figure 2 presents an example of the three curves for one experiment. Each curve has two flat regions corresponding to the machine being inactive, which are separated by a period of activity comprising about 7000-8000 samples of the signal in question. The number of samples depends on the welding time and the sampling frequency of the measurement system. The data had to be pre-processed to enable modelling with a Random variables method. The pre-processing consisted of removal of the flat regions and calculation of

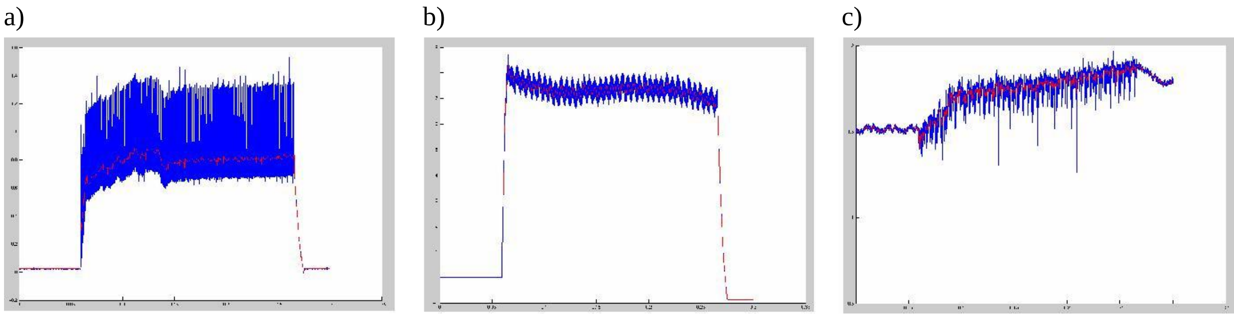
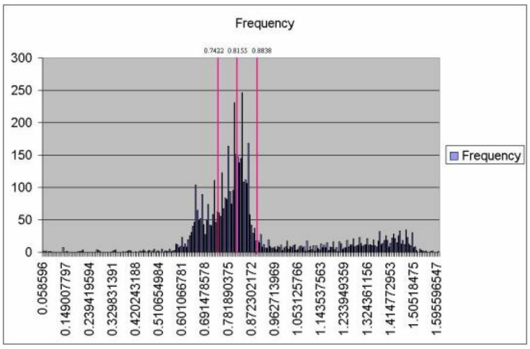


Figure 2: Signal curves of a) voltage, b) current and c) compression force for a single welding spot.

The class limits of the welding spot diameter are the only limits that the reader needs to know to be able to read this paper. Figure 4 b) presents the distribution and classification of the diameters. The diameters were distributed into three classes. Class 1 contained spots with diameters of less than 4.0 millimeters, class 2 the ones with diameters ranging from 4.0 to 5.275 mm and class 3 values greater than 5.275 mm. 49 observations fell into class number one, 88 into class two and 55 into class three. The observations in class one are of special importance, since they present bad quality welding spots. A method and results for identifying the different quality classes is presented in the results section of this article. Especial care is taken to recognize the low quality joints (class 1) and the good quality joints (classes 2 and 3).

a)



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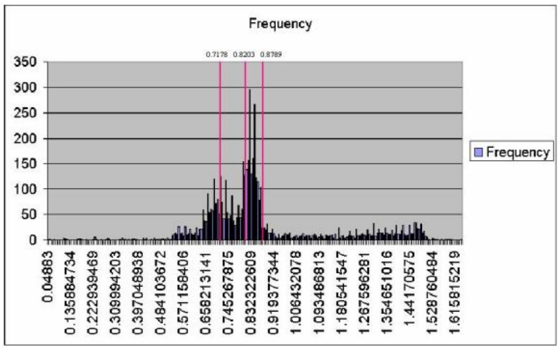

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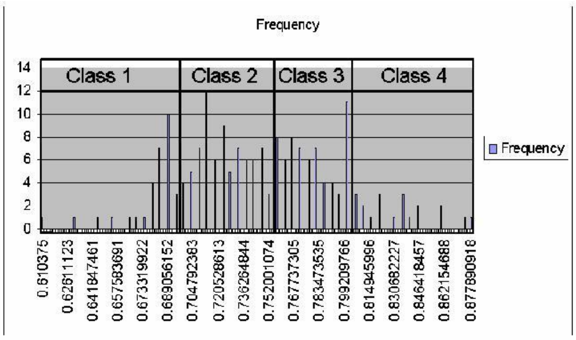

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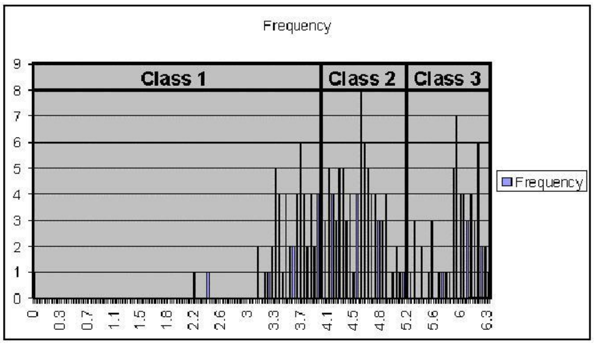


Figure 4: a) Histogram of the lower fractiles of the voltage curves and their classification, b) histogram of the diameters of the welding spots and their classification.

