

Refractory Condition Monitoring and Lifetime Prognosis for RH Degasser

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INTRODUCTION

In the steelmaking industry, there is a demand for process optimization and predictability of the refractory based on information recorded during the production process [1–3]. The amount of recorded data has recently increased dramatically and machine learning and artificial intelligence (AI) techniques are exploited to filter out useful information for modeling the production process and the most influential parameters [4–6]. In this paper, the aim is to predict the refractory life-time based on data acquired during production. In total, 110 process parameters were preselected to build a statistical model to determine the influence on refractory wear by using machine learning techniques.

RH degassers are widely used for steel refining in secondary steelmaking, especially in integrated steel mills. In addition to the main tasks, i.e. decarburization or reduction of nitrogen and hydrogen, the RH degasser also has the ability for alloying, heating, and deoxidizing. Also, the steel cleanliness is improved due to the steel recirculation process. There are a significant number of references on the use of the RH degasser in steelmaking available [7–17].

The RH degasser consists in principle, of a refractory lined vessel with two snorkels at the bottom and the gas off-take on the top followed by a vacuum pump system (Figure 1).

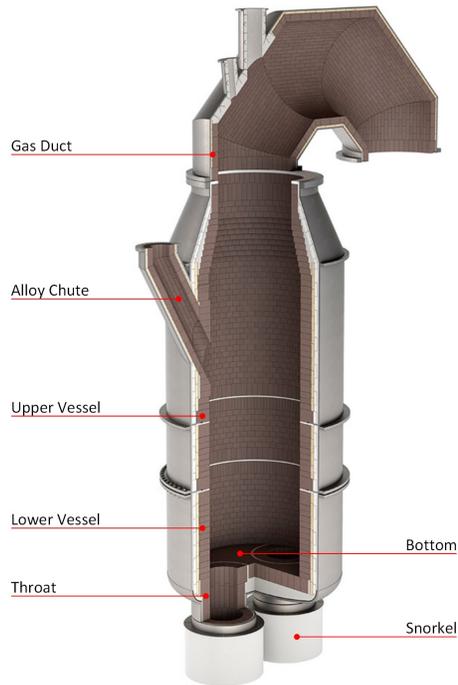


Figure 1: Schematic view of a RH degasser [16,18].

Specifically, either by lifting the ladle or by lowering the RH vessel the snorkels are immersed into the melt. By evacuating the vessel, the steel rises into both snorkels. One of the snorkels is equipped with gas injection pipes where predominately argon is introduced. This so-called lift gas creates the steel circulation through the vessel back into the ladle via the outlet snorkel. This continuous steel circulation is influenced by several parameters e.g. lift gas rate and inner diameter. The principle of a RH treatment is shown in Figure 2.

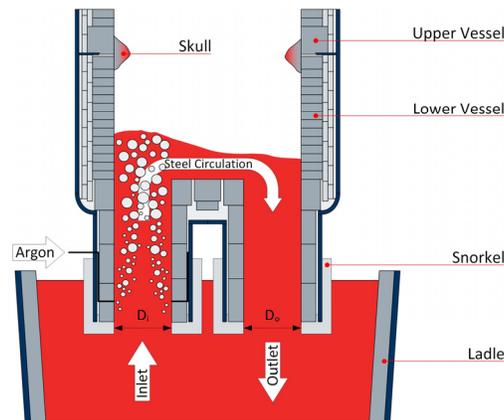


Figure 2: Schematic cross section during a RH treatment.

The treatment time is defined as duration between submersion (dip in) and removal (dip out) of the snorkels into the melt and varies from 15–45 minutes depending on the steel grade. The following operation modes of the RH degasser are common in addition to steel refining: vessel pre-heating, holding the RH vessel under hot condition, vessel deskulling with either an oxygen or natural gas burner, snorkel cleaning, and gunning during idle time.

