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On assessing grindability of recycled and ore-based crankshaft steel: an approach combining data analysis with material science

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Abstract

Material-related grindability variations when grinding recycled and ore-based steel can significantly impair the process efficiency during finishing of automotive crankshafts. To address this problem and to achieve more robust grinding processes, the underlying causes of variation need to be understood. The present work investigates the feasibility of using quality data obtained during production to study grindability variations and identify material-related effects. Analysis of non-destructive inspection protocols indicates steel supplier-dependent differences in grindability. However, no systematic grindability differences between recycled and ore-based steel could be identified. Possible correlations between grindability and material characteristics obtained from supplied steel certificates are discussed.

Keywords: Grinding; Grindability; Steel

1. Introduction

Automotive crankshafts for heavy-duty vehicles need to be able to sustain severe in-service loads. Cyclic bending and torsional stresses require high fatigue resistance of the crankshaft in order to function properly during the component's lifetime. During manufacture, special attention is paid to finishing operations and assessment of surface integrity by employing non-destructive testing procedures like the Barkhausen noise analysis [1]. In this way it is ensured that finished surfaces meet the design requirements and are free from defects such as thermal damage (e.g. grinding burn). Variations in the input material can lead to grindability inconsistencies which causes process disruptions and scrapping of components, affecting the overall efficiency and productivity of a production line.

Following the general definition of machinability, the grindability of a material can be defined as the ease at which a certain material can be ground under given process conditions. Grindability of a material may therefore be assessed by one or more of the following criteria:

- Mechanical: e.g., specific grinding energy (relating to material flow stress, strain, strain rate, hardness, etc.)
- Tribological: friction and wheel wear (caused by grit/bond fracture and attrition processes – such as microchipping)
- Thermal: caused by high grinding temperatures (leading to workpiece burn, tempering, residual stresses and/or material phase transformations such as rehardening).

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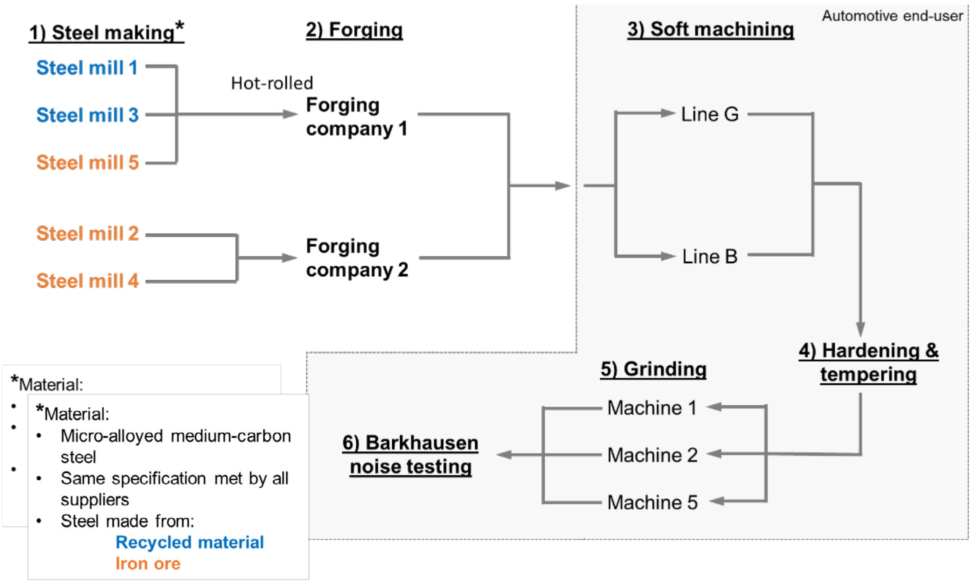


Fig. 1. Schematic of the material flow and processing steps involved in manufacture of the investigated crankshaft type prior to superfinishing

In the present case, grindability issues primarily concern thermal aspects, namely uncontrolled high temperatures during grinding leading to unfavorable tensile residual stresses, tempering of the induction hardened surfaces, or in the most severe cases phase transformations or formation of cracks in the ground surfaces [2]. One source for such problems is suspected to be metallurgical variations in the input workpiece material, when steel batches obtained from different suppliers are fed into production lines. Specifically, some automotive companies perceive steel from suppliers producing recycled steel as more prone to thermal damage during grinding as compared with virgin, ore-based steel.

