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Scrap management by statistical evaluation of EAF process data

Erik Sandberg[a,*], Barry Lennox[b], Patrik Undvall[c]

[a]Process Metallurgy Department, MEFOS—Metallurgical Research Institute AB, Lulea 97125, Sweden
[b]University of Manchester, Manchester, UK
[c]Ovako-Hofors AB, Hofors, Sweden

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Abstract

The electric arc furnace (EAF) is a process for melting steel scrap with electricity. In this paper a method for estimating scrap properties based on the evaluation of historical process data is discussed and a series of scrap management strategies based on the estimated properties are suggested. Data from four Swedish EAFs have been analysed and on-line software applications have been developed and installed at one steel plant. The results from this study show that it is possible to use partial least squares to provide accurate estimates of the levels of impurity (Cu, Sn, As) and alloy content (Cr, Ni, Mo) in scrap grades. The degree of explained variation (R^2) obtained in this study ranges between 40% and 70% for impurity elements and 70% and 100% for alloy elements. The mean prediction errors (RMSEE) are in some cases small enough to improve steel quality control in terms of chemical analysis. To ensure that the estimates remain consistent with scrap quality, it is suggested that the prediction models be updated on a regular basis.

Keywords: Steel industry; Electric arc furnace; Statistical analysis; Linear multivariable systems; Multivariate quality control; Optimisation problems

1. Introduction

Steel scrap is the most important raw material for electric steelmaking, contributing between 60% and 80% of total production costs. In addition, the degree of which the electric arc furnace (EAF) process may be controlled and optimised is limited by fluctuations in scrap quality. Therefore quick estimations of properties of different steel scrap grades are very important for improving the control and optimisation of the EAF process. Most countries have national classification systems for steel scrap, but there is also a European classification system that the EU-countries use for international scrap trade (Birat, Le Coq, Russo, Gonzales, & Laraudogoitia, 2002). Steel scrap is usually graded in terms of size distribution, chemistry, density, origin and processing method. Some meltshops have internal classification systems that further divide the standard scrap grades into subtypes, and also a number of internal scrap grades (scrap produced within the steel plant). However, the scrap grading systems are designed for commercial purposes and the variation in scrap properties within each scrap grade is high.

In general scrap properties may be divided into two main categories, physicochemical properties and process related properties. Physicochemical properties (chemical composition, density, specific surface area, size distribution, melting temperature, specific heat capacity, metallic/organic/oxidic content) are only dependent on the particular scrap grade and are best determined by controlled experiments in laboratories. Process related properties (yield coefficients, specific energy consumption, contribution to chemistry of steel and slag, contribution to basket and furnace filling degree, contribution to dust generation and off gas composition) depend on both the process conditions and the other materials in the scrap mix. Therefore, the process-related properties for the same scrap grade may vary considerably between different meltshops.

Chemical analysis, conductivity, metal content and size distribution may be measured or estimated for individual

*Corresponding author. Tel.: +46 920 201994; fax: +46 920 255832.
E-mail addresses: Erik.Sandberg@mefos.se (E. Sandberg), Barry.Lennox@manchester.ac.uk (B. Lennox), Patrik.Undvall@ovako.com (P. Undvall).

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pieces of scrap and/or random samples but the fluctuation in scrap quality is often too large for these measurements to be representative for the whole population of a scrap lot on the scrap yard.

Experimental design methods have been proposed to set up a series of experimental heats that can then be used to estimate the scrap properties (Birat et al., 2002). However, because of the variation in process conditions and fluctuations in scrap quality each experiment would have to be repeated several times. The number of experiments needed to get estimations for all scrap grades can therefore be very high, depending on the number of scrap grades that are used, rendering this approach unsuitable.

An alternative to designed experiments is to firstly extract large quantities of data from process databases (Birat et al., 2002). Advanced statistical methods can then be used to analyse the combined effect of scrap mix and process conditions on the end conditions (chemical analysis of the liquid steel, energy consumption and metal yield). This is the approach investigated in this work.

The objective of this study is to estimate process related properties for several meltshops through the statistical evaluation of process data collected from the respective EAFs. Details of the participating meltshops are given in Table 1.

The strategy was to begin by developing prediction models for steel chemical analysis, specific electrical energy consumption and yield. By analysis of the regression coefficients of these models, it is shown in Section 6 that the mean of the desired scrap properties can be estimated for some scrap grades. Some scrap management software applications based on the estimated properties are then discussed in Section 7. Besides the applications mentioned in Section 7, better estimation of scrap properties will allow more detailed definition of initial conditions for various MPC applications based on dynamic process models for EAFs (Bekker, Craig, & Pistorius, 2000; Oosthuzen, Craig, & Pistorius, 2004).

2. Collection of process data

The first step is to consider which parameters may be relevant to the end conditions that are to be predicted. The parameters assumed to be relevant are listed in Table 2. Depending on the capabilities of the process logging systems of the meltshops, variables representing the parameters listed in Table 2 may or may not be available in the historical database.

2.1. Variable availability

In this section a brief overview of the considerations and important aspects of the data logging and availability of variables representing the relevant process parameters is discussed. A summary of the available data at the four participating meltshops is presented in Table 3. Table 3

Table 1
Participating meltshops

Meltshop name	Location	No of heats	Products
Ovako Steel AB	Hofors, Sweden	3716	Bearing steels
Fundia Special Bar AB	Smedjebacken, sweden	3837	Long products (low alloyed)
Sandvik Materials Technology	Sandviken, Sweden	3085	Stainless and speciality steels
Fundia Armering AS	Mo I Rana, Norway	969	Reinforcement bars (carbon grades)

Table 2
Relevant parameters for end conditions in EAFs

Parameter	End condition			Parameter	End condition		
	1	2	3		1	2	3
Weight of materials in the charge mix (scrap, alloys, coke, slagformers)	x	x	x	Burner and lance practice (position and penetration depth)	x	x	x
Consumption of coal and oxygen via lances	x	x	x	Distribution of scrap in baskets and furnace		x	x
Consumption of gas, oil and oxygen via burners	x	x	x	Slag carry over		x	x
Weight and composition of the hot heel (metal and slag)	x	x	x	Slag foaming conditions	x	x	x
Thermal status of the furnace		x		Alloys and slagformers in ladle		x	x
Temperature of the charge material mix		x		Furnace and basket filling degree		x	
Heating profile	x	x	x	Power-on, power-off and tap to tap times		x	x

1—Chemical analysis, 2—energy consumption, 3—yield.

