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Quality assessment of resistance spot welding joints of AISI 304 stainless steel based on elastic nets

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ABSTRACT

In this work, the quality of resistance spot welding (RSW) joints of 304 austenitic stainless steel (SS) is assessed from its tensile shear load bearing capacity (TSLBC). A predictive model using a polynomial expansion of the relevant welding parameters, i.e. welding current (WC), welding time (WT) and electrode force (EF) and elastic net regularization is proposed. The predictive power of the elastic net approach has been compared to artificial neural networks (ANNs), previously used to predict TSLBC, and smoothing splines in the framework of a generalized additive model. The results show that the predictive and classification error of the elastic net model are statistically comparable to benchmarks of the best pattern recognition tools whereas it overcomes correlation problems and performs variable selection at the same time, resulting in a simpler and more interpretable model. These features make the elastic net model amenable to be used in the design of welding conditions and in the control of manufacturing processes.

1. Introduction

Resistance Spot Welding (RSW) is, according to Becker et al. [1], one of the primary methods to join sheet metals for automotive components due to the fact that, as indicated by Khodabakhshi et al. [2], it has the highest throughput. In addition to the automotive industry, RSW of stainless steel (SS) sheets is also widely used, as pointed out by Kianersi at al. [3], in transportation vessels, home and office items, kitchen furniture and utensils and building applications. Feng et al. [4] stated that 4000–6000 RSW joints are used in each vehicle; as emphasised by Martín et al. [5], such a large number of RSW joints makes attractive the use of tools capable of reliably assessing the quality of RSW joints from its welding parameters that, thus, allow, as mentioned by Pereda at al. [6]: (i) warning in real time about potentially detrimental drifts in the RSW process; and (ii) assisting directly in quality control of the RSW process, reducing post-welding testing.

Özyürek [7] indicated that structures employing RSW joints are usually designed so that these joints are loaded in shear when the parts are exposed to tension or compression loading. Zhou et al. [8] reported that static tensile shear test is the most common laboratory test used in the determination of weld strength because of its simplicity. Thus, in the present work, the quality of the RSW joints is assessed from its tensile shear load bearing capacity (TSLBC), which is the peak load value obtained during the tensile shear test. Hasanbaşoğlu and Kaçar [9] and Kong et al. [10] agreed that the most important factor affecting TSLBC is the size of weld nugget, which, as explained by Raoelison et al. [11], is formed from the solidification of the molten metal after a heating by Joule effect.

Some previous works have already developed tools for assessing the effect of RSW parameters on welding quality. Identifying the most appropriate approach to build a predictive model is a challenging task. Wolpert [12] showed that there is no learning algorithm better than all the others on all the contexts. Consequently, it is necessary to run computational experiments in order to find out which are the techniques with the best performance for the particular case under consideration. Martín et al. [13] created a

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tool based on ANNs for the classification of ultrasonic oscillograms obtained from RSW joints. Li [14] carried out a fault diagnosis method in manufacturing processes using a functional regression approach. Moshayedi and Sattari-Far [15] proposed a finite element model to investigate the distribution of temperature and nugget formation during RSW process, as well as to study the effect of welding current (WC) and welding time (WT) on weld nugget size. Ma and Murakawa [16] studied the weld nugget formation process by using a finite element model which considered the coupling of the electrical field, thermal field and mechanical field during RSW process. Han et al. [17] used statistical models to study several forms of estimating the mechanical strength of RSW joints. Luo et al. [18] monitored in real-time the change of WC and electrode voltage in the secondary circuit and, thus, the dynamic resistance across electrodes was used to characterize the weld nugget growth. Martín et al. [19] developed a model based on artificial neural networks (ANNs) to predict the TSLBC of RSW joints from WT, WC and electrode force (EF) but with the drawback that ANNs are "black boxes", i.e. they lack explanatory power. Therefore, as pointed out by Martín et al. [20], the underlying knowledge captured by the network during its training is not transparent to the user and, consequently, ANNs do not offer any interpretability of the results.

Depending on the purpose of the model, this issue can be relevant for model selection. Predictive accuracy is a common criterion for selecting a model. However, as pointed out by several authors [21,22], model simplicity and interpretability make it significantly easier to move from pattern recognition to knowledge extraction, that may be more useful to define, control and optimize industrial processes. In these cases, decision tools are more likely to be accepted if the results can be understood and explained [23], which means that among different models with predictive accuracy rates not statistically different in terms of a given significance, the simpler and more interpretable model will be preferred.