Currently, the lifetime prognosis for the refractories is based on operational experience and on the close cooperation with the in-house refractory department and refractory supplier. This situation runs the risk for unplanned shutdowns with uncoordinated sequence aborts, which leads to low productivity at higher costs.

The demand for RH treated steel grades is very high, which increases the pressure for high plant availability and therefore high refractory lifetime. The high refractory lifetime is especially important for the operation with a single type RH degasser,

since a vessel change takes at least several hours' time. To gain high and predictable refractory lifetimes, the aim was to determine the main influencing factors for refractory wear and build a statistical model for predicting the refractory condition. This enables the maintenance of the RH vessel including its idle times to be planned and avoids unscheduled shut downs due to red puncture. As a consequence, the productivity of the RH degasser can be optimized and an improvement achieved in order to organize the operation and interaction in the steel plant. These arguments were the motivation for voestalpine Linz to initialize this project on one of the 4 RH degassers.

In particular, 110 process parameters were used to build a statistical prediction model for the refractory lifetime and refractory wear. These parameters were recorded and stored at the level 2 (L2) for each RH degasser treatment campaigns. A campaign ends with a relining service of the lower part of the vessel together with the snorkels, i.e. replacing bricks and mounting prefabricated snorkels. At the end of the campaign, the remaining thickness of the lining was measured and protocolled. This information was used in the prediction model, in addition to the process data.

DATA PROCESSING

The data processing pipeline for predicting the refractory lining wear is shown in Figure 3. It builds on methods from machine learning and artificial intelligence to determine the conditions of the lining based on process parameters. The aim is to predict the wear and the lifetime of the lining. Furthermore, the most influential production parameters on the wear of the lining can be determined. Additionally, understanding the influence and correlation of process parameters will help to identify causes for unwanted process anomalies and incidents.

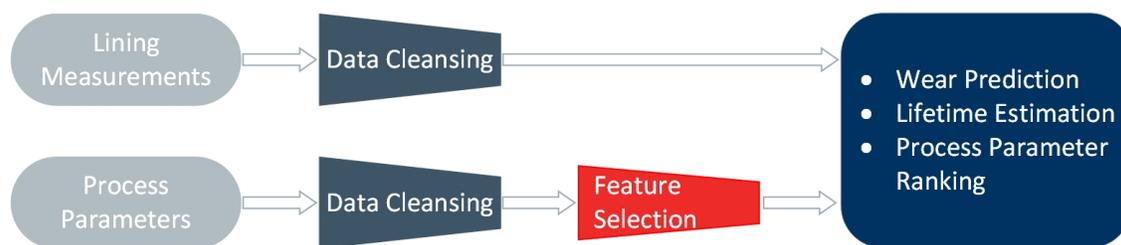


Figure 3: Data processing pipeline for wear prediction.

Data Sources

Two main data sources are available: Process data and brick thickness measurements.

Lining Measurements

At the end of a production campaign, the lining of the RH degasser was measured manually with a ruler (Figure 4 (a, b)). In particular, the remaining lining thickness was determined. Furthermore, the data provides the initial lining thickness and lining repair information. The layer thickness measurement was carried out as follows, the lower part of the degasser's vessel is divided into eight sectors of 45° as shown in Figure 4(c).