Table 3
Summary of collected process variables (number of variables of each type for each meltshop)

Variable	Name	Meltshop number				Quality
		1	2	3	4	
Weight of scrap grades (kg)	W_S	22	25	91	11	OK
Weight of scrap baskets (kg)	W_B	1–3		1–5		OK
Weight of scrap layers in baskets (kg)	W_L	6–9				
		5–7	OK			
Volume of scrap in baskets (m^3)	V_B	1–3		1–5		Low accuracy in measurements
Total scrap weight (kg)	W_{Tot}	1	1	1	1	OK
Total scrap volume (m^3)	V_{Tot}	1		1		Low accuracy in measurements
Electrical energy consumption (kW h)	E	1	1	1	1	OK
Lance oxygen consumption (m^3n)	O_2L	1	1	1	1	OK
Lance coal consumption (kg)	C_L	1	1	1	1	Low accuracy in measurements
Burner oxygen consumption (m^3n)	O_2B	1	1			OK
Burner oil consumption (kg)	Oil	1	1			OK
Last steel temperature (°C)[a]	T_{EAF}	1	1	1	1	High degree of missing data
Maximum steel temperature (°C)	T_{MAX}			1		High degree of missing data
First temperature in ladle (°C)	T_{LF}	1		1		OK
Power-on time (min)	P_{ON}		1	1	1	OK
Power-off time (min)	P_{OFF}		1	1	1	Time before first power-on and after last power-off included
Tap-to-tap time (min)	TTT	1	1	1	1	OK
Slag former consumption (kg)	W_{SF}	1	2	3	1	Low accuracy in measurements
Steel chemical analysis (%)	A_X	22	19	20	17	In some cases too high round-off errors in database
Weight of liquid steel (kg)	W_L	1	1	1	1	Low accuracy in measurements

All variables are scalars, indices referring to individual grades, baskets, elements or measurements.
[a]In most cases the all-melted temperature.

also includes comments about data quality, which is discussed in Section 2.2.

Generally the weight and analysis of the liquid steel, the charge material mix and total consumption of coal, gas, oil, oxygen and electricity is available for every heat. The composition of the hot heel can be estimated as the composition of the previous heat.

However, the weight of the hot heel is generally not logged and neither is the weight of the slag heel. Slag samples are not taken regularly and are therefore not available for most heats. In case of stainless steelmaking the most common practice is to pour all the remaining slag in the end of the heat together with the steel into the ladle.

The heating profile (continuous measurements of electrical power/voltage/current, flow of coal/oil/gas/oxygen through lances and burners) is in some cases logged, but is often discarded after a few weeks and not always available.

Slag foaming conditions and lance/burner practice (position of lances and burners during operation) are difficult to monitor and generally not logged. Off gas analysis is possible, but uncommon on a regular basis in electric steelmaking shops.

The distribution of scrap in the baskets can be estimated by keeping track of the amounts and in which order different scrap grades are loaded (a "loading profile"). A possible approximation for the distribution of scrap in the furnace is to assume that the scrap will have the same distribution of layers as were loaded into the basket.

Filling degree for baskets is in many cases monitored and logged. If all baskets have the same volumes (or different but known volumes) it can be used as an indicator of scrap density.

For temperature measurements it is important to keep in mind that a temperature measurement is not very useful for statistical evaluation if it is not time-stamped (in terms of time or electrical energy input). Usually only one temperature sample is taken at a specified power-on time or kW h/ton scrap when all scrap is supposed to be melted.

If the time (or electrical energy) for the temperature sample is stored in the process logging system together with the temperature measurement itself then the final temperature can be estimated based on the remaining power-on time or electrical energy.

Thermal state of the furnace is not measured directly, but can be estimated from other process variables. The most important variable is time since last tapping. The position of roof (open/closed) and electrodes (up/down) during long power-off times will also affect the cooling rate, but the relationship is highly non-linear. Usually the thermal state of the furnace is characterised as either hot or cold and the breaking point is about 24 h of power-off, regardless of position of roof and electrodes.

2.2. Data quality

The quality of the logged variables may differ from plant to plant. Before including any variable in a statistical

analysis it is important to investigate the general accuracy of the values in the historical database. The presence of occasional errors is not important in this aspect and considered in Section 4.1.

There are three main issues to consider: measurement accuracy, logging accuracy and round-off errors. Engineers and technicians from the participating steel plants were asked to evaluate the logged values of the relevant process variables according to the three important issues. General comments on various types of process variables for EAFs are given in this section and specific comments on variables included in the study are given in Table 3.

For weights of charge materials, the accuracy is primarily dependent on the accuracy and calibration of the scales. But it is also important to ensure that the weights refer to the correct material. Since the operator usually enters the weights (or at least the material ID) manually it is up to him if he wants to report any deviations from the standard recipe. Caution is advised if the deviations from the scrap recipes are very small.

Slag formers and coke/coal added in the charge material mix or through the slag door are sometimes estimated as the weight of a number of fixed quantities (big bags, buckets, shuffles, etc.). The weights of those "units" are assumed to be constant and therefore the accuracy of the logged weights depends strongly on the consistency of the estimated weights of these "units".

For the weight of liquid steel the uncertainty of the measurements are due to problems establishing the tare weight of the ladle and the unknown amount of carry over slag from the EAF. The problems can be reduced if the ladle is weighed before tapping and after deslagging.

Measurements of process parameters like consumption of oxygen, coal, electricity, oil and natural gas are usually logged automatically. Usually the flow is monitored, and the consumption is calculated by integration over the whole heat. The accuracy of this type of logging is sensitive to the accuracy of the flow measurements which can vary a lot between different meltshops.

The flow of carbon is difficult to measure and therefore the consumption is usually estimated as the weight difference in the storage silo that was used for the particular heat before and after that heat is finished.

The accuracy of temperature measurements is good, but in some cases the measurements fail and the temperature is missing in the process logs (or replaced by an error code). In many cases the operator enters the temperature measurements by hand and similarly to the scrap weights it is up to the operator to choose which temperature to enter.

The error introduced by the analysis equipment for chemical composition of steel samples is generally very low compared to the uncertainty introduced by the inhomogenity of the liquid steel. The same can be argued for slag samples, except that the inhomogenity issues are much more serious for slag than steel.

