Linear welding power prediction measurement-based models

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1. Introduction

The linear welding process enables to manufacture parts for the construction, building and mining industries, where components such as brackets or anchors are used. These products are often responsible parts of constructions, making their quality a factor in human safety, and is therefore a key aspect of manufacturing. The speed of manufacturing in this process is high, and the fluctuation and variability of parameters is significant, making it imperative that maintaining quality at the manufacturing stage through parameter monitoring must also include predicting these parameters in advance to allow time for a possible response even before unacceptable deviations from acceptable process parameter values occur. Key process parameters include current parameters (power, amperage, voltage) and their derivative – welding temperature. Based on these, it can be predicted whether the resulting weld will have satisfactory strength [1–3]. Since the range of products produced at the plant is considerable, and the different dimensions and thickness of the pipe to be welded determine the setting of the right parameters for it, the models must receive the thickness and diameter of the given material at the input in order to correctly predict the power with which the process should be carried out to achieve the right welding temperature.

2. Temperature prediction models

The research aimed to develop models using data mining and machine learning from production data from the process to predict weld temperatures based on current parameters. A number of machine learning algorithms were used, which have already proven their effectiveness in materials engineering and metal processing applications [4–7]. Two different datasets were worked on. Among others, a model was developed based on results from a pyrometer placed on a measuring device. This was data from work-in-progress – cleared of downtime and changeovers, start-ups and process extinctions. Only data for work-in-progress production. Data: 12 575 records. Using the automatic network architecture search algorithm (Automatic Neural Networks), the space of possible architectures and different number of layers and neurons in hidden layers, as well as MLP and RBF architectures, different types of activation functions were searched, determining the optimal network architecture. Validation quality of correlation $R = 0.945$ was obtained, determination coefficient was $R^2 = 0.893$. The second dataset included results from real production (with downtime, startup and quench), data was sampled every half second and temperature delay was added to represent the actual weld heating delay. Data: 50 400 records. The developed model had a correlation

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coefficient R = 0.992, determination coefficient $R^2 = 0.984$. Even better results were obtained using Random Forest (Table 1).

Table 1. Comparative analyses of temperature prediction results.

Model	MSE	RMSE	MAE	R^2
Random Forest	613.4	24.76	16.98	0.986
Ada Boost	690.4	26.27	16.81	0.984
Regression Tree	895.9	29.93	19.76	0.979
Linear Regression	926.7	30.44	22.21	0.978
Neural Network	2214.6	47.06	28.31	0.984

3. Power prediction models

The key process parameter affecting the welding temperature and thus the most important quality factor turned out to be the power of the current. Tasking the right power for a given size and material of the welded profile is the most important task of the operator. Based on material testing, it is possible to determine in what power range welds of the expected strength are produced, and where is the limit below which the process does not maintain the expected quality. However, material tests are expensive, and they are destructive tests, so they require the destruction of the sample and thus the product. Having production data and temperature prediction models to determine whether the process temperature was appropriate, it was possible to perform process data filtering obtaining learning sets with given characteristics, allowing the development of models that, as an output, made it possible to determine what power was appropriate for the process carried out for particular profiles: material, diameter and thickness. A knowledge base was acquired, which in the next step was used to develop inference models using fuzzy logic.

4. Results

The developed model allows prediction of safe power levels for given input parameters: material, diameter and wall thickness. The fuzzy logic model was implemented in the process control system. The Fuzzy Inference System (FIS) model derived from MATLAB is parsed into Fuzzy Lite Language (FLL) format, which enables the use of the fuzzylite library. Implementation of subsequent models involves using the base class FuzzyModel and implementing procedures, along the lines of PowerMaterialModel for subsequent aggregates. The model was tested on samples that had material test results and on real data from the welding process. A particularly important aspect was that the suggestions made by model should not indicate suggestions below the minimum acceptable power. An error in the opposite direction – excess power – is not so harmful. The results indicated a good fit of indications $R^2 = 0.73$, MAE = 9 kW, the predicted power never exceeded the allowable minimum. Average over-delivery relative to the minimum: 17.3 kW (Table 2).

Table 2. Comparative analyses of temperature prediction results.

Metric	Abbreviation	Value
Residual Sum of Squares	RSS	145.24
Mean absolute error	MAE	9.31
Relative mean square error	RMSE	0.014
Relative Average Deviation	d	0.09
Correlation coefficient	r	0.86

a) b)

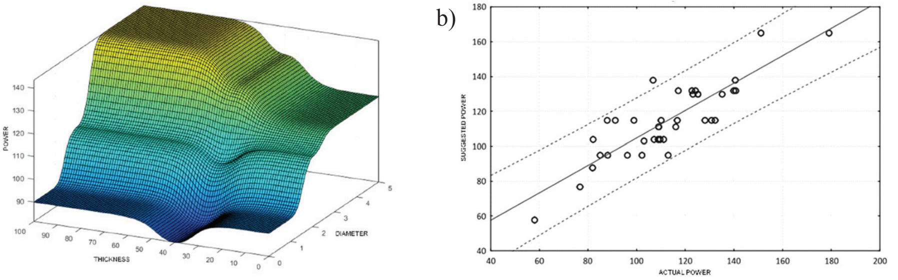

Figure 1. Inference surface in fuzzy logic (a). Prediction quality analysis – $R^2 = 0.73$, MAE = 9kW, the predicted power never exceeded the allowable minimum (b).

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