

Product Design Model for Impact Toughness Estimation in Steel Plate Manufacturing

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Abstract— The purpose of this study was to develop a product design model for impact toughness estimation of low-alloy steel plates. Based on these estimates, the rejection probability of steel plates can be approximated. The target variable was formulated from three Charpy-V measurements with a LIB transformation, because the mean of the measurements would have lost valuable information.

The method is suitable for all steel grades in production and it is not restricted to a few test temperatures. There were differences between the performances of different product groups, but overall performance was promising.

Next the developed model will be implemented into a graphical simulation tool that is in daily use in the product planning department and already contains some other mechanical property models. The model will guide designers in predicting the related risk of rejection and in producing desired properties in the product at lower cost.

I. INTRODUCTION

A Part of steel quality is determined by its mechanical properties. One of these qualities is impact toughness (or notch toughness), which describes how well the steel resists fracturing at a predefined temperature when a hard impact suddenly hits the object. The property is crucial in steel products that are used in cold and harsh environments *e.g.* ships, derricks and bridges.

Impact toughness can be measured with a Charpy-V impact toughness test (CVT), which has standardized specifications that define the dimensions of test pieces, the type of notch (U or V), test force, testing temperature, etc. The test piece is broken with a pendulum and the energy (in joules, J) absorbed in fracturing is measured. The test is performed on three different samples from every steel plate, and it is accepted if the average of the measurements is higher than the requirement. In addition, typically only one of the measurements is allowed to be 30% under the requirement (there are some exceptions specified by the customer). The CVT equipment is illustrated in Figure 1. The absorbed energy is calculated from the difference in the heights h_0 and h_1 .

The stronger the steel, the lower the impact toughness, and this brings a challenge to steel research, as the goal is to find ways to combine both of these qualities in a product. At room temperature steel can perform well in the impact toughness test, but when the temperature falls, its performance weakens. In this study, the most demanding steel qualities are tested at temperatures as low as -100°C .

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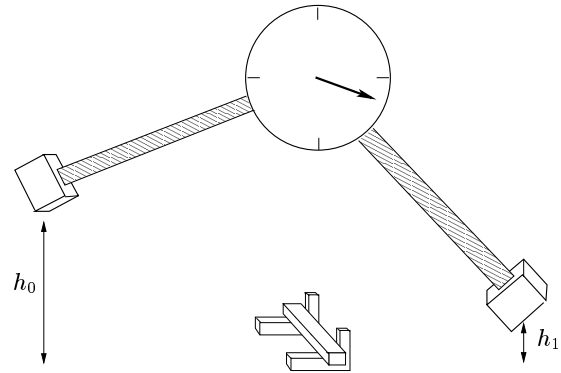


Fig. 1. Charpy-V test equipment.

Transition behaviour is typical for ferritic steel qualities. However, the impact toughness of these qualities can be affected by chemical composition and thermomechanical treatments. The effect of carbon concentration on transition behaviour is illustrated in Figure 2. Steel's behaviour is ductile at higher temperatures (the area is called the upper shelf) and it gets brittle at low temperatures (the lower shelf). The transition temperature is determined from the average of the upper and lower shelves. When the carbon concentration is low, the transition region from ductile to brittle is narrow, the upper shelf is high, and the slope between the shelves is steep. An increase in the carbon concentration lowers the upper shelf and also widens the transition region. The effect of other alloying elements and process parameters on transition behaviour is similar (or reversed, if the parameter has a positive effect on impact toughness). [1]

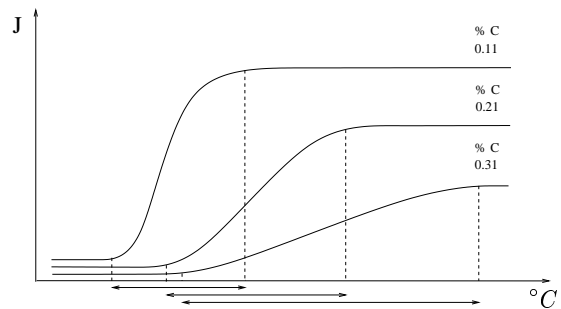


Fig. 2. Effect of carbon concentration to transition behaviour (temperature on the x-axis and absorbed energy on the y-axis).