In order to facilitate more extensive use of recycled steel and to maximize its sustainability benefits [3], potential detrimental effects on manufacturing processes such as grinding need to be identified and the underlying reasons for such behavior need to be determined.

The aim of the present study is to investigate the feasibility to utilize data obtained during crankshaft production to identify grindability variations. In particular, systematic grindability differences between steel batches from suppliers producing recycled or ore-based steel are addressed.

2. Case background

The identification of input-material variations and its effect on grindability is complex. Firstly, metallurgical variations in large parts such as automotive crankshafts are challenging to detect as metallographic examinations are localized and time consuming. Secondly, only a few scientific studies addressing the effect of material microstructure on grindability have been published and mainly focus on differences between various steel grades [4–7]. To the best of our knowledge, material variations when grinding batches of the same steel grade from different suppliers have not been addressed so far. The lack of fundamental understanding of material effects on grindability therefore makes it difficult to correlate observed microstructural characteristics to the specific grinding response.

To overcome the limitations of experimental approaches, data analysis and machine learning have been applied to improve manufacturing systems [8] and crankshaft production in particular [9]. The present work builds upon a similar approach while focusing on the effect of input material on crankshaft production.

2.1 Crankshaft manufacturing sequence

The investigated component is a six-cylinder crankshaft used in heavy-duty trucks that is made of a micro-alloyed medium carbon steel grade (38MnVS5). The manufacturing sequence (production chain) of crankshafts and the corresponding material flow are illustrated in Figure 1. The input material is supplied by five different steel mills in form of hot-rolled round bars, which are subsequently forged into crankshaft blanks by two different forging companies. Crankshaft blanks are then delivered to the automotive OEM/end-user where they are fed into one of the two soft machining lines (“Line G” or “Line B”). Among others, the bearing surfaces and radii of the crankpins and mains are machined close to the final dimensions during this step. Subsequently, machined crankshafts merge into one flow where they undergo induction hardening of the crankpin and main journal surfaces followed by a tempering heat treatment to attain the desired combination of hardness and residual stresses. Subsequent grinding of the crankpin and main journals is performed in one of the three grinding machines, followed by non-destructive testing by means of Barkhausen noise (BHN) analysis. The crankshaft grinding process is patented by Scania and involves parameters revealed in [1].

2.2 Description of utilized data

The data sources utilized in this study comprised material certificates obtained from the steel mills (“input data”) including steel mill name, batch number, batch-specific chemical composition and (in some cases) rating of non-metallic inclusions. In addition, non-destructive BHN testing protocols obtained from the automotive end-user (“output data”) were studied. BHN measurements give indications of

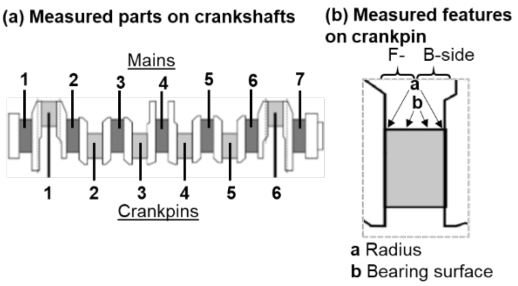


Fig. 2. Schematic of the investigated crankshaft type (a) and the features with specific locations of BHN measurements exemplified on a crankpin (b). At each location, the measurement is done 360° around the circumference of the feature

the surface integrity (quality) obtained after grinding and thereby act as an indirect grindability measure.

The BHN measurement results were obtained around the circumference of ground surfaces on crankpin and mains. The measurements were done using a Rollscan 200 Barkhausen noise analyser while rotating the crankshaft. A summary of the specific locations measured can be found in Figure 2 and Table 1. For each crankshaft a total of up to 38 individual locations were measured. In addition to the measurements, each BHN protocol contained information on the processing route (identifying soft machining line, grinding machine, and number of crankshafts that have been ground since last dressing of a grinding wheel) and the steel batch number, which enabled to link each crankshaft to the respective material certificate. A total of 535 protocols, each concerning one crankshaft were included in this study. The crankshafts were ground over the period of two years.