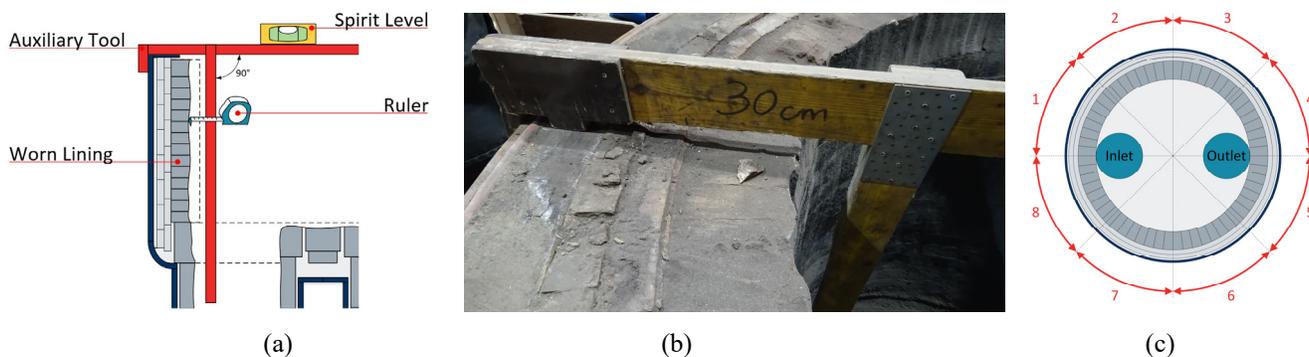


Figure 4: (a) Sketch of the measurement, (b) measurement of remaining brick length, and (c) measurement sectors of the lower part of the vessel.

The minimal thickness was measured for each sector and brick layer, shown in Figure 4 (c). In total, one measurement record contains measurements of 20 brick layers and 8 sectors per brick layer. Furthermore, the minimal thickness of the lining for the bottom of the degasser was provided. These types of measurements are prone to human failure, leading to missing or incorrect measurement values. To avoid this, we introduced a data cleansing stage to remove outliers.

Several prediction models were built for areas with large wear rate. Hence, the following so-called hot spots (HS) were defined: (1) wall inlet (section 1 and 8, layer 1 to 7); (2) wall outlet (section 4 and 5, layer 1 to 7); (3) vessel bottom (section 1 to 8, layer 1). In the remainder of the paper, the reported results are for the HS wall outlet as the model for the remaining HSs is identical, only the thickness measurements were different. The average wear rate per treatment of the vessel lining and the HS areas 1, 2, and 3 are shown in Figure 5.

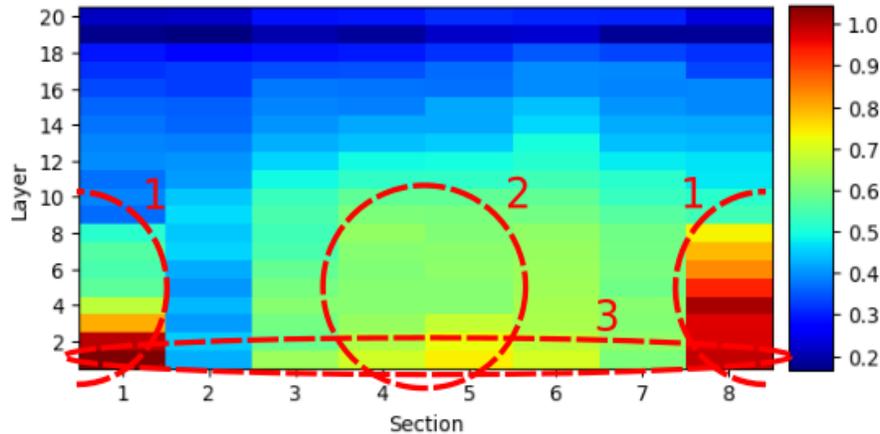


Figure 5: Average wear per treatment in [mm] for the lower section of the vessel. The marked hotspots (HSs) are wall inlet (1), wall outlet (2) and bottom (3).

Process data

During each treatment, 110 process parameters were preselected and recorded such as temperatures, consumptions, durations, chemical additions etc. Similar as for the lining measurements, these process parameters require preprocessing and data cleansing. Furthermore, we supplement these process parameters with additional features derived from the process parameters. The most important process parameters for wear prediction are determined automatically through a feature selection stage as discussed below.

Preprocessing and Cleansing

A regression model could not be applied directly to data containing missing features. Furthermore, data samples which extremely deviate from the usual values, often referred to as *outliers*, could perturb model training and therefore impair prediction accuracy. Hence, data preprocessing and cleansing is necessary in many applications. This is especially important in case of small data sets, where discarding incomplete samples or samples containing anomalies results in the loss of a significant portion of the available data.

