Weldability Prediction of AHSS Stackups Using Support Vector Machines

H. T. Tran, K. Y. Kim, and H. J. Yang

***Abstract*—Resistance welding is the most commonly used method for joining purpose of steel sheets. Aims to increase efficiency and maintain or reduce the weight of vehicles, Advanced High Strength Steels (AHSS) have been used to build up material for vehicle structures. This research aims to exploit the ability of prediction by using Support Vector Machines (SVM) and comparing to Artificial Neural Network (ANN) model. The experiment result showed that Support Vector Machines has a positive and better predict result compared to ANN. The predict accuracy of SVM is 92% while ANN shows 88.9%.**

***Index Terms*—Resistance spot welding, support vector machines, artificial neural network, prediction.**

I. Introduction

Nowadays, new and advanced materials have been continuously evolved for automobile manufacturers to create products that meet high performance requirements while reducing the weight of products. Due to the competitiveness of the manufacturing industry, the automobile manufacturers want to develop product design tools that can help to achieve engineering efficiency, cost, and quality product improvements. Prediction is one of the tasks to evaluate weldability in resistance spot welding, which is a core joining method in the automobile manufacturing.

Advanced High Strength Steels (AHSS) is investigated since AHSS is a new material that is used commonly in body structure of vehicle manufacturers and transport (e.g. car, train, ship and aircraft etc.). Some significant advantages of AHSS are obtained compared with mild steels: namely weight reduction without compromising safety and durability for passengers. These advantages enable the improvement of fuel consumption, and reduction of hazardous emissions. Furthermore, AHSS sheet materials are relatively low cost, demonstrate higher strength and better crash worthiness capabilities [1]. Hence, AHSS material is considered as a better choice for automobile structural components.

There are many machine learning techniques that have been proposed by researchers in forecasting, such as artificial neural networks, genetic programming, and support vector machines. These techniques are vital when traditional techniques no longer match with nonlinearities and non-stationary of data. Recently, Support Vector Machines (SVM) has been found as one of the most effective approaches for prediction. This method has been applied in many fields and achieved good results (e.g., cancer diagnosis system [2], liquefaction prediction [3], and prediction of logistics enterprise competitiveness [4]). SVM is a flexible method when working in nonlinear models even though all data do not have the same functional form since its function is non-parametric and operates locally [5]. If parameters and kernel functions (e.g., RGB kernel function) are appropriately chosen, SVM can be robust even when a noise exists in data. Compared to SVM, other approaches such as Artificial Neural Network (ANN) often converges on a local optima rather than global. While SVM is less prone to over fitting, ANN often over fits if the training step goes on too long. Therefore, SVM is selected for prediction in many fields in real world.

In this paper, we propose using of SVM model to predict weldability in AHSS stackups. The experimental result shows that SVM is outperforming and shows better result than the ANN method as the prediction accuracy of SVM is 92% while ANN shows 88.9%.

The remainder of this paper is organized as follows. In Section II, we briefly review about resistance spot welding and several techniques which have been used. In Section III, we focus on materials and our proposed method. The experimental result and discussion are presented in Section IV. Finally, in Section V we will conclude our discussion.

II. Related Work

There are many techniques is used in resistance spot welding in the literature. However, most of them are used with old materials and not efficiency for welding. In additional, the cost for experiment is expensive and inappropriate to apply for state-of-the-art current technology. Bappa Acherjee *et al.* [6] used response surface methodology to predict weld strength and seam width for laser transmission welding of thermoplastic. D. J. Radakovic and M. Tumuluru [7] used finite element modeling and fracture mechanics calculations to predict the resistance spot weld failure mode and loads in shear-tension tests of advanced high-strength steels (AHSS).

A. G. Thakur and V. M. Nandedkar [8] exploited application of Taguchi method to determine resistance spot welding conditions of austenitic stainless steel AISI 304. Taguchi method was also used by Mr. Niranjan, Kumar Singh,

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and Dr Y. Vijayakumar [9] for optimization of resistance spot welding of austenitic stainless steel AISI 301L.

G. Weber and S. Göklü [10] introduced about process reliability and resistance weldability for uncoated and hot dip zinc coated high-strength TRIP steels based on multidimensional weldability lobes as well as electrode wear results for these special AHSS.

Several techniques are used for modeling and process analysis were exploited by Luo Yi *et al.* [11] in resistance spot welding on galvanized steel sheet, S.M. Hamidinejad *et al.* [12] also processed analysis of resistance spot welding on galvanized steel sheets used in car body manufacturing.

In additional, Darshan Shah and Dhaval P. Patel [13] used artificial neural network to predict weld strength in resistance spot welding. Neural network is also a powerful technique for online quality assessment in RSW [14] and development, evaluation for industrial resistance spot welding process control and weld quality assessment [15].

With regard to the works mentioned, we propose to apply SVM to predict the weld strength in resistance spot welding. The experimental simulations demonstrate that the applied method provides better prediction performance up to 3.37% improvements over ANN approach. The details of applied method will be presented in the next sections.