Table 1. List of measured (“x”) locations on the various crankshaft features during BHN analysis. Locations not included in the BHN measurements are indicated by “-“.

Feature		Crankpins 1 to 6	Mains 1 to 7
Radius	F-side	X	-
	B-side	X	-
Bearing surface	F-side	X	X
	B-side	X	X

2.3 Principle of Barkhausen noise analysis

The measurement principle of BHN is based on the Barkhausen effect, which occurs during magnetization of ferromagnetic materials. Magnetization causes the material’s magnetic domains to align with the external magnetic field causing movement of domain walls. Interactions of moving domain walls with pinning sites in the probed material (e.g., dislocations, stresses, grain boundaries) lead to generation of noise-like signal that can be detected and measured by a suitable sensor [10].

The BHN signal is mainly affected by a few material characteristics, namely the material’s residual stress state, hardness, and microstructure. The correlation between BHN and material characteristics (i.e., surface integrity) can be utilized in quality control of machined surfaces [11,12]. During grinding for example, surface-quality problems like grinding burn (thermal damage) can occur as a result of exceedingly high grinding temperatures leading to shifts toward more tensile residual stresses and/or lower hardness [13]. Both these changes in material characteristics result in an increase in BHN intensity during inspection [10]. In contrast, comparably lower BHN measurements would indicate more favourable surface integrity, namely shifts toward more compressive residual stresses and/or no softening of the ground material. In practice, during crankshaft production, BHN measurements above a specified threshold therefore alert potential grinding problems which lead to further inspection (e.g., magnetic particle testing [14]) or can cause part-rejection, i.e., scrapping of the component.

3. Data analysis

Analysis of the data was conducted using the statistical data analysis software JMP© PRO (Version 15.2.1.0) by SAS. The output BHN data was both correlated over time and between crankshaft features. Minor autocorrelation (~0,2) per feature, originating from long-term process drift, was removed by fitting integrated moving average models IMA(1,1) to each feature time series. After removal of the diachronic correlation, the remaining strong synchronic correlation between various crankshaft features and locations are shown in Figure 3. The colours and their levels show the type and strength of correlation (red: positive relationship, blue: negative or inverse correlation, grey: no correlation). In general, correlations are primarily positive, i.e., an increase of one location’s BHN tends to be associated with other locations on the crankshaft increasing as well. However, the strength of correlations vary, strong positive correlations are seen between BHN measured on the same features (e.g., correlation coefficients of close to +1 between different pin radii) and less strong or limited correlations are seen between different features (e.g., correlation coefficients around +0.4 between pin radii and main bearing surfaces). This sub-grouping of correlations likely originates from the grinding process, e.g., from slightly different set-up protocols depending on type of crankshaft feature, rather than from input material differences.

Apart from correlations, the colour map in Figure 3 with its 38x38 elements illustrates the multidimensional nature of the output data. Due to the strong correlations and

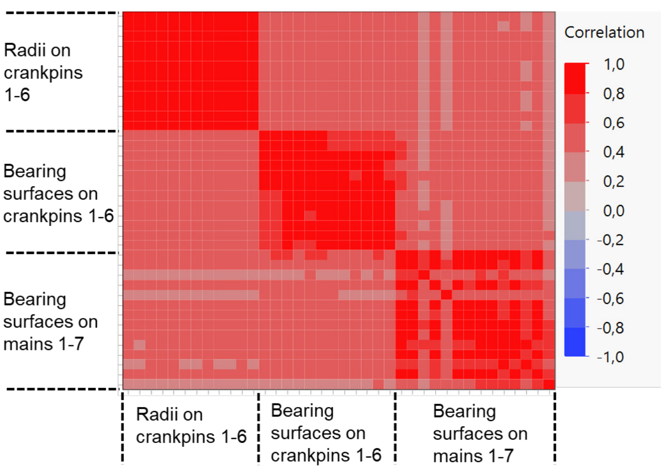


Fig. 3. Colour map showing correlations between BHN measurements on different crankshaft features