In general, an outlier is a data sample that does not fit to other samples of the same group. In particular, the definition of criteria under which data points are considered as outliers is necessary. Once an outlier is identified, it can be removed and possibly replaced by a reasonable value. Various approaches exist to detect outliers; an overview is provided in [19]. In this work, the following methods were used:

- **Threshold-Based Outlier Detection:** Given the knowledge that a parameter must lie in certain boundaries, the data can be easily filtered.
- **Statistical Outlier Detection:** Assuming that parameters underlie a particular statistical distribution, values can be tested whether they deviate from the presumed distribution (Figure 6). Common practices are e.g. *Grubb's Outlier Test* and the *Z-Score method*.
- **Quantile Based Outlier Detection:** By removing all values that exceed or are below of a given quantile, e.g. discarding the data set's one percent of lowest and largest values, the data is free of the most extreme values. These values are not necessarily outliers per definition, and a particular number of data points are removed in any case. This method may be considered as a combination of threshold based and statistical outlier detection.

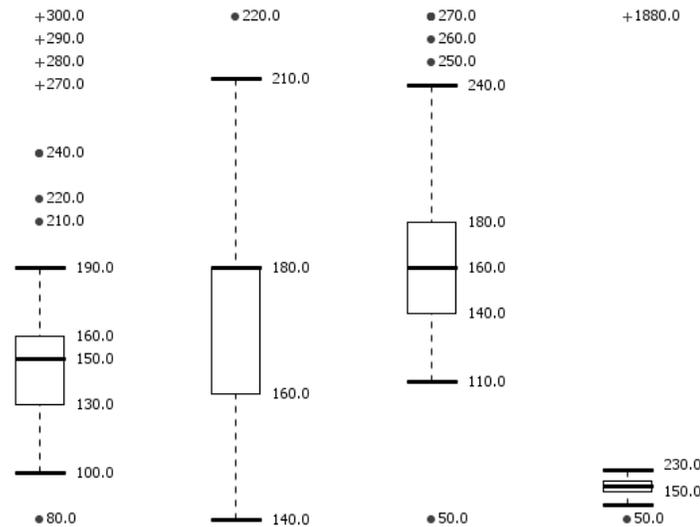


Figure 6: Data points outside the boxplot whiskers are potential outliers.

Replacing missing values with a guess or estimate is known as *imputation*. Applying imputation completes the data sets for any conventional regression method. A drawback is that imputation techniques may introduce a bias in the data. The data model, e.g. a probability distribution of the feature values would fit to the biased training samples but not necessarily to the true distribution. This can result in a performance loss of the machine learning model. Various different imputation techniques exist – an excellent overview is provided in [20]. In this work the following techniques were considered:

- **Constant Value Imputation:** Following the principle that a complete data sample is better than discarding information, the simplest method is to replace a missing value with a constant value. As this neglects the characteristics of the available data, the added bias may become large, especially for cases with many missing features.
- **Mean Value Imputation:** Replacing a missing value by the arithmetic mean of a feature is known as mean value imputation and can be a practicable concept especially for features with low variance over the whole data set.
- **Nearest Neighbor Imputation:** Imputing a value of a data sample that is most similar to the sample with the missing value. A measure of similarity could be for example the Euclidean distance. If the k most similar data samples are considered, the value to impute can then be aggregated from these samples, e.g. by taking the mean or median value. This technique is known as k -nearest neighbor imputation.
- **Next Known Value Imputation:** Assuming that some parameters may only change slowly over time, and given the missing data point is part of a time series, imputing the last or next known value may be a reasonable choice.

Finally, outlier detection and feature imputation must be treated with extreme care so that important information is not lost or blurred. It is strongly advocated that experts of the physical process be incorporated in the decision to ensure that accurate assumptions are made.