Steel's behaviour in the transition region brings uncertainty to modelling, because in this area the force required to break the steel stick can vary dramatically. Factors that raise

the transition temperature have a negative effect on impact toughness, as well. Furthermore, if the grain size is not uniform in the product, the transition temperature is affected by the biggest grain size instead of the average grain size.

In the literature, the most common concern in impact toughness modelling is the behaviour inside the transition region (the upper and lower shelf energies, the slope between them, and the ductile-to-brittle transition temperature). [2][3] Charpy-V modelling of weld seams is probably the most widely studied application area. [4]

Both neural networks and traditional regression methods have been used in modelling [5], but only a few of the studies have concentrated on how to handle three measurements of every product. Golodnikov *et al.* used a quadratic regression model for CVT modelling with a small data set. The test was performed only on one steel grade and only at one test temperature. [6] In this study the goal was to develop a product design model for all steel grades and test temperatures in production, so that the model can be utilized to predict the related risk of rejection.

II. TARGET VARIABLE SELECTION

Because there are two different rules for rejection, the target variable of the impact toughness model should be able to recognize both of them. In the transition region, there will be a high probability of getting high variability between the measurements. These measurements can show upper shelf energy, lower shelf energy or something between them. Because of this variability, averaging often hides the evidence on increased risk of rejection. Thus, the average of the three measurements does not serve well as the target of modelling.

Instead, in this study it is suggested that Taguchi's quality loss function (larger-the-better) and the signal-to-noise ratio lead to better performance, and thus, the target is the transformation

$$LIB = -\log_{10} \left(\frac{1}{3} \sum_{i=1}^3 \frac{1}{z_i^2} \right),$$

where variable z_i is the i th measurement in the test series of one plate. The transformation is suitable when it is desired that the optimal value is near the average and the deviation of the observations is small. [7]

This transformation will react more effectively to rejections caused by one low measurement than average of three measurements. In the current data set, over 60% of the Charpy-V rejections were caused by this, and in some cases the average of the measurements would ignore these rejections completely. Because the reason for this kind of behaviour in the CVT is difficult to explain, the performance of the LIB model is not as high as with the average model in general. Nevertheless, it is more important to try to explain the rare rejections than to perform well with well-behaving observations that would not be rejected anyway. The LIB transformation strongly shrinks the upper part of the measurement scale, and thus, increases the relative influence

of the lower part where the rejections actually happen. The dependence between the measurements and their average is illustrated in Figure 3. The observations inside the ellipse are not recognized by the average, although a large part of them should be rejected. In Figure 4, in the similar

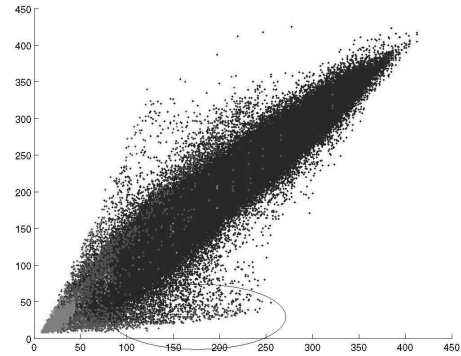


Fig. 3. Dependence between Charpy-V measurements and their average (measurements on the y-axis and the average on the x-axis).

illustration of the LIB transformation, it can be seen that the lowest measurements form a boundary. In other words, if the LIB is 4, which is equivalent to 100 J, every one of the measurements is guaranteed to be at least 60 J. Therefore, because the purpose of the model is to recognize the plates that would be rejected, the LIB transformation is a more suitable target.