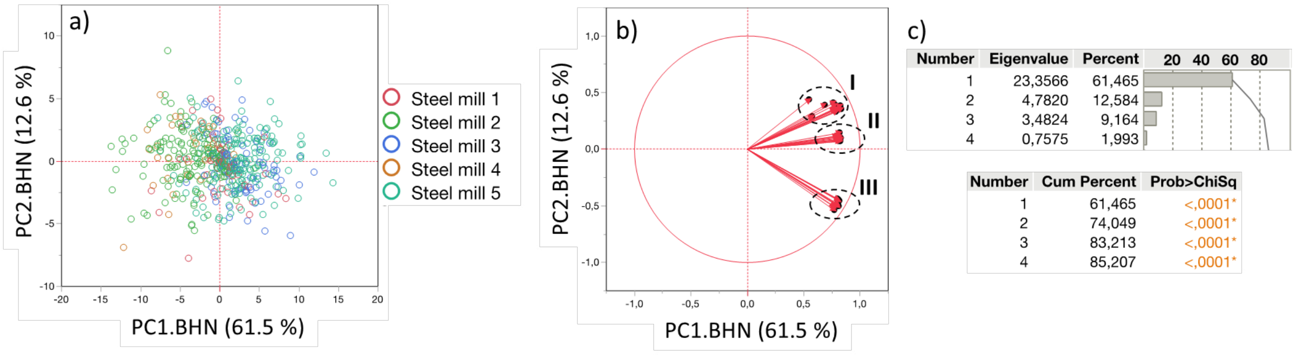


Fig. 4. PCA of output data (BHN measurements). (a) Scatterplot of the data as function of first two components (PC1.BHN and PC2.BHN) with colouring according to steel suppliers, (b) loadings of the original variables with PC1.BHN and PC2.BHN (I: Main bearing surfaces, II: Crankpin bearing surfaces, III: Crankpin radii). (c) List of characteristics of first 4 principal components.

multidimensionality, the dimensions of the data were reduced using principal component analysis (PCA). PCA enables to extract the data's most significant information and to get simpler representations of the respective data set by significantly reducing the number of variables. Results of the PCA on the residuals (after auto-correlation removal) of the output BHN data are shown in Figure 4. As seen in (c), around 83 % of the variation in the BHN measurements can be described with 3 principal components (PCs), where the first component explains 60% of the variation in the data. A scatterplot showing the data plotted as a function of the first two components ("PC1.BHN" and "PC2.BHN") is provided in Figure 4a. The loading plot in Figure 4b shows how strongly the first two PCAs are influenced by each characteristic. PC1.BHN contains information on the general level of BHN and explains the largest part of the variations in the data. PC2.BHN and PC3.BHN capture differences between the various measurement locations (see crankpin radii, crankpin, and main bearing surfaces in the loading plot). Generally speaking: PC1.BHN explains the general colour (red) tone in Figure 3 and PC2.BHN and PC3.BHN explain the difference between the feature sub-groups.

The analysis of the input data (material certificates), i.e., the correlations between elements and inclusion ratings are shown in Figure 5. A total of 26 elements and 8 inclusion ratings are included and many strong positive and negative correlations between elements and inclusions can be seen. When looking at the steel mills individually (see Figure 5b), one can observe significant differences in correlation matrices indicating that, even though all steel batches meet the same steel grade specification, the individual steel mills produce distinct chemical compositions with substantially different correlation between elements (bearing in mind that some of this variation might originate from differences between characterization equipment and analysis procedures at each steel mill).

Additionally, it can also be seen that not all steel mills consistently provide the same information in their material certificates. For example, steel mills 2 and 4 do not report inclusion ratings and they report fewer elements as compared with the other suppliers. This issue of missing information could be resolved by more stringent requirements by the end users / buyers of steel.