REFRACTORY MODELLING AND PREDICTION

A statistical model for predicting the wear rate can be determined by regression analysis. In classical regression the target value t is continuous and the model input are the selected process parameters x . The target t is in this case the maximal wear rate in the specified HS region, i.e. the maximum of the refractory wear of the HS normalized by the campaign length. The regression model is a (possibly nonlinear) function mapping from the input x to the target value t as $t=f(x)$. The aim was to exploit only the most influential process parameters x in the regression model. Therefore, they were automatically determined by feature selection algorithms.

Feature Selection

John *et. al.* [21] divide the feature selection algorithms into two major groups: the filter approach and the wrapper approach. The filter approach assesses the relevance of the features from the data set which is mainly based on statistical measures. The effects of the selected features on the regression performance are neglected. In contrast, the wrapper approach uses the performance of the regression model as part of the feature search for evaluating the feature subsets. John *et. al.* [21] claim that the wrapper approach is more appropriate, since the selection of a feature subset takes the regression model into account and achieves a high predictive accuracy on unknown test data. However, this approach is associated with high computational

costs. Due to this a selection method was used, which was computationally efficient but may result in a suboptimal feature subset of process parameters. In particular, sequential feature selection algorithms were used [22]. They search in a sequential deterministic manner for the possibly suboptimal best feature subset. Basically, forward and backward selection algorithms were available. Sequential forward selection (SFS) was used, where in each iteration one feature among the remaining features is added to the subset, so that the subset optimizes the evaluation criterion J . The cross-validated root mean square error (RMSE) of the regression model was used as evaluation criterion J . One of the drawbacks of the SFS algorithm is that there is no mechanism for rejecting already selected features. Once a feature is included in the feature subset, it cannot be discarded from the subset at a later stage of the search, even if it becomes superfluous. This effect is called nesting [22].

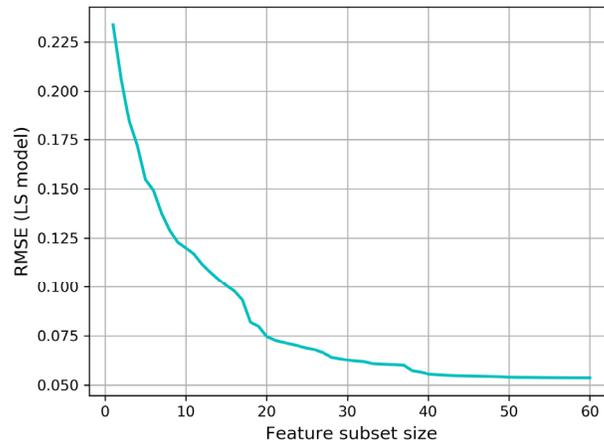


Figure 7: Sequential forward selection.

In Figure 7, the cross-validated RMSE J of the regression model for a feature subset size from 1 up to 60 (x-axis) is shown. When using the best 10 features, i.e. feature subset size of 10, in the regression model, an RMSE lower than 0.125 was obtained. When using a feature subset size of ~ 40 , the best regression performance is obtained. In summary, feature selection provides a list of the most influential and helpful features for the regression model.

Regression

In this study, linear regression and deep neural network regression was used. Deep neural networks [23] are one of the most successful models in pattern recognition. It consists of perceptrons which commonly are nonlinear basis functions with weight parameters w . Many perceptrons are combined in each layer of the network (Figure 8) and a neural network model simply performs a nonlinear mapping from x to a target vector t by means of the weights w . Those weights can be learned by the backpropagation algorithm. Regularization is important during training of a neural network to avoid over-fitting. Weight decay and dropout was used for regularization.

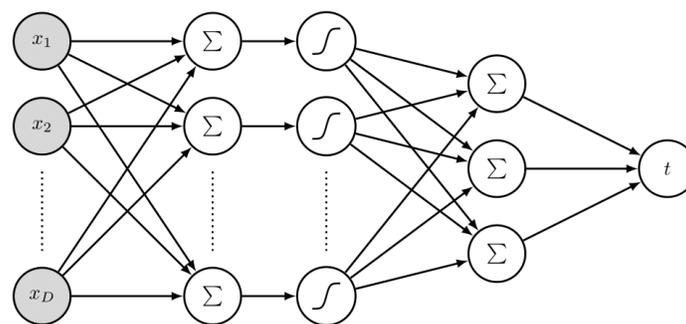


Figure 8: Multilayer perceptron.