III. Weldability Prediction

A. Resistance Spot Welding

Resistance Spot Welding (RSW) is one of the most common joining methods of the electric welding process in automotive manufacturers. The weld (or nugget) is created by a combination of force, current and time. The principle of resistance spot welding is based on the basic formula of Joule heating:

$$Q = I^2Rt \tag{1}$$

where Q is generated heat, I is the current passing through the sheet metals, R is the resistance of the metals and the contact interfaces, and t is the time of the current flow. Fig. 1 shows an example of electric resistance spot welding.

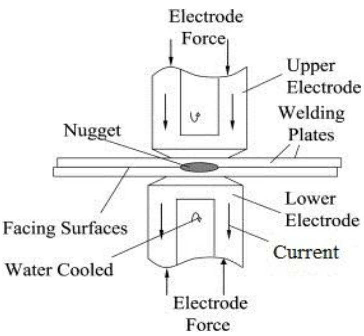

Fig. 1. Electric resistance spot welding (source at [16]).

RSW uses the resistance of the material to be welded to current flow that causes a localized heating in the part [17]. The force is caused by the tongs and electrode tips and the current flows create heat for welding. The welding current is an important parameter in resistance welding, which defines the heat generation by the power. In resistance spot welding, amperage values are very high and it creates a lot of heat in a short time. Therefore, the welding time must be strictly controlled. If the welding time is prolonged, expulsion will occur even the electrode may stick to the work piece [18]. In addition, coating is an important factor in determining the difficulty level of welding - uncoated steel is easier to weld in the comparison with coated steels.

B. Support Vector Machines

Support vector machines is a model proposed by Vladimi Vapnik and Carolina Cortes in 1995 [19]. This is a supervised learning model and is based on statistical learning theory. The main idea of SVM is to map input data into a high-dimensional feature vector. This model can be extended to be used in making prediction, which also called as support vector regression. (See Fig. 2).

In this paper, Support Vector Regression is used to predict the weldability in resistance spot welding. The weldability prediction is to answer if a given material stack ups can be welded or not. In regression issues, consider a dataset $D = \{x_i, a_i\}_{i=1}^{N}$ where x_i is a vector of model input, a_i is the desired result and N is the total number of data pattern. The general form of Support Vector Regression [20] estimating function is;

$$Y_i = f(x) = w.\phi(x) + b \tag{2}$$

where Y_i is the corresponding scalar output, w and b are the estimated coefficients, and $\phi(x)$ is the feature vector of input x.

The problem of nonlinear regression can be presented by minimizing the regularized risk function;

$$R(C) = C\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(d_i, y_i) + \frac{1}{2}\|w\|^2 \tag{3}$$

where

$$L_\varepsilon(d, y) = \begin{cases} |d - y| - \varepsilon, & |d - y| \geq \varepsilon \\ 0, & others \end{cases}$$

$L_\varepsilon(d, y)$ is Vapnik's ε-insensitive loss function which will equal zero if Y_i is within the ε-tube, C is the regularization constant, ε is the precision parameter presenting the distance of the tube located around regression function, d is the actual value at period i, Y is the estimation value at period i. Finally, $\frac{1}{2}\|w\|^2$ is the norm of weight vector is used to calculate the flatness of the function.

Next, we use two variables ξ and $\hat{\xi}$ to represent the distance from the point of actual values to the boundary values, then the eq. (3) can be expressed in the following constrained form;

$$R(w, \xi, \hat{\xi}) = \frac{1}{2}\|w\|^2 + C\frac{1}{N}\sum_{i=1}^{N}\left(\xi + \hat{\xi}\right) \tag{4}$$

Subject to:

$$d_i - w\phi(x_i) - b_i \leq \varepsilon + \xi_i$$

$$w\phi(x_i) + b - d_i \leq \varepsilon + \hat{\xi}_i$$

$$\xi_i, \hat{\xi}_i \geq 0,\ i = 1, 2, ..., N$$

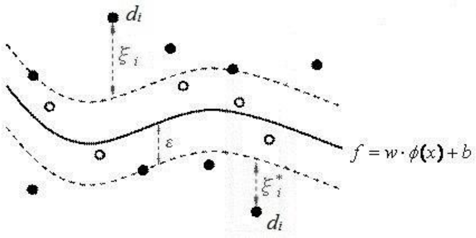

Fig. 2. Parameters of support vector machine.

Langrangian form α_i and $\hat{\alpha}_i$ which satisfy equality $\alpha_i \times \hat{\alpha}_i = 0$ where $\alpha_i \geq 0$ and $\hat{\alpha}_i \geq 0$;

$$L(w_i, \xi, \hat{\xi}, \alpha_i, \hat{\alpha}_i, \beta_i, \hat{\beta}_i) = C\frac{1}{N}\sum_{i=1}^{N}\left(\xi + \hat{\xi}\right) + \frac{1}{2}\|w\|^2$$

$$-\sum_{i=1}^{N}\alpha_i\left[w_i\phi(x_i) + b - d_i + \varepsilon + \xi_i\right]$$

$$-\sum_{i=1}^{N}\hat{\alpha}_i\left[d_i - w_i\phi(x_i) - b + \varepsilon + \hat{\xi}\right] - \sum_{i=1}^{N}\left(\beta_i\xi + \hat{\beta}_i\hat{\xi}\right) \tag{5}$$