4. Correlations between material data and Barkhausen noise measurements

Commonalities regarding processing route between crankshafts with relatively high BHN are seen in the distribution plots in Figure 6. For crankshafts with PC1.BHN > 5 (that corresponds to a high BHN number, see Figure 6a), the components' distribution (dark green) across grinding machines is similar to the overall distribution (light green) of all analysed crankshafts (see Figure 6d). The same relative

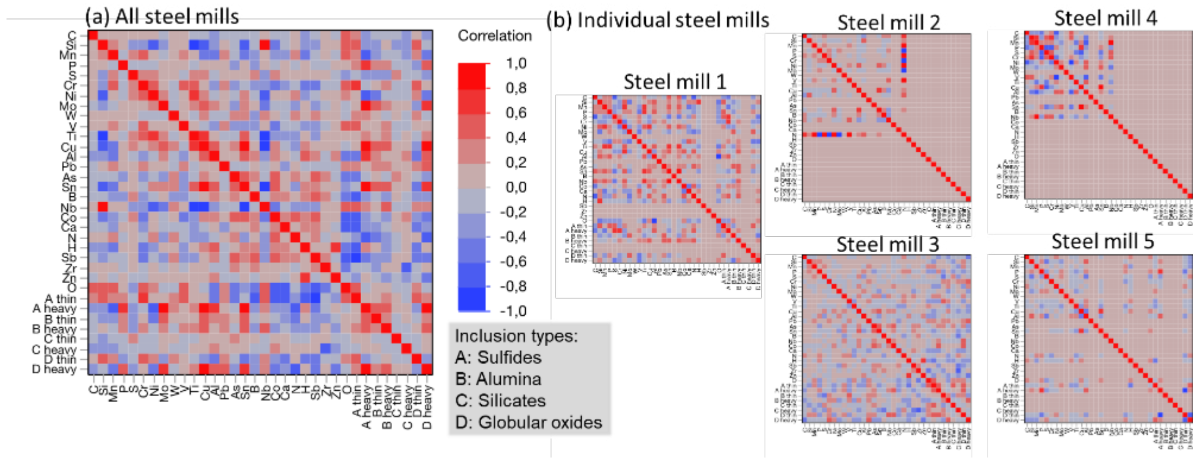


Fig. 5. (a) Overall correlation between elements and inclusion ratings. (b) Separate correlations stratified for different steel mills. Note that steel mills 2 and 4 do not report inclusions and report fewer elements compared with the other suppliers.

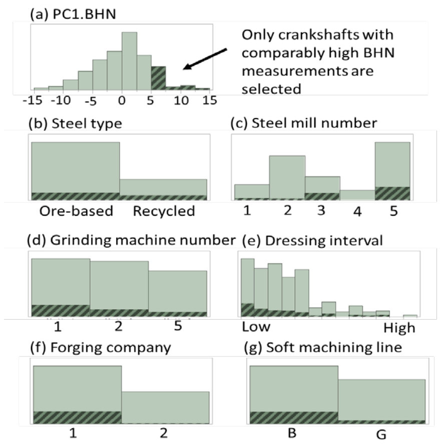


Fig. 6. Processing characteristics of crankshafts with relatively high BHN. Selection of crankshafts with PC1.BHN > 5 and corresponding distributions across different classifications.