RESULTS

Setup

In total, 22 RH degasser campaigns were recorded over almost one year. The campaign length, i.e. the number of treatments, varied up to 200. In total, ~4400 data samples were available. 11 selected features (process parameters) were used for the regression model and results for the HS wall outlet are reported. In addition to the deep neural network model (MLP), results for a simple linear regression (LS) were also shown. All reported results use 22-fold cross validation, i.e. the regression model was trained on 21 campaigns and the model performance was reported on the remaining campaign.

Results and Discussion

Figure 9 shows the measured and the predicted wear for all 22 campaigns (x-axis) using the deep neural network (MLP) and the linear (LS) regression model. Both models showed similar performance with this data set. The MLP regression model works well for 15 campaigns where the absolute prediction error is lower than ~10 mm. The largest absolute prediction error is 37 mm for campaign 11. Detailed results are summarized in Table I. The deep neural network regression model performs on par with the LS model while the maximal absolute prediction error of the LS model is lower.

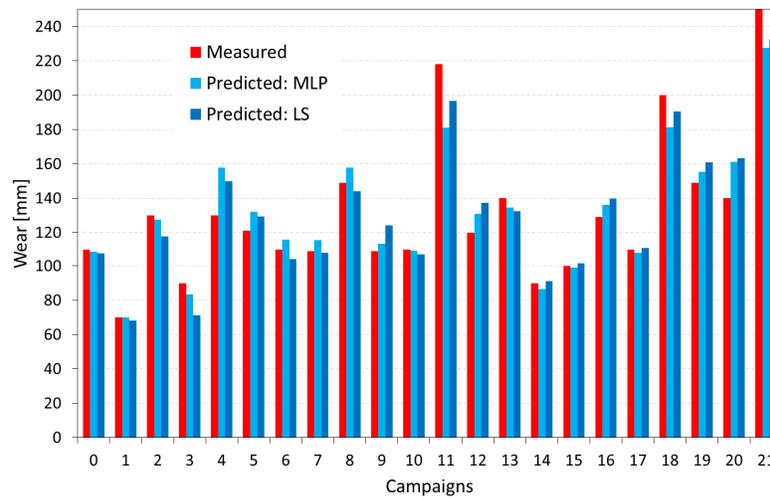


Figure 9: Wear prediction for each campaign using a MLP and LS regression model.

Table I: Measured and predicted wear in [mm].

Campaigns	mm				
	Measured	Predicted MLP	Absolute Difference Measured - MLP	Predicted LS	Absolute Difference Measured - LS
0	110	109	1	107	3
1	70	70	0	68	2
2	130	128	2	118	12
3	90	83	7	71	19
4	130	158	28	150	20
5	121	132	11	129	8
6	110	116	6	104	6
7	109	116	7	108	1
8	149	158	9	144	5
9	109	113	4	124	15
10	110	110	0	107	3
11	218	181	37	197	21
12	120	131	11	137	17
13	140	135	5	132	8
14	90	87	3	91	1
15	100	99	1	102	2
16	129	136	7	140	11
17	110	108	2	111	1
18	200	181	19	191	9
19	149	155	6	161	12
20	140	161	21	163	23
21	250	228	22	233	17
Average			~10		~10

Figure 10 shows campaign 0 and campaign 11 in more detail. In particular, the increase in the wear is shown over the campaign length (treatments). The red line is the measured wear at the end of the campaign – it is interpolated linearly over the campaign length. For campaign 0 in Figure 10(a), both regression models perform well, whereas for campaign 11 in Figure 10(b), the LS model slightly outperforms the MLP. For campaign 0, the prediction error for the MLP and the LS is 1 mm and 3 mm; for campaign 11, the error is 37 mm and 21 mm, respectively.