III. METHODS

A random variable method was used to study the relationships between the variables. It is a suitable tool for this task, because it allows examination of the effects of the different variables on the diameter in the form of easily understandable probabilities.

A Random variables method consists of nodes (variables) and their connections. More specifically, they are a subclass of graphs with no loops and only directed connections. An example of a Random variables method is shown in Figure 5. A node that is the origin of an arrow pointing to another node is called a parent and the destination node of the arrow is called a child. A child node has a probability distribution conditional on that of its parents, i.e. the probability of the child being in a certain state varies according to the state of its parents. It is to be noted about the network connections that they do not necessarily represent causal relationships. Some authors are in favor of the causal interpretation while others are more cautious. If the network has been formed based solely on data, it is inappropriate to interpret the connections as being causal.

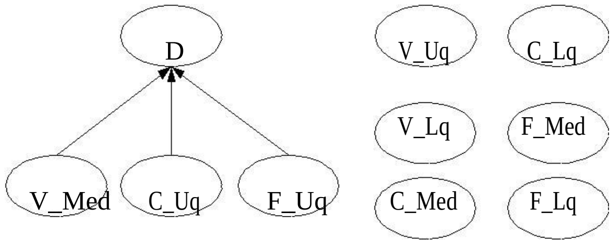
One of the computational benefits of Random variables methods is that a node is conditionally independent of all the other nodes, given the state of its parents. In other words, if a

vector of data $\mathbf{y}_k = (y_{1k}, y_{2k}, ..., y_{Ik})$, where I denotes the number of nodes in the network structure, is observed, the joint probability of the event is:

$$p(\mathbf{y}_k) = \prod_{i=1}^{I} p(y_{ik} \mid \textit{parents of } y_{ik} \textit{ in the observed state}).$$

This results in a major reduction of calculations, since the probabilities need to be calculated only conditional on the parents of each node, not conditional on the whole set of variables [12]. When dealing with large groups of variables, numbering up to hundreds, this property becomes a crucial point [7].

a)



The name "Random variables method" is due to the fact that prior probability distributions can be assigned to the distributions of the variables or the network structure. These distributions are then updated based on observations using the formula of Method. If no prior information of probability distributions is available, a uniform probability distribution can be used.

The Random variables method structure can be generated based on expert information, with an automatic search algorithm or by combining these two techniques. The search algorithms compare different structures based on measures for the goodness of fit. These measures include, for example, the Methodian quality measure, the minimum description length measure, which originates from coding theory, and information measures. It is also common to include a penalty factor for excessively complex structures in models of this kind. One such penalty term is the well known ½ *Dim* (*B*) log *n*, where *Dim(B)* is the number of parameters needed to describe the joint probability distribution of network structure *B*, and *n* is the number of observations. For more information on Random variables methods, are recommended.

IV. RESULTS

Figure 5 shows the Random variables methods used in the study. The nodes denote the variables and the edges between the nodes the interactions between the variables. The network structure of 5 a) was generated using an automatic search algorithm implemented in the software [13]. The algorithm established the connections between the variables based on the data measured from the welding events and the features calculated from the data. In this network structure the welding spot diameter is interacting with the median of voltage, upper quartile of current and the upper quartile of compression force. The disconnected nodes did not have an effect on the welding spot diameter according to the search algorithm. Figure 5 b) shows another interesting configuration. In this network the variables interacting with the diameter of the welding spot are the median of voltage, the median of force and the upper quartile of force.

b)

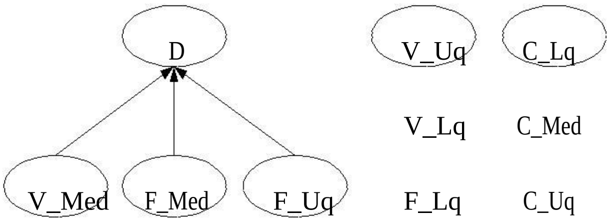


Figure 5: The Random variables methods used in the study. The one on the left shows the initial network, the one on the right shows the network where C_Uq has been replaced with F_Med. D = welding spot diameter, V = voltage, C = current, F = compression force. Lq = lower quartile, Med = median, Uq = upper quartile.