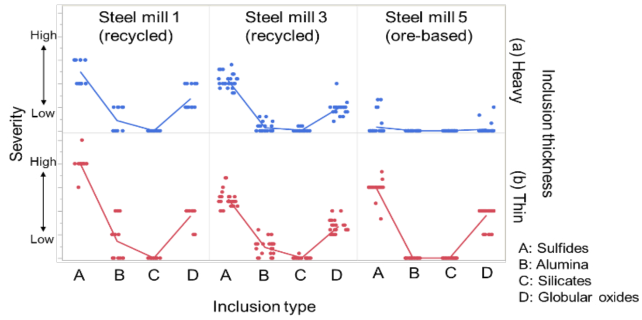


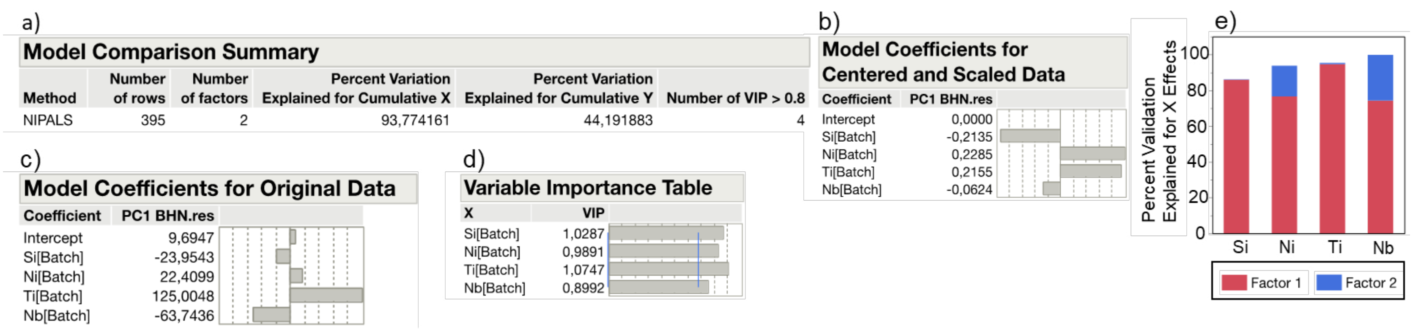
Fig. 7. Reported inclusion ratings of material supplied by three of the investigated steel mills.

number of crankshafts have been processed in all machines. Similarly, their distribution across the dressing intervals (Figure 6e) and soft machining line (Figure 6g) are approximately following the same shape/trend as the distribution of all measured crankshafts, which indicates that high BHN numbers are probably caused by other factors. However, when looking at the steel sources in Figure 6c, one can see that the majority of the selected crankshafts with high BHN values originate from two steel suppliers, specifically steel mills 3 (recycled steel) and 5 (ore-based steel) which both supply their steel to forging company 1. As a result, high BHN results are not confined to only recycled steel but also occur for ore-based steel batches. Instead, high BHN appears to primarily occur for material from specific steel suppliers, here steel mills 3 and 5, independently of steel type (ore/recycled).

To obtain a better insight into possible reasons for the identified supplier-specific differences in BHN, the respective material data reported in the certificates was studied. The types and amounts of non-metallic inclusions present in the steel batches can impact grindability and the resulting surface quality. Hard oxide inclusions, in particular, are expected to have an impact on the grinding process by acting as abrasive particles when coming in contact with the grinding wheel (grits and bond). The impact of hard, abrasive particles on wear of grinding wheels has been investigated previously by Badger [4]. Attritious wear of grinding wheels (i.e., wear by abrasion) was reported to lead to dulling/flattening of the wheel's grits which in turn increases the wheel-workpiece contact area which significantly increases specific grinding energy, heat input and temperature in the grinding zone. Grinding of steel with relatively high amounts of hard oxide inclusions would therefore lead to enhanced rates of wheel wear that ultimately leads to deterioration of obtained surface integrity, which should be reflected in increasing BHN values. In the present case, the information on inclusions was only available for three of the steel mills. Note that the reported inclusion ratings are in accordance with "Method A" in ASTM E45 standard [15].

Steel mills 1 and 3 (both producing recycled steel) reported higher severity ratings of oxide inclusions as compared with steel mill 5 (ore-based), see inclusion types B, C, and D, in Figure 7. This is primarily the case for the heavy (i.e. comparably thick) inclusions shown in (a - upper panels). According to the preceding discussion on the potential effect(s) of oxide inclusions on wheel wear and resulting surface integrity, grinding of steel from suppliers 1 and 3 should be subjected to higher wheel-wear rates compared to steel from supplier 5. This is however not reflected in the BHN results for these steel mills (see Figure 6) indicating that the differences in BHN between steel mills 3 and 5 (high BHN) compared with steel mill 1 (low BHN) cannot be explained by only oxide inclusion amounts. The amounts of soft and deformable sulphide inclusions (type A) for steel mills 1 and 3 (recycled) is also higher for the ore-based steel mill 3, see inclusion type A in Figure 7.