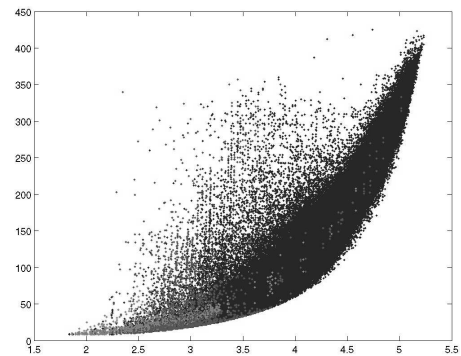


Fig. 4. Dependence between Charpy-V measurements and their LIB transformation (measurements on the y-axis and LIB on the x-axis).

The purpose of this study was not to model impact toughness as a mechanical property of steel. Instead, the focus was on developing a model for product design to help in designing the manufacturing process for steel grades.

III. PRODUCT DESIGN MODEL

The data mining research group at the University of Oulu has studied the mechanical properties of steel plates for years, and models of tensile strength, yield strength and elongation have been developed earlier. [8] Because of the complicated nature of impact toughness, the first task in the research was to find out if the property could be modelled at this extent

at all. A further motivation was to include the model in a simulation tool that the product design department uses to evaluate a product's mechanical properties and the confidence of achieving them.

When a customer orders steel plate with specific quality requirements, the product design group plans the chemical composition, possible treatments during melting (*e.g.* vacuum degassing) and some production requirements for heating, rolling and thermomechanical treatments. The model will guide the designers not to use too much working allowance when keeping the product within tolerances, and thus, to produce desired properties in the product at lower cost. If the steel mill has only a few products and a large volume of every grade, optimization of the process parameters is easier task than in the case where the mill competes with high quality, short delivery time and a large product range. In the latter case, tools that help product design will directly reduce the number of rejections and delays.

Multilayer perceptron networks (MLP) are commonly used for complex and nonlinear system modelling. It has been proved that a network with one hidden layer and sigmoid activation functions can approximate any smooth function. However, sometimes two hidden layers are needed if discontinuities exist in the modelled function. This complicates optimization of the network, and initialization of the network will have a high impact on performance. [9][10]

IV. DATA COLLECTION

The data were collected at Ruukki's steel plate mill in Raahe in 2002-2007 and they consist of information about over 200,000 low-alloy steel plates and over 70 variables. Of the plates rejected after the CVT, 63% were rejected because of one too-low measurement. The CVT was performed on the majority of the steel plates at -20°C , but the test area varied from $+20^{\circ}\text{C}$ to -100°C . The chemical composition of steel defines a large part of its impact toughness, and heating, rolling and thermomechanical treatments can improve it further.

Careful pre-processing was performed in order to exclude defective observations and redundant variables, for example unnaturally low measurements and misperformed tests. The final data included 202,667 observations and 42 variables. The data were normalized into a range of $[-1, 1]$ before training.

V. RESULTS

The MLP networks of the product design models were implemented with Matlab R2007b. The data were divided into training (50%), validation (25%), and test sets (25%). The independence of the data sets was verified by not allowing plates from the same melting to belong to different sets. A resilient back-propagation algorithm with early stopping regularization was used for training, and hundreds of networks of different sizes with random initialization were trained. The best network had two hidden layers with 39 and 5 neurons. The results of this model can be seen in Table I.

TABLE I

RESULTS OF THE TRAINING DATA AND THE INDEPENDENT TEST SET.

	R	MSE
train	0.8747	0.0487
test	0.8676	0.0502

The overall correlation between the target and estimated values of the test set was 0.87. The scatter plot between the predicted LIB values and the model error is illustrated in Figure 5. Over 96% of the observations lie between the lines $[-0.5, 0.5]$. Observations with a residual of less than -1 in the lower right corner are plates that had a very low LIB, but the model failed to recognize them. There are no similarities between these plates that could explain the poor result. There might be plates that were produced differently than planned (some of the critical process stages did not work as planned). The most probable explanation is the nature of the phenomenon itself. The existence of slag inclusions near the fracturing causes low measurement values, and another test piece from the same plate could have much higher values. Also, when the test is performed in the transition region, uncertainty in modelling grows.