Unlike ANNs, regression techniques do offer interpretability of the results. Cho and Rhee [24] proposed simple linear and nonlinear regression models to estimate weld strength and nugget diameter of RSW joints of low-carbon steel sheets, comparing the obtained results with those of ANNs. They found better prediction accuracy for ANNs.

A common approach to improve the performance of linear regression approaches capturing non-linear effects consists on obtaining extra regressors from the initial predictors, for instance, by using polynomial expansions. However, this procedure is not without its drawbacks. Predictors obtained this way are very correlated, the complexity and interpretability of the model increases, and there is an important risk of overfitting.

The elastic net regularization method proposed by Zou and Hastie [25] is used in this work to simultaneously obtain an interpretable and accurate predictive model. This approach produces simple and interpretable models while maintaining a good performance (even in the presence of several highly correlated variables), by means of reducing the number of predictors, identifying the most important ones and shrinking coefficients. In the present study, different polynomial expansions are implemented and compared to the performance of ANNs, previously used for this problem, and with smoothing splines, a very flexible, although not interpretable, regression approach. The differences among the results were found not statistically significant. The simple, accurate and interpretable regression model obtained by applying elastic net regularization makes easier the design and optimization of the welding operation conditions and the control of the manufacturing process while its predictive accuracy is statistically comparable to that of the black box techniques. Additionally, the obtained model was analyzed as a binary quality classification tool. Again, the performance of the model used as a classifier is competitive compared to the best welding pattern recognition algorithms found for welding quality control.

The structure of the paper is as follows: First of all, the experimental procedure is described. Initially, the composition and material properties are analyzed in detail. Then, a description of the welding conditions as well as an explanation of the test selected to assess the quality of each spot is given. The next section presents the different data analysis methods studied, focusing at first on theoretical aspects of the different techniques and on the framework of comparison of all of them. Afterwards, the results and discussion are provided for both prediction and classification. The last section is devoted to the conclusions.

2. Experimental procedure

2.1. Materials and equipment

The chemical composition and the mechanical properties of the AISI 304 austenitic SS sheets welded by RSW are, respectively, shown in Tables 1 and 2. The sheet thickness was 0.8 mm.

The AISI 304 austenitic SS sheets were welded with a single-phase alternating current (AC) 50 Hz equipment by using water-cooled truncated cone RWMA Group A Class 2 electrodes with 16 mm body diameter and 4.5 mm face diameter.

2.2. Welding of the tensile shear test specimens

The controlled parameters in the RSW process were: (i) WT that varied from 12 to 2 cycles, with a 1 cycle step decrease; (ii) WC that varied approximately from 6.5 to 1.5 kA RMS with a 0.5 kA RMS step decrease; and (iii) EF that took only two values: 1000 and 1500 N. These three parameters are, as stated by Aslanlar [26], the most important welding parameters in RSW.

Thus, there were 242, i.e. $11 \times 11 \times 2$, different welding conditions and a tensile shear test specimen was spot welded for each of these 242 welding conditions. The tensile shear test specimens were prepared according to [27] (see Martín et al. [19] for more details).

The weld nugget of the RSW joint is a cast dendritic microstructure with coarser grains than the polygonal austenitic grains of the adjacent metal, as shown in Fig. 1.

2.3. Quality assessment from TSLBC values

A TSLBC value was obtained from each of the 242 tensile shear tests that were performed at a crosshead speed of 2 mm/min, which, according to Marashi et al. [29], allows to consider the test as static.

The minimum acceptable TSLBC value was set at 5.93 kN and, therefore, the RSW joints whose TSLBC value was: (i) equal to or greater than 5.93 kN, were considered acceptable; (ii) less than 5.93 kN, were considered unacceptable. This criterion was based on the weld nugget diameter recommended by JIS Z 3140 [30]:

$$d \geq 5\sqrt{t} \tag{1}$$

where d is the weld nugget diameter and t is the sheet thickness;

Table 1
Chemical composition of the AISI 304 austenitic SS sheets (wt%).

C	Cr	Ni	Si	Mn	Mo	Al	Co
0.08	18.03	8.74	0.426	1.153	0.36	0.003	0.17
Cu	Nb	Ti	V	W	S	P	Fe
0.39	0.02	0.004	0.05	0.03	0.002	0.019	Bal.