3. Statistical methods

A comparison of different types of statistical prediction models for end conditions in EAFs have shown that many types of multivariate prediction models (MLR—multi linear regression or OLS—ordinary least squares, PCR—principal component regression, PLS—partial least squares or projection on latent structures) give similar prediction accuracy (Sandberg & Lennox, 2003; Sandberg, Lennox, & Undvall, 2004). Details about multivariate prediction methods may be found in the literature (Geladi & Kowalski, 1986; Wise & Gallagher, 1996).

In the study (Sandberg & Lennox, 2003; Sandberg et al., 2004) the three modelling techniques gave similar results in terms of R^2 (degree of explained variance) and root mean square error of estimation (RMSEE) on the training data, but cross validation showed much better performance on new data for PCR and PLS. The difference in prediction accuracy on new data for PCR and PLS were negligible, but the optimal number of latent variables (components) were about three times lower for PLS, thus PLS was selected as the preferred model-type for this project.

PLS is a projection method where both the cause variables ($\mathbf{X}$) and the response variables ($\mathbf{Y}$) are decomposed into scores ($\mathbf{T}$ and $\mathbf{U}$) and loadings ($\mathbf{P}$ and $\mathbf{Q}$) of latent variables according to

$$\mathbf{X} = \mathbf{T}\mathbf{P}^{\mathrm{T}} + \mathbf{E}, \tag{1}$$

$$\mathbf{Y} = \mathbf{U}\mathbf{Q}^{\mathrm{T}} + \mathbf{F}. \tag{2}$$

Eqs. (1) and (2) are called the "outer relations". Regression between $\mathbf{X}$ and $\mathbf{Y}$ is done on the latent variables $\mathbf{U}$ and $\mathbf{T}$ via the "inner relation":

$$\mathbf{U} = \mathbf{T}\mathbf{B} + \mathbf{H}. \tag{3}$$

Combining Eqs. (2) and (3) will give the "mixed relation":

$$\mathbf{Y} = \mathbf{T}\mathbf{B}\mathbf{Q}^{\mathrm{T}} + \mathbf{F}. \tag{4}$$

The goal of the decomposition of $\mathbf{X}$ and $\mathbf{Y}$ is to minimise $\mathbf{F}$ while keeping the t-scores (column vectors of $\mathbf{T}$) and u-scores (column vectors of $\mathbf{U}$) orthogonal. In PLS the decomposition can be done in several ways. The most common one is the NIPALS algorithm (Geladi & Kowalski, 1986; Wise & Gallagher, 1996). Regardless of which algorithm is used, calculation of an additional loading matrix for $\mathbf{X}$ called $\mathbf{W}$ is necessary. t-scores are then calculated with

$$\mathbf{T} = \mathbf{X}\mathbf{W}(\mathbf{P}^{\mathrm{T}}\mathbf{W})^{-1}. \tag{5}$$

Hence, regression coefficients ($\boldsymbol{\beta}$) that relate $\mathbf{Y}$ to $\mathbf{X}$ ($\mathbf{Y} = \boldsymbol{\beta}\mathbf{X} + \mathbf{F}$) can be obtained by combining Eqs. (4) and

(5), as shown in the following equation:

$$\boldsymbol{\beta} = \mathbf{W}(\mathbf{P}^{\mathrm{T}}\mathbf{W})^{-1}\mathbf{B}\mathbf{Q}^{\mathrm{T}}. \quad (6)$$

4. Data pre-processing

4.1. Identification of outliers/bad data

Upper and lower limits for each variable described in Table 3 have been set individually for each participating meltshop. The limits are based on physical limitations of the process, and represent the maximum and minimum values that these variables should have under normal process conditions as well as start-up and shutdown heats. Any values outside these limits were considered to be measurement errors, typing errors or corrupt database entries.

These limits were set carefully in co-operation with process engineers at the meltshops. If any limit is exceeded the value of that particular variable is deleted and treated as a missing value and estimated as described in Section 4.2.

4.2. Estimations of missing values

Many multivariate data analysis projects rely on automated routines for the estimation of missing data. Some common methods for estimation of missing values are described by Nelson, Taylor, and MacGregor (1996). These methods work well if the degree of missing data is moderate (not more than 20% for any variable or observation) and randomly scattered through the dataset.

Unfortunately the missing data from electric steelmaking is not randomly scattered. When the total scrap weight is missing or out of specified limits as described in Section 4.1, the portion of total scrap load for individual scrap grades and specific consumption of other materials cannot be calculated as described in Section 4.3 and have to be considered missing.

Missing process data usually results from a malfunction of the logging system and therefore there are heats or blocks of heats where all data is missing. The same is true for chemical analysis, except that such data is handled by a separate logging system which tends to be more reliable than the normal process logging.

Due to these facts, only a small portion of the missing data can be estimated automatically. Therefore, a significant part of the heats (5–20%, sometimes even more depending on the capabilities of the logging systems) have to be discarded.

A simple alternative is to estimate the missing values as the mean values for the actual steel-grade. This is a dangerous strategy and may introduce large errors in the dataset. It is only recommended if the mean values over a longer period are to be calculated, as for prediction of yield for a series' of heats (described in Section 4.3).

4.3. Calculation of secondary variables

The data in Table 3 is not in optimal form for fitting of regression models. Firstly, the response variables specific consumption of electrical energy and metallic yield have to be calculated. Secondly, all variables to be predicted (chemical analysis of the liquid steel, specific electrical energy consumption, and metallic yield) should have higher correlation to the portion of total scrap load and specific consumption of materials than to the measured weights available in the databases. Listings of secondary variables are given in Table 4 together with calculation formulas for

Table 4
Calculation of secondary variables and their significance to end conditions numbered as in Table 2

Variable	Name	Formula	Significance*		
			1	2	3
Scrap grade fraction of total scrap load	F_S	W_S/W_{Tot}	H**	L**	H**
Scrap grade fraction of 10 ton scrap layers (bottom of furnace)	F_{SLB}	[a]	—	L**	—
Scrap grade fraction of 10 ton scrap layers (bottom of furnace)	F_{SLT}	[a]	—	L**	—
Basket weight fraction of total scrap load	F_B	W_B/W_{Tot}	L	L	L
Scrap density in basket (kg/m^3)	D_B	W_B/V_B	L	L	L
Total scrap density (kg/m^3)	D_{Tot}	W_{Tot}/V_{Tot}	L	L	L
Specific electrical energy consumption (kW h/ton)	E_S	E/W_{Tot}	L	—	L
Specific Lance oxygen consumption (m^{3}n/ton)	O_2L_S	O_2L/W_{Tot}	L	H	H
Specific Lance coal consumption (kg/ton)	CL_S	C_L/W_{Tot}	L	H	L
Specific burner oxygen consumption (m^{3}n/ton)	O_2B_S	O_2B/W_{Tot}	L	L	L
Specific burner oil consumption (kg/ton)	Oil_S	Oil/W_{Tot}	L	L	L
Specific slag former consumption (kg/ton)	W_{SFS}	W_{SF}/W_{Tot}	L	H	H
Yield	Y	W_L/W_{Tot}	L	—	—
Hot heel chemical analysis (%)	HH_X	Previous A_X	L	—	—