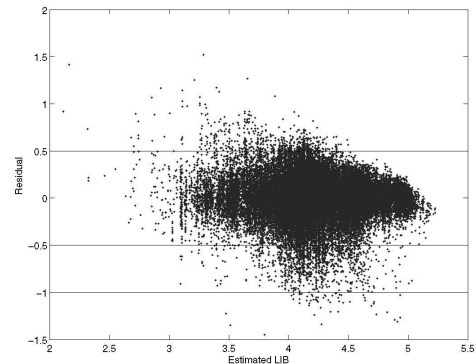


Fig. 5. Scatter plot between the predicted values and the model error for the independent test set.

Because the user is interested in the rejection probability and not just the LIB transformation, the predicted values were transformed back to the J-scale and the prediction errors were reanalyzed. The restoration of the J-scale can be done with

$$J = \sqrt{10^{LIB}}$$

The J-scale transformation is lower than the average of three measurements, and thus, it is not a precise estimation of the joule scale, but because the model is used the rejection probability estimation, this will not restrict its usability. The percentage accuracy of the model can be seen in Table II. Restoration of the original scale is considered only for two rejection boundaries. The logarithmic scale skews the model error, and accuracy examination in the J-scale will not work well for larger values.

Nearly half of the production (47%) belongs to product group 1, which had the best accuracy. This group typically

TABLE II

PERCENTAGE OF CORRECT RESULTS (A RESULT IS INTERPRETED TO BE CORRECT IF THE ERROR IS $< q$) FOR TWO PREDICTION GROUPS.

$ pred_err < q$	pred $< 60J$	pred $< 120J$
10J	65.66%	35.57%
20J	88.55%	59.98%
30J	93.63%	74.77%
40J	96.21%	84.10%
50J	97.65%	90.29%

gets lower than average Charpy-V values, because impact toughness is not a critical quality of these products. The results for three different product groups are shown in Table III. The group 3 is left out from the table, because these products get higher CVT values than 60J.

TABLE III

PERCENTAGE OF CORRECT RESULTS (A RESULT IS INTERPRETED TO BE CORRECT IF THE ERROR IS $< q$) FOR THREE PRODUCT GROUPS (PREDICTED VALUE $< 60J$).

$ pred_err < q$	group 1	group 2	group 4
10J	68.28%	66.05%	45.45%
20J	90.12%	90.54%	72.73%
30J	94.73%	94.43%	85.71%
40J	96.76%	97.13%	92.86%
50J	98.24%	97.64%	96.75%

If the histograms of the original LIB values were plotted separately for each group, it could be seen that groups 3 and 4 have significantly different distributions compared with groups 1 and 2 (Figure 6). Their impact toughness requirement is higher and they are more demanding to manufacture. There are only two observations from group 3 below the lower line in Figure 5. The result reflects the shapes of the distributions.

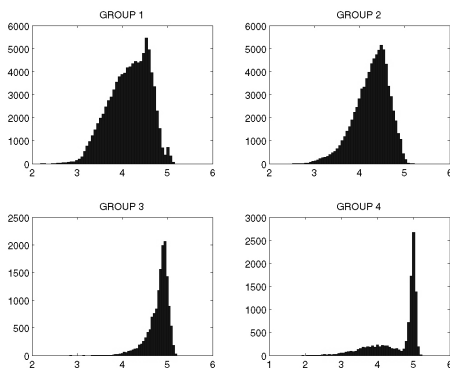


Fig. 6. LIB histograms of four product groups.

VI. CONCLUSIONS

This study analyzed impact toughness and its modelling. The study showed that it is possible to form a product design

model for a whole steel plate production line, including all possible test temperatures. The results were most promising for two product groups that form almost 85% of the production volume.

Hierarchical models or separate models for different steel grades were considered at the early stage of the study, but including all the steel grades in one model made it possible for the products to learn from each other. Therefore, the ongoing development of new products is less demanding for modelling. Further research will study the feasibility of other methods, like quantile regression in CVT modelling.

Next, the model will be implemented into a graphical simulation tool that is in daily use in the product planning department and already contains other mechanical property models [11]. The simulation tool is utilized to plan composition and production settings for product modifications and new products and to maintain the regulations for the production methods of existing products.

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