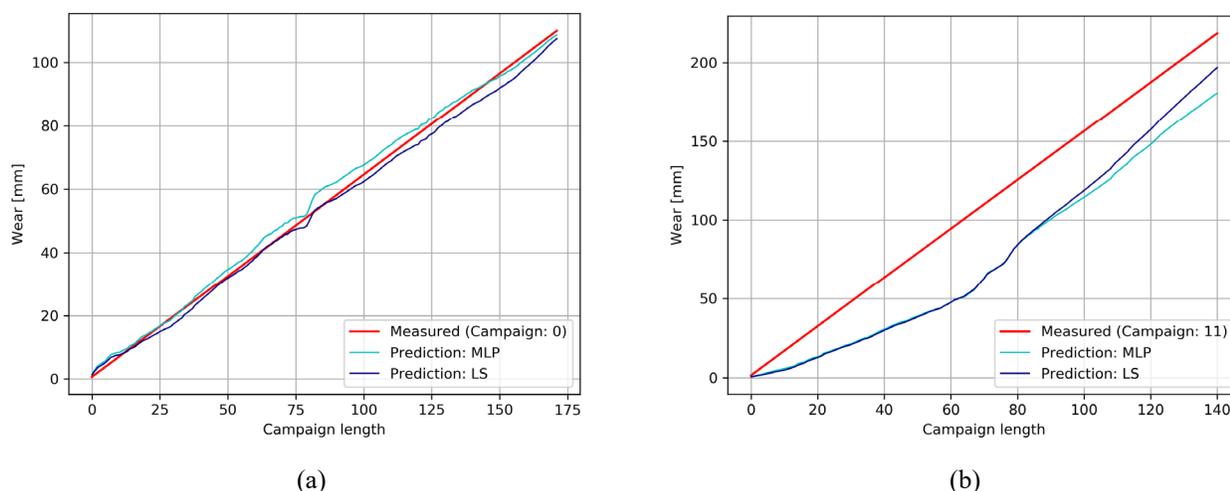


Figure 10: (a) Wear of campaign number 0, and (b) wear of campaign number 11.

CONCLUSIONS

In this paper, the refractory life time based on process data recorded during steel refinement of a RH degasser at voestalpine Linz, Austria was predicted. The process data and lining measurements are prone to outliers and missing data values. Therefore, outlier detection and feature imputation techniques have to be used. Both steps have to be carefully considered so that no important information is lost. It is strongly recommended that steelmaking experts are incorporated into these steps. Furthermore, sequential feature selection was performed to determine the most useful features for the prediction model. In particular, results for a linear and a nonlinear regression model used to predict the refractory wear were obtained. Both models perform on par with an average prediction error of ~10 mm of the brick wear using data of 22 campaigns.

In future work, we plan to supplement the process data with the vessel shell temperature which is measured by an infrared imaging system. With this additional knowledge source, the aim is to further improve the accuracy of the prediction model.

REFERENCES

1. K. Herzog, G. Winter, G. Kurka, K. Ankermann, R. Binder, M. Ringhofer, A. Maierhofer, "The Digital Transformation of Steel Production," *AISTech*, 2017, Conference proceedings, pp. 504–513.
2. G. Kurka, G. Hohenbichler, "TPQC- Through- Process Quality Control," *9th Int. Steel Congress*, May 2016, Beijing, China, Conference proceedings.
3. R. Steiner, G. Lammer, C. Spiel, C. Jandl, "Refractories 4.0," *BHM*, 2017, Vol. 162, No. 11, pp. 514–520.
4. G. Lammer, R. Lanzenberger, A. Rom, A. Hanna, M. Forrer, M. Feuerstein, F. Pernkopf, N. Mutsam, "Advanced data mining for process optimizations and use of A.I. to predict refractory wear and to analyze refractory behavior," *AISTech 2017*, Conference proceedings, pp.1195–1207.
5. A. Viertauer, G. Lammer, P. Bloemer, "Refractory Condition Monitoring and Lifetime Prognosis", *7th International Congress on Science and Technology of Steelmaking*, 13.-15. June 2018, Venice, Italy.
6. Pending Patent Method for determining the condition of a fire-resistant lining of a metallurgical melting vessel applications EP 2 789 960 B1.
7. R. J. Fruehan. *Vacuum Degassing of Steel*, *Iron and Steel Society*, 1990, Warrandale, P.A.