All variables are scalars, indices referring to individual grades, baskets, elements or measurements.
*H—high significance, L—low significance, '—' not included in model.
**Overall significance for group of variables. Individual scrap grades have highly variant significance.
[a]Calculations described in Section 4.3.

each secondary variable, except for Scrap grade fraction of 10 ton scrap layers in baskets which are calculated as described in this section.

At first, all baskets are divided into a number of 10 ton layers in two different ways. Layer 1b starts at the bottom of the basket and layer 1t starts at the top. The weights of each scrap grade (or other material) in each 10 ton scrap layer is calculated based on the loading sequence of the layers found in the historical databases (the loading profile). Each scrap grade weight in each layer is then divided by the total weight of the scrap layer (10 tons for all layers except the last that can be between 0 and 10 ton).

Earlier tests have shown that prediction results for yield and energy consumption on individual heats are poor (Sandberg et al., 2004). This can be attributed to disturbances from the hot heel, the residue left in the furnace after tapping. The effect of the hot heel can be removed if the secondary variables in Table 4 are calculated as averages for a series of heats between emptying of the furnace rather than individual heats. However, in many meltshops the periods between emptying of the furnace are very long. In such cases a moving average over the latest heats are used instead.

It should be pointed out that none of these procedures will increase the prediction accuracy for individual heats. The heat-series approach is used to get general estimates of how the process-settings and raw materials affect energy consumption and yield, not for increased prediction accuracy.

4.4. Variable transformations

The standard practices in PLS-modelling are to mean-centre and scale all variables to unit-variance (UV). However, in this study the variables have been divided into blocks that are scaled separately. Once the scaling of the variables in each block is done, the blocks are scaled to equal total variance to give each block equal opportunity to influence the prediction results. The practice is called block scaling, and the blocks are described in Table 5.

The reason for not using standard UV scaling for all variables is that the calculation of secondary variables already divided the variables into natural blocks with appropriate internal scaling. It is, for example, "fair" to give scrap grades with large variance in "scrap grade fraction of total scrap load" higher chance of influencing the prediction result than the scrap grades with low variance.

The variables in the energy consumption block are not measured in the same units, and therefore this block is UV-scaled. The chemical composition block is also UV-scaled, although all variables have the same units. The reason for this is that the elements should be considered equally important, regardless of the variance.

Tests with logarithmic transformations of the chemical analysis have been made and showed that such transformations do not provide any benefits in this application (Sandberg & Lennox, 2003; Sandberg et al., 2004).

Table 5
Blocks of variables

Variable block	Variables[a]	Scaling type
Scrap weights	F_S (e.g. shredded, thinplate, heavy)	Mean-centre
Scrap density	D_B, D_{Tot}	Mean-centre
Scrap distribution in baskets	F_{SLB}, F_{SLT}	Mean-centre
Slag formers	W_{SFS} (e.g. lime, dolomite, quartz)	Mean-centre
Energy consumption	E_S, $O2L_S$, CL_S, $O2B_S$, Oil_S	Mean-centre Unit variance
Temperature	T_{EAF}, T_{MAX}, T_{LF}	Mean-centre
Time	P_{ON}, P_{OFF}, TTT	Mean-centre
Hot heel composition	HH_X	Mean-centre Unit variance

[a]As described in Tables 3 and 4.

4.5. Model development

As a first step, prediction models for chemical composition of the liquid steel, electrical energy consumption and yield were fitted on all available heats in the datasets. The software used in the fitting was Matlab 6.5 with PLS toolbox 2.0. The datasets were then divided into smaller subsets (continuous blocks) and separate prediction models were fitted on each subset. Each model was then validated on the following block of data and also the full dataset.

The process of dividing the data into smaller subsets was then continued until the validation showed significant signs of overfitting. The criterion for overfitting was that the prediction accuracy of the subset model should not be significantly less than the accuracy of the original model ($R2$ for validation data less than 95% of $R2$ for training data), developed using all the data, when applied to data from the following month. The number of required latent variables (components) differs for each plant and model, but generally 5–10 components are needed for prediction of steel chemistry and 2–4 components for prediction of yield and specific energy consumption.

The validation procedure showed that data from at least 500 heats (about 2 months of production) is needed to create a model that has almost equal reliability (in terms of $R2$ on new data) to the model fitted on all the data. Considering this, the PLS models can be updated on a bi-monthly basis. Hence the estimations made by the models would never be based on heats that are older than 3 months. However, scrap quality is likely to have some variation (with smaller amplitude) within 2 months that can be monitored as described in Section 7.2.

5. Prediction results

The prediction results presented in the section refer to models fitted on all available heats for each meltshop. RMSEE and degree of explained variance (R^2) have been calculated for each predicted variable and are displayed together with the mean and standard deviation of the actually measured variables in Tables 6 and 7. In addition to the elements in Tables 6 and 7, predictions of Al, B, Ca, N, Nb, Pb, Sb, Si, Ta, Ti, V, W were also made. However, both the variance and the degree of explained variance (R^2) for these elements were low.

The number of decimals for analysis of elements in Tables 6 and 7 has been set to the same precision that can be found in the historical databases at the meltshops. In the case of calculated variables (like specific energy consumption and yield) the precision has been calculated based on the precision of included original variables.