To obtain indications of other potential underlying material-related reasons for the variations in BHN, a multivariate analysis using Partial Least Square (PLS) regression was conducted. PLS is a regression method that can handle correlations in both predictors (input "x", here material data) and responses (output "y", here the principal component PC1-3.BHN representing the BHN measurements) [16]. Only PC1.BHN showed any relationship with the material data, which further confirms that PC2.BHN and PC3.BHN are process related as discussed in section 3. The refined analysis on PC1.BHN is a stepwise process starting with all input data (26 elements and 8 inclusion ratings). Using a VIP (Variable Importance for the Projection)



a) Model Comparison Summary

Method	Number of rows	Number of factors	Percent Variation Explained for Cumulative X	Percent Variation Explained for Cumulative Y	Number of VIP > 0.8
NIPALS	395	2	93,774161	44,191883	4

b) Model Coefficients for Centered and Scaled Data

Coefficient	PC1 BHN.res
Intercept	0,0000
Si[Batch]	-0,2135
Ni[Batch]	0,2285
Ti[Batch]	0,2155
Nb[Batch]	-0,0624

c) Model Coefficients for Original Data

Coefficient	PC1 BHN.res
Intercept	9,6947
Si[Batch]	-23,9543
Ni[Batch]	22,4099
Ti[Batch]	125,0048
Nb[Batch]	-63,7436

d) Variable Importance Table

X	VIP
Si[Batch]	1,0287
Ni[Batch]	0,9891
Ti[Batch]	1,0747
Nb[Batch]	0,8992

Fig. 8. Summary of PLS model

threshold of >0,8 for when to keep a factor, the model was trained on 70% of the data, validated on 15% and holding back the remaining 15% of the data for model testing. The data sub-sets were randomly picked/stratified for steel mills, which means that the same ratio of the data from each sub-group was used for training, validation and testing the model in each step. After several steps of factor screening the final model is summarized in Figure 8. Two latent factors based on four elements were used in the final model. With those four elements, almost 94% of the variation in the input can be explained and it captures 44% of the variation in the BHN data (Figure 8a), leaving the rest of the variation to other sources, such as measurement system reproducability and repeatability (that is precision). Figure 8b and c show the regression coefficients for the centred and scaled data and the original data, respectively. Figure 8d shows the significance of the elements as factors in the model and Figure 8e shows that latent factor 1 captures most of the variation and factor 2 adds some explanation on the Ni and Nb, that indicates a potential pairwise connection between these elements in the data.

In summary, almost half of the variation in BHN can be explained by the proposed statistical model with Si, Ni, Nb, and Ti as the influential elements. It was seen that steel batches with low amounts in Si and Nb combined with high amounts in Ni and Ti tend to be correlated with unfavourable high BHN values. In contrast, the opposite combination of the four elements (high amounts of Si and Nb combined with low amounts of Ni and Ti) tend to be associated with comparably low BHN values. The part of the BHN variations that cannot be explained by the proposed model is likely connected to effects that are not captured in the present study, such as process-variations along the manufacturing value chain (e.g., heat treatment) and/or lack of material data from certain steel suppliers. It is therefore suggested to test the indications identified in this study under controlled hardening and grinding conditions in a laboratory environment where these elements can be varied independently in a controlled experimental design while excluding differences in measurement systems and material-processing variations. For this purpose, custom-made test batches of steel with systematically varying amounts of the potentially influential four elements could be compared regarding their microstructures and respective grindability.

5. Conclusions

A data-analysis approach to identify grindability variations in crankshaft production has been presented. BHN measurements on more than 500 crankshafts have been utilized as indicators of grindability of the same crankshaft steel grade supplied by various steel mills – producing either recycled or ore-based steel. Even though distinct differences in BHN values after grinding have been observed for the different steel suppliers, no significant indications for systematic differences when comparing grindability of recycled steel with ore-based steel have been found. Grinding of recycled steel does not necessarily result in unfavourable BHN results. Vice versa, grinding of ore-based steel does not automatically result in more favourable BHN measurements. The analysed material certificates revealed that despite meeting the same material specification, steel supplied by different steel mills shows small but distinct variations in chemical composition and element correlation. Of those, a sub-group of Ni, Si, Ti, and Nb appear to correlate with BHN most significantly as a group, in pairs or individually. Any influence of steel inclusions to the varying BHN has not been detected but may contribute to the remaining variation in the data which was not explained by the sub-group of elements. The indications given in this study can be used as a base for dedicated grinding experiments to test the influence of the elements of interest systematically while excluding other processing-related variations. Further development and extension of the presented material science/data analysis approach could aid to address material variations and their effects on a wide variety of manufacturing processes involving processing of metallic materials.

Acknowledgements

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