8. H. Presslinger, K. Jandl, A. Jungreithmeier, R. Rathner, „The RH Process at VOEST-ALPINE Stahl Linz GmbH- Optimization of Refractory Materials and New Metallurgical Findings”, *RADEX- Rundschau*, Heft 4, 1992.
9. A. Jungreithmeier, P. Reisinger, K. Jandl, A. Viertauer, E. Pissenberger, „Vacuum Degassing at voestalpine Stahl“, *BHM*, 147. Jg. (2002), Heft 5, 138-144.
10. T. Molinari, R. Reiterer, A. Viertauer, R. Exenberger, “Optimized Refractory Solutions for High Performance Ladles and RH- degassers”, *EOSC*, 2003, Graz, Austria.
11. D. Tembergen, R. Teworte, R. Robey, „RH- Metallurgy“, *Millenium, Steel 2008*, pp. 104-108.
12. D. Tembergen, T. Eichert, “Progressive Steelmaking with different Vacuum Technologies”, *Stahl und Eisen*, 2012, Vol. 132, No. 11, pp. 90–101.
13. D. Tembergen, „Sekundärmetallurgische Prozess Technik“, *Metallurgie der RH- Anlage, VDEh Stahl Akademie*, 2014, 24. – 26. March, Krefeld, Germany.
14. A. Pezza, M. Abel, M. Hein, T. Wieting, „Consistentently good results with commissioning vacuum plants“, *Stahl und Eisen*, 2012, Vol. 132, No. 12, pp. 107-113.
15. A. Pezza, W.-A. Buehler, J.-D. Martinez Cerezo, M. Reising, “Vacuum Plant Metallurgical Results”, *Stahl und Eisen*, 2018, Vol. 138, No. 1, pp. 31-41.
16. A. St-Jacques, M. Heiligenbrunner, Improved Concave Lining Design for the Bottom of RH Degassers, *RHI Bulletin*, 2013, 01, pp. 41-44.
17. A. Gantner, M.-W. Egger, J. Lehner, “Experiences with the new secondary metallurgy No. 3 at voestalpine Stahl Linz”, *6th European Oxygen Steelmaking Conference*, 7.-9. September 2011, pp. 384-392, Stockholm, Sweden.
18. W. Winkler, R. Exenberger, G. Grimm, A. Gantner, “Development of RH- degassing lining concepts at voestalpine Stahl Linz – an overview”, *14th Biennial Worldwide Congress UNITECR*, 15.-18 September 2015, Proceedings No 272, Vienna, Austria.
19. Hodge, Victoria, and Jim Austin. "A survey of outlier detection methodologies", *Artificial intelligence review* 22.2, 2004, pp. 85-126.
20. J. W. Grzymala-Busse and W. J. Grzymala-Busse, “Data Mining and Knowledge Discovery Handbook”, O. Maimon and L. Rokach, Eds. Boston, MA: *Springer US*, 2010, vol. 1.
21. G.H. John, R. Kohavi, and K. Pfleger, “Irrelevant features and the subset selection problem”, *11th International Conference on Machine Learning*, 1994, pp. 121–129.
22. J. Kittler, “Feature set search algorithms”, In C.H. Chen, *Pattern Recognition and Signal Processing*, 1978, pp. 41–60. Sijtho and Noordho.
23. I. Goodfellow, Y. Bengio and A. Courville, “Deep Learning”, *MIT Press*, 2016.