Generally R^2 for each element is similar for the different meltshops. However, R^2 may differ considerably between plants for elements that are used as alloys in the final product. R^2 is very high if alloy elements or ferro-alloys are part of the charge material mix (like Cr, Ni and Mo at Sandvik Materials Technology). The difference in R^2 is

Table 6
RMSEE and mean values for predicted variables

	Ovako steel		Fundia special bar		Sandvik materials technology		Fundia armering	
	RMSEE	Mean	RMSEE	Mean	RMSEE	Mean	RMSEE	Mean
As	0.001	0.008	0.001	0.010				
C	0.13	0.23	0.029	0.081	0.13	1.16	0.028	0.111
Co	0.002	0.013			0.01	0.06		
Cr	0.08	0.28	0.02	0.07	0.71	15.74	0.027	0.118
Cu	0.029	0.187	0.03	0.24	0.03	0.20	0.041	0.359
Mn	0.04	0.17	0.03	0.07	0.16	0.85	0.027	0.104
Mo	0.02	0.04	0.01	0.03	0.10	1.05	0.005	0.026
Ni	0.06	0.16	0.02	0.13	0.55	7.42	0.025	0.168
P	0.003	0.008	0.003	0.011	0.002	0.021	0.005	0.018
S	0.004	0.025	0.006	0.037	0.003	0.013	0.005	0.043
Sn	0.002	0.009	0.003	0.017			0.005	0.017
Yield[a]	1.0	90.6	0.4	90.6				
kW h/ton (liquid)[a]	9	479	6	431				
kW h (scrap)	19	439	17	390				

[a]Mean for approximately the latest 20 heats.

Table 7
R^2 and standard deviation for predicted variables

	Ovako steel		Fundia special bar		Sandvik materials technology		Fundia armering	
	R^2 (%)	Std.dev	R^2 (%)	Std.dev	R^2 (%)	Std.dev	R^2 (%)	Std.dev
As	56	0.002	43	0.002				
C	33	0.16	28	0.034	93	0.47	10	0.030
Co	8	0.002			85	0.03		
Cr	47	0.11	35	0.03	99	6.63	23	0.031
Cu	50	0.042	47	0.04	94	0.13	50	0.058
Mn	31	0.05	26	0.03	97	0.94	15	0.029
Mo	53	0.02	34	0.01	99	1.10	28	0.006
Ni	62	0.10	57	0.03	99	6.02	12	0.027
P	26	0.004	30	0.004	93	0.008	36	0.006
S	40	0.006	45	0.008	47	0.005	47	0.006
Sn	41	0.002	70	0.006			32	0.006
Yield[a]	52	1.5	72	0.8				
kW h/ton (Liquid)[a]	50	12	46	8				
kW h/ (Scrap)	37	24	13	18				

[a]Mean for approximately the latest 20 heats.

smaller but still noticeable if the alloy elements are only present in the alloyed internal scrap grades (like Cr, Ni and Mo at Ovako Steel).

Another explanation for the high R^2's at Sandvik is the wide range of chemical composition on the final products. This wide range also force the models to be calibrated for a large region, making the prediction accuracy for each sub region (groups of similar steel grades) less than what could be expected if sub models for each group of steel grades were developed. In fact, for most of the alloy elements the mean prediction error is higher at Sandvik than at the other meltshops.

For elements that are not used as alloys (like As, P, S, Sn) the mean prediction errors are similar for all meltshops, even if the R^2 values are quite different. This indicates that the variations in scrap quality (in terms of impurity elements) are similar for all investigated meltshops.

6. Estimation of scrap properties

Scrap properties are estimated by allowing the prediction models to calculate the chemical composition, electrical energy consumption and yield for hypothetical "pure" heats. A pure heat is a heat with scrap mix containing 100% of the scrap grade whose properties are to be estimated, and 0% of all other scrap grades. All process parameters are set to their mean values.

An example of the estimated Cu-content for various scrap grades at Ovako Steel AB is shown in Fig. 1. Confidence limits (95%) have been calculated based on an Eq. (7) suggested by Nomikos and MacGregor (1995). Scrap management personnel at Ovako Steel have found these estimations to concur rather well with their own estimations which are very rough and based on specifications from scrap suppliers and experiences of scrap management personnel

$$y = \hat{y} \pm t_{N-R-1,\alpha/2}\sqrt{\mathrm{RMSEE}_y}\sqrt{(1+\mathbf{t}(\mathbf{T}^{\mathrm{T}}\mathbf{T})^{-1}\mathbf{t}^{\mathrm{T}})}. \quad (7)$$

In Eq. (7) $\mathbf{t}$ is the t-score vector for the pure heat simulation, $\mathbf{T}$ is the t-score matrix for the data (N heats) used to fit the PLS-model with R components (latent variables) and $t_{N-R-1,\alpha/2}$ is the critical value of the studentised variable with $(N-1-R)$ degrees of freedom and confidence level $\alpha/2$.

For the case presented in Fig. 1 the term $\mathbf{t}(\mathbf{T}^{\mathrm{T}}\mathbf{T})^{-1}\mathbf{t}^{\mathrm{T}}$ is negligible compared to 1 for pure heat simulation of all scrap grades, meaning that confidence limits will be the same for all scrap grades. However, Eq. (7) does not consider the difference in variation of properties within a scrap grade. Grades with high variation should have larger confidence limits, and vice versa. Large variation in material properties should normally be reflected in large confidence limits in the estimation of the regression coefficients, but for PLS-regression confidence limits cannot be calculated for individual variables. This is explained mathematically by Nomikos and MacGregor (1995).

Confidence limits aside, there is a potential problem with pure heat simulations which is that the models are forced to work outside of their calibration region since there are very few "pure" heats in the data used to develop the statistical models. This problem occurs for all types of statistical models fitted on normal production data. In the case of multivariate projection models (such as PLS models), it is possible to analyse the effect of this deviation from normal conditions by looking at the estimates of the X-variables ($\hat{\mathbf{X}} = \mathbf{T}\mathbf{P}^{\mathrm{T}}$, derived from Eq. (1)).

If the estimated value for fraction of total scrap load for the investigated scrap grade is close to 100% while the values for other scrap grades are close to 0% the prediction can be trusted to represent the chemical analysis of a pure heat. In multivariate prediction terminology, this would be referred to as a low square prediction error in X-space (SPE_X).