The welding spot diameters can be studied by examining the class probabilities of the diameter. These probabilities are calculated conditionally on the values observed from the other variables. Table 1 shows some of the most interesting class probabilities of the welding spot diameter based on the configuration of Figure 5 a). In this discussion of the results the rows of the tables are marked with vectors like This triplet is used to identify the configuration where the first variable (*V_med* in table 1) has value 1, the second variable (*C_uq*) value 1 and the third variable (*F_uq*) value 3. Under the columns marked with D are the probabilities of the welding spot belonging to a certain class. The last column shows how many of the observations belonged in the configurations.

From the rows (1, 1, 3) and (1, 2, 3) it can be read that with these values it is almost certain that the welding spot belongs in the diameter class number 1, containing all the low quality welds. The obvious drawback is the lowest possible number of observations in these configurations. Rows (2, 1, 1) and (2, 3, 1) present configurations where it is almost certain that the observations belong in the class with the highest quality welding joints. In the rows (2, 1, 2), (2, 1, 3), (2, 2, 2), (2, 2, 3), (2, 3, 2) and (2, 3, 3) the probabilities are more equally distributed amongst all the classes. The meaning of these six configurations in practice is that it is harder to distinguish the better quality joints from the low quality joints within these configurations. The rest of the configurations listed in the table show high probabilities of the welding spots belonging in the good quality classes. The rest of the configurations did not contain significantly many observations in class number one, that is why they are not listed in the table.

Table 2 shows the probabilities associated with the network in Figure 5 b). The rows (2, 2, 2) and (2, 3, 3) are the only rows where the probabilities have been distributed more evenly amongst the classes. present cases where the welding spot belongs with high certainty in the lowest quality class. The rest of the rows present cases where the probabilities are distributed so, that the welding spot belongs almost certainly in the higher quality classes (D = 2 or D = 3).

The rules presented in the tables above can be easily implemented in practice, because of their simplicity. For the same reason it is also easy for humans to understand them. The more equally distributed probabilities in Tables 1 and 2 present cases where the quality of the welding spot is not that certain. These results make it easier to identify such situations and to continue with appropriate actions.

The probabilities and results presented above were used to present some of the most interesting results acquired with these techniques. Presentation and analysis of all combinations of variables and their respective probabilities would not only have been tiresome for the reader but would also have taken too much space. However, these results show the idea and some results of the research. Using the probabilities assigned with the Random variables methods, it is possible to discover combinations that lead to different sizes of the welding spot and therefore also to different quality classes. The problem with classified data is that, if there are many classes but few observations, not enough observations may not fall into the different configurations of the classes to allow reliable conclusions to be drawn. Fortunately in this study this was not a serious issue. The main contribution of this work is to demonstrate that a methodology of this kind is applicable in the field.

Variables and their classes			*Welding spot diameter*			
V_med	*C_uq*	*F_uq*	*D = 1*	*D = 2*	*D = 3*	*# obs*
1	1	3	0.986	0.007	0.007	1
1	2	3	0.993	0.003	0.003	1
2	1	1	0.002	0.002	0.995	3
2	1	2	0.739	0.087	0.174	23
2	1	3	0.498	0.498	0.003	2
2	2	1	0.001	0.001	0.999	10
2	2	2	0.588	0.294	0.118	34
2	2	3	0.499	0.499	0.001	6
2	3	1	0.001	0.001	0.998	6
2	3	2	0.250	0.375	0.375	16
2	3	3	0.498	0.498	0.003	2
2	4	2	0.001	0.499	0.499	6
3	1	2	0.001	0.997	0.001	5
3	2	2	0.000	0.904	0.095	41

Table 1: Probabilities from the Random variables method. V_uq = voltage median, C_uq = current upper quartile, F_uq = force upper quartile, D = welding spot diameter, #obs = number of observations in the configuration.

Table 2: Probabilities from the net with a different configuration. The upper quartile of current has been replaced with the median of force (*F_med*).

V. CONCLUSIONS

The study began with pre-processing of the signal curves for voltage, current and compression force. Pre-processing consisted of purging of the curves of irrelevant data, calculating features to characterise the curves and classifying the data. The features calculated from the curves were histograms. The quartiles and median of the histograms were used to characterise the curves. Furthermore, a histogram of the quartiles and medians was used to classify the data, so that it could be used with the Random variables method tool. The use of Random variables methods to study the relationships between quality and measured data seems to be a novel approach, since a review of the earlier research on spot welding did not reveal previous reports with similar methodology.

Two Random variables methods were constructed to study quality. The first yielded some important information about the reasons for the diameters falling into certain categories. The other one, augmented with an additional variable, clarified the relationship even further. These early results indicated that the reasons for low-quality welding spots could be identified using Random variables methods. Furthermore, the usage of the methodology allowed us to develop simple rules for understanding the curve-to-quality relationships of the welding process.

The study showed that these techniques are applicable to studying the quality of welding spots.

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