The dual form of the nonlinear SVR can be expressed as (after applied Karush-Kuhn-Tucker conditions);

$$Q(\alpha_i, \hat{\alpha}_i) = \sum_{i=1}^{N} d_i(\alpha_i - \hat{\alpha}_i) - \varepsilon\sum_{i=1}^{N}(\alpha_i + \hat{\alpha}_i)$$

$$-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \hat{\alpha}_i)(\alpha_j - \hat{\alpha}_j)K(X_i, X_j) \tag{6}$$

Subject to:

$$\sum_{i=1}^{N}(\alpha_i - \hat{\alpha}_i) = 0$$

$$0 \leq \alpha_i, \hat{\alpha}_{ii} \leq C,\ i = 1, 2, \ldots, N$$

α_i and $\hat{\alpha}_i$ are the Lagrange multipliers that satisfy the condition where $\alpha_i \times \hat{\alpha}_i = 0$. A kernel function is used to map the data into a high-dimensional feature space. (See Fig. 3).The Radial Basis Function (RBF), one of the most common kernel functions is used in this paper. This function can be denoted as follows:

$$K(x_i, x_j) = \exp\left(-\frac{1}{2\delta^2}\|x_i - x_j\|^2\right) \tag{7}$$

where δ is the width of the RBF and also determined by user.

The RBF function is satisfying Mercer's theorem [21], hence it can be used as a kernel function.

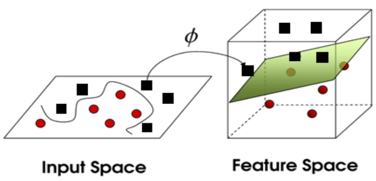

Fig. 3. Function of ϕ maps into higher dimensional feature space (Free source at sta.uwi.edu).

IV. Experimental Results

Parameter selection is an important step to obtain positive results in prediction. One of the tasks that we need to do in prediction of resistance spot welding system is reducing the amount of data to process. In feature reduction stage, we need to select a subset of features from the initial set that keep most of the information of data, and the less relevant features are removed.

In our experiment, the selected parameters are weld current, weld force, weld time, thickness of steels, coating and nugget width. The parameters are mutual influence and interdependence. Before the data enter into the system, the variables are converted from design variables to nominal variables to help the system can understand these parameters' meaning. In this experiment, the parameters are set as follows; the weld current ranges within 7 kA to 13 kA; the weld force is from 900 lbs to 1520 lbs; the welding time is within the range 21- 41 cycles and the thickness is setting approximate 1 mm – 3 mm; The sheet metal can be coated or not.

In order to conduct experiment, a nonlinear support vector regression method is used to train the SVM. Since a kernel function must be selected from the functions, the radial basis function is adopted in this work. To determine the values for the parameters, we used grid search method [22]. The grid search is a straightforward method using exponentially growing sequence of Capacity (C) and Epsilon (ε) to identify good parameters, in which it will select the best parameters of C and ε with the lowest regression errors. In this research, the radial basis function is selected as Kernel type whose value of sigma is 0.6, value of degree is 5 and values of C and ε are 100 and 0.01, respectively.

The result of experiment is almost based on welding parameter setting. The final result is showed in Table I. As illustrated in Fig. 4, within the range of 7 kA – 11 kA, the predict result is very good, because the predict values almost closed to the actual values. From 11 kA to 13 kA, we have supplement Hot-Dip Galvanizing (HDG) coating factor on the steels, therefore, the predict result is not good. Typically, uncoated steel is comparatively easy to weld; however, when HDG coating adds, the resistance spot welding process becomes more difficult and complex. In 14 kA – 16 kA range, we tried the different thickness with two steel sheets and the results are not very good because heat propagation on two steel sheets is different. In overall, the accuracy of experiment calculated for SVM archives 92% and ANN archives 88.9% as shows in Table I.

TABLE I: The Result of Two Methods

Method	Accuracy (%)
ANN	88.9
SVM	92

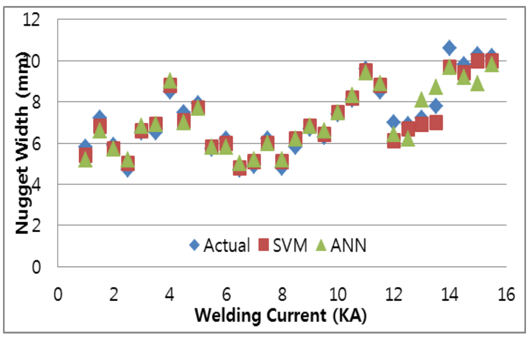

Fig. 4. Experimental result.

V. Conclusions

In this work we present an approach to predict nugget width in resistance spot welding. The experiment result shows the higher prediction ability of SVM compared ANN. It can be concluded that through appropriate selection of parameters SVM can replace some of the neural network based model for nugget width in resistance spot welding prediction application. In additional, the settings of welding parameters are great influence to the prediction ability. In the future research, we are going to find the best method that improve the accuracy and have the ability to solve problems with different combination of coating and thickness of steel sheets.

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