If SPE_X is high, the combination of settings in X-variables (scrap mix composition) is outside of the model calibration region, and the estimate made by the model must be considered to be unreliable. The occurrence

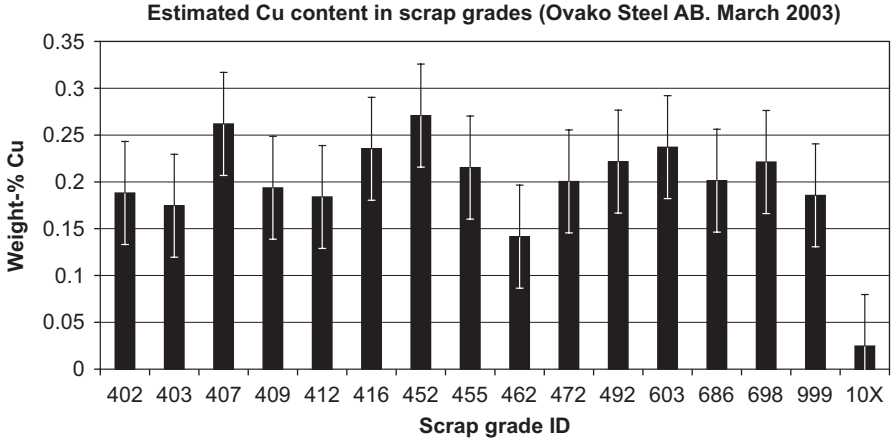

Fig. 1. Estimated Cu content with 95% confidence limits for some scrap grades at Ovako Steel AB.

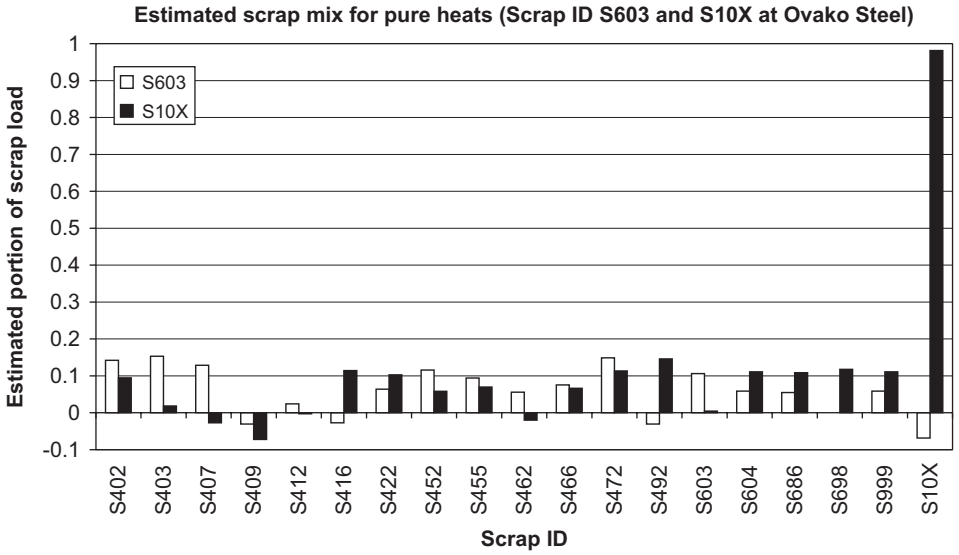

Fig. 2. Estimated scrap mix for pure heat simulations for scrap grade S603 (white bars) and S10X (black bars) at Ovako Steel.

of pure heats with high SPE_X does not have any system implications; it only means that for this particular combination of scrap grades the prediction made by the PLS model cannot be trusted.

Examples of estimated scrap mix for pure heat simulations with two scrap grades at Ovako Steel (S10X and S603) are given in Fig. 2. Ideally all bars should be 0 except the one being tested in the pure heat simulation that should be 1 (100% of total scrap load).

From Fig. 2 it is clear that the estimated properties of scrap grade S603 would be unreliable since the estimated scrap load portion of S603 in the S603 pure heat simulation (the white bars) is low and not significantly different than any other estimated scrap load portion.

However, for scrap grade S10X the situation is much better. The pure heat simulation of this scrap grade (the black bars) gives an estimated portion of total scrap load for S10X close to 1 and low estimations of all other scrap grades. In this case it is very likely that the scrap properties estimated by pure heat simulation are correct.

The reason why this technique does not work for certain scrap grades at certain steel plants is that in those cases there is no significant correlation between that particular scrap grade and steel chemistry, or between that scrap grade and any other scrap grade used at the steel plant. The reason for lack of correlation has to be determined on a case-by-case basis, but this problem generally occurs for scrap grades that are rarely used, scrap grades that are used in similar amount in all heats and scrap grades that are used in small amounts.

The situation could be improved if scrap mix recipes were modified to include experimental scrap mixes. The experimental scrap mixes would be designed to solve a specific statistical problem, such as too little variance in specific scrap grades or too much or too little co-variation with other scrap grades. In multivariate data analysis terms this would be equivalent to increasing the variation range of latent variables (t-scores) and introducing new latent variables (components).

7. Scrap management applications

In this section it is described how the prediction models can be used for development of industrial scrap management applications. In all the proposed applications described in this section it is assumed that the prediction models are continuously updated (refitted on at least 500 new heats) every 2 months to compensate for the dynamic variations in scrap properties.

Pilot installations of most proposed applications (on-line) have been made at Ovako Steel in Hofors (Sweden) and are currently being evaluated by operators and engineers. The applications were developed at MEFOS and sub-routines from the software SimcaQP were included. This required the previously developed Matlab PLS Toolbox models to be refitted in SimcaP. The migration from Matlab to Simca was done without any change in model parameters, i.e. loadings (**P, W, Q**) and regression coefficients (**B, β**) were exactly the same.

7.1. Preliminary prediction of steel analysis

The objective for this application is to give the operator information about how to load the second and subsequent baskets based on the composition of the previously loaded baskets.

A preliminary prediction of steel analysis is made as soon as actual values of loaded scrap weights in the first basket to be melted in the heat are available in the process database (usually directly after the last layer has been loaded). Missing data (process settings and scrap weight in subsequent baskets) is estimated as average values. This

gives a prediction of how the steel analysis would be if the heat would proceed normally from here on.

The preliminary prediction of steel analysis is compared with the quality limits for the current steel-grade. Under the assumption that the prediction errors are normally distributed the risk ($P(y>y_{\max})$) of breaking any analysis limits ($y_{\max}$) can be calculated using the student t-distribution function $f(x)$ with 499 degrees of freedom, see Eq. (8). If the risk exceeds a limit value a warning is issued to the operator.

$$P(y>y_{\max}) = F(x,r) = F\left(\frac{\hat{y}-y_{\max}}{\mathrm{RMSEE}_y}, 499\right). \quad (8)$$

Prediction errors are in case of alloy elements fairly normally distributed. For impurity elements, the distribution of residuals has a slightly heavier right tail (positive residuals) than left tail (negative residuals) compared to normal distribution. This is caused by the fact that when levels of impurity elements are very high, the reason is usually a few pieces of scrap that have completely different chemical composition (foreign objects like pieces of copper or tin) than the rest of the pieces in the lot it was taken from. The implication of this is slightly overestimated levels of impurity elements, except in the extreme cases when foreign objects have been melted.

If a warning is issued the operator can make adjustments to the standard scrap mix recipe in the following baskets of the heat to compensate for irregular loading in previous baskets. The method can also be used by the scrap recipe management personnel to try new recipes for different steel-grades and see how it will affect the steel analysis.

If the proposed scrap recipes are outside of the models calibration region (abnormal co-variance) a warning is issued to the operator informing them that the calculated steel analysis may be inaccurate.

The effectiveness of this application depends on the prediction accuracy of each element that is monitored. Higher prediction accuracy will give higher selectivity (less percentage of false alarms). The higher the selectivity the lower the warning limit for analysis failure can be set without risking too many false alarms.

The warning limit for risk of analysis failure must be estimated individually for each element at each meltshop. One way of doing this is to try different risk limits and compare the number of false and proper alarms during a period of time. The percentage of false alarms should not be higher than 50% for any element, and false alarms should not occur for more than 5% of the heats (with normal co-variation).

Tests on data from Fundia Special Bar (3800 heats) have shown that a warning limit at 60% risk of analysis failure for Cu and 40% for Sn is appropriate, see Fig. 3. The risk limit should be the lowest value where the number of false alarms (triangular markers) is lower than the number of proper alarms (square markers).

Another factor influencing the number of alarms from this application is the safety margins for chemical composition. If the final chemical composition always is far from the limits, the number of alarms from this application would obviously be quite low. Also, the percentage of false alarms would increase, since the few analysis failures that do occur would be due to melting of extremely deviant pieces of scrap (like large copper blocks and batteries) that can not be detected by statistical models.

7.2. Monitoring of scrap quality

The objective of this application is to give the scrap manager the possibility to follow trends in scrap quality. Deviations can be detected by monitoring the prediction

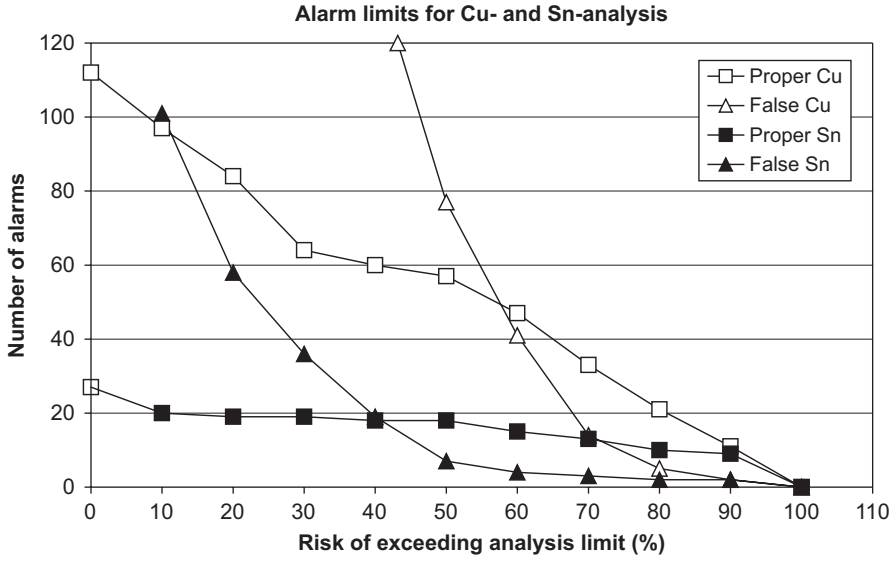

Fig. 3. False and proper alarms for high Cu- and Sn-content given by the scrap management application for primary prediction of steel analysis.

errors. After each heat is finished several statistical tests are performed on the residuals of the previous 20 heats to determine if the scrap quality has changed since the statistical prediction models were fitted. 20 heats were found to be an appropriate number in order to minimise false alarms while keeping the tests selective (fewer number of heats–more false alarms).

In all tests it is assumed that the prediction errors are normally distributed ($\mu = 0$, $\sigma = \text{RMSEE}$). As discussed in Section 7.1 the assumption of normality is fairly accurate in most cases. The tests that are conducted are specifically designed for this application and any resemblances to previously published statistical tests are coincidental. The tests are now discussed.

7.2.1. Mean-value test (M-test)

A test to determine if the mean value of the scrap property has changed. If the M-test is positive (i.e. the mean prediction error for variable y for the 20 latest heats, $\bar{y}$, is different from zero) the mean content of the element that caused the alarm has changed in at least one of the scrap grades that were used in the period. The test is conducted on the test variable T which is calculated by

$$T = \frac{\bar{X}}{\text{RMSEE}}\sqrt{n}, \tag{9}$$

where $n = 20$ (the number of heats). T will follow the normed normal distribution $N(0,1)$ and $\bar{X}$ is considered larger than 0 if $|T| > x_{1-\alpha/2}$ where α is the significance level. By checking whether T is negative or positive it can be determined if the mean content has increased or decreased.

Unfortunately, this test does not reveal which of the scrap grades have changed. This has to be determined by manual inspection of the scrap lots and the loading protocols from the relevant period. Until the cause of the deviation has been determined, it is recommended that cleaner scrap grades are used more frequently.

7.2.2. Variance test (S-test)

A test to determine if the variance of the scrap property has changed. If the S-test is positive, the internal variation in the scrap property for at least one of the scrap grades has changed. Like for the M-test, the cause of the deviation must be investigated manually and more clean scrap grades should be used until the problem is corrected. The S-test is performed on the test variable T calculated by

$$T = \frac{\text{RMSEP}^2}{\text{RMSEE}^2}(n-1), \tag{10}$$

where n is the number of heats, RMSEP is the root mean square prediction error for the n heats and RMSEE is the root mean square error of estimation for the prediction model. T will follow the χ^2-distribution and RMSEP is different from RMSEE if $T < x_{\alpha/2}$ or $T > x_{1-\alpha/2}$, where α is the significance level.

7.2.3. Co-variance test (D-test)

A test to determine if the "normal operation mode" of the furnace has changed. This includes both the scrap loading and the process settings. The D-test is performed on a specific prediction model. In multivariate prediction terminology the D-test is equivalent to a combined SPE_X and T^2 test. Test variables and limits for critical regions for SPEx and T^2 are described by (Wise & Gallagher, 1996). Repeated alarms indicate a stable change of process conditions. All scrap management applications based on prediction models should be turned off until the problem is corrected or new prediction models are fitted on data collected after the change.

The most common reason for alarms for change in scrap quality is that scrap is taken from the bottom of a pile at the scrap yard. It is commonly known fact that the scrap quality is lower for scrap at the bottom of piles. This is usually compensated for by using more "clean" scrap when finishing off the last part of a pile. The prediction error will still be higher than normal though and the effect of the decreased scrap quality can be estimated.

The effectiveness of all the statistical tests depends on the accuracy of the prediction models. For elements with low degree of explained variance, the predictions will always be close to the mean value, regardless of the scrap mix and process settings.

This means that the selectivity of the M-test and the S-test will decrease. Alarms for changed levels (or variance) of elements in scrap would be given every time the mean (or standard deviation) of the investigated element is significantly different from the reference period, regardless of which scrap grades are used during the investigated period.

7.3. Monitoring of scrap properties

By logging regression coefficients or estimated scrap properties for expired models (older than 2 months) variations in scrap properties for long periods of time can be monitored. The scrap properties for each month are estimated by pure heat simulations with the model fitted on data from the previous 2 months of production. An example of this is given in Fig. 4. 95% confidence limits are calculated with Eq. (7).

The validity of the estimated scrap properties depend on the prediction accuracy of the statistical models but also on the variance and co-variance of the scrap grade weights. The properties for scrap grades that were rarely used (or used in almost constant amount from heat to heat) in the training data are uncertain and may vary significantly from model to model.

If there are strong correlations between certain scrap grades PLS models will have difficulties in distinguishing between their properties. For example, if there is a linear relationship between scrap grade Y and X ($Y = a + bX$) their estimated properties will be similar even though the actual properties can be very different.

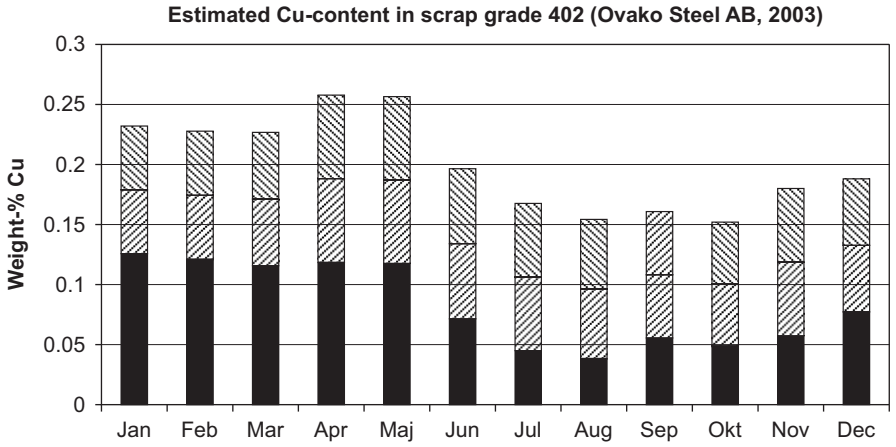

Fig. 4. Variation in estimated copper content in scrap grade 402 during 2003 at Ovako Steel AB. The dashed areas represent 95% confidence limits.

In this aspect, a correlation is considered strong if it is significant and there are no other significant correlations between grades X or Y to any other scrap grade. Significance for correlations can be measured in terms of correlation coefficients (R), but no formal limits for R have been set in this project. As discussed in Section 6, the situation could be improved with the use of test melts. In this case, the test melts would be designed to reduce the correlation between X and Y and introducing correlations for X and Y to other scrap grades.

7.4. Optimisation of scrap mix recipes

The estimated scrap properties may also be used to calculate "value in use" for each scrap grade. If the content of alloy and impurity elements, yield coefficient and specific energy consumption for a scrap grade are known, its real value considering price, quality and melting costs can be calculated. If the prediction models are continuously updated a new "value in use" may be calculated every 2 months. Scrap mix recipes could then be dynamic in the sense that they may be revised every 2 months. This would be an improvement since scrap recipes today are almost never revised.

The safety margins in scrap recipes depend on the mean prediction errors for the elements. Dynamic scrap recipes will reduce the prediction errors and the safety margins, thereby increasing the blending options and allow for increased use of "dirty" scrap grades.

8. Conclusions

Current results show that PLS prediction models for chemical analysis based on normal process measurements and charge material weights can explain 40–70% of the variation in content of tramp elements (Cu, Sn, As) and 70% to almost 100% of the variation in content of alloy elements (Cr, Ni, Mo). Electrical energy consumption, yield, content of oxidisable elements (C, Si, Mn) and impurity elements (P, S) are more difficult to predict (degree of explained variance below 30%).

However, degree of explained variance is not the only prediction quality measurement to consider. RMSEE is of equal or even greater importance, since it sets the limits for how well the scrap mix can be optimised to meet certain quality restrictions regarding chemical composition for the liquid steel.

Estimations of levels of tramp elements and alloy elements in scrap grades and ferro-alloys can be made for every 500 heats (about 2 months), if the number of commonly used materials in the charge material mix does not exceed 25. This enables narrower safety margins on the steel analysis, fewer melts out of analysis limits and possibilities to use more cheap scrap and long-term quality monitoring of scrap grades.

Short-term deviations (within 2 months or 500 heats) in the general scrap quality can be detected by looking at SPC-charts for prediction errors. Statistical tests may give hints to the source of the deviation (responsible scrap grades), but visual inspection of the scrap yard or spot checks of the scrap lots are needed to confirm the suspicions.

Regarding prediction of yield and energy consumption, no reliable prediction models could be developed for on-line prediction of individual melts. The most probable reason for this is the variations in hot heel weight and absence of dynamical process data (continuous measurements of oxygen- and gas-flow, temperature and electrical parameters).

The moving average or melt series approaches described above have reduced the interference by the hot heel so that estimations of average values for specific energy consumption and yield coefficients for individual scrap-types could be calculated.

The accuracy of all predictions (especially prediction of energy consumption, yield, oxidisable elements and refinable elements) could increase if dynamic process data were included in the models (this model type is called PLS-Batch).

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