Digital Optimization of Refractory Maintenance

Digital technologies are transforming industry at all levels. Steel has the opportunity to lead all heavy industries as an early adopter of specific digital technologies to improve our sustainability and competitiveness. This column is part of AIST's strategy to become the epicenter for steel's digital transformation, by providing a variety of platforms to showcase and disseminate Industry 4.0 knowledge specific for steel manufacturing, from big-picture concepts to specific processes.

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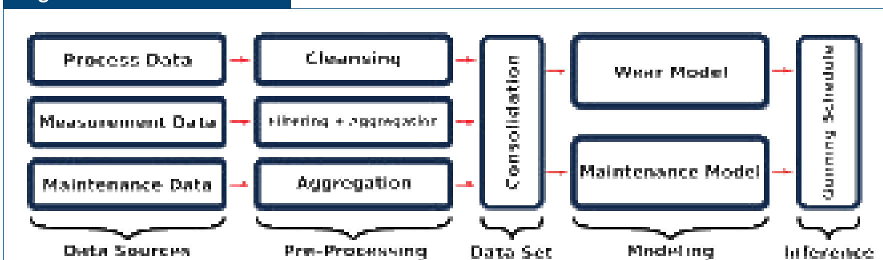
In steelmaking, refractory material is in use where structures are exposed to high temperatures, in particular where metal is in liquid phase, e.g., furnaces, ladles, torpedo cars and molds.[1] In furnaces, a lining of refractory bricks protects the vessel hull from mechanical stress and from direct contact with its molten content. Due to abrasion, the lining wears over time and needs to be replaced before it reaches a critical thickness in order to prevent the vessel from damage or a hull breakthrough in worst case. In a furnace, particular areas underlie higher stress and therefore are worn out more rapidly than others. These areas, referred to as hot spots, are repaired from time to time, in order to achieve a balanced refractory brick thickness and subsequently to extend the life cycle of a lining. Since refractory maintenance usually means an interruption of normal operation and therefore a productivity loss, optimizing the maintenance procedure and schedule can help to minimize refractory cost and operational downtime. Usually, maintenance is scheduled based on experience and operational constraints. This work aims to provide data-driven approaches that are agnostic to subjective opinion. Methods of direct and indirect monitoring of the refractory status are addressed, predicting the remaining life of the lining and estimating the effect of gunning repair. Furthermore, approaches to advising a maintenance schedule based on historical data records are discussed. This work concentrates on maintenance of a basic oxygen furnace (BOF). Nevertheless, the presented concepts can be adapted to other vessel types, given the required process and measurement data. Fig. 1 gives an overview of the data processing chain discussed in detail in the remainder of this paper.

The depicted data processing chain consists of five stages. In the first stage, the raw data is loaded from different sources, i.e., process data, lining measurements and maintenance recordings. The raw data is then pre-processed, i.e., cleaned, filtered, aligned and aggregated, and subsequently merged into a data set that contains the relevant information for model building. In the modeling stage, relationships between input (e.g., process parameters) and output data (e.g., thickness measurements) are established. In the final stage, these models are utilized for inference, e.g., for

Figure 1



Data processing chain.

predicting refractory wear or proposing maintenance activities.

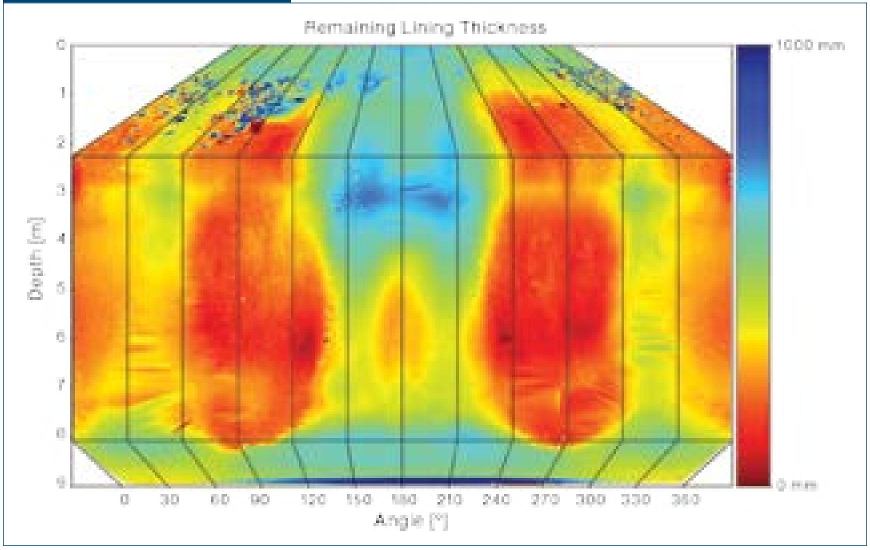
The maintenance advisory strategies presented in this work are built upon the concepts exploited on data of an electric arc furnace (EAF).[2] The refractory wear model design describing the relation of process parameters and decrease of lining thickness was previously investigated for a Ruhrstahl-Heraeus (RH) degasser in Reference 3.

Data Sources

Process Data — Process parameters such as temperatures, consumptions, durations and chemical composition additions are recorded on a per-heat basis. Usually, these process parameters require pre-processing and data cleansing.[4] The most important parameters with influence on refractory wear are either selected by process experts or determined automatically through a feature selection stage.

Measurement Data — Measurements of the lining surface are taken in irregular intervals. The data is usually provided as point clouds in cylindric coordinates with origin at the measurement device's position. For each scanned surface point, the corresponding lining thickness is provided and is calculated from a static model of the vessel shell. The precision and therefore the reliability of laser measurements often suffer from inaccurate positioning of the scanning device and of optical disturbance (e.g., smoke and dust). Thus, appropriate corrections and data filtering are often necessary to improve the data quality. Fig. 2 shows a laser scan in the style of a settlement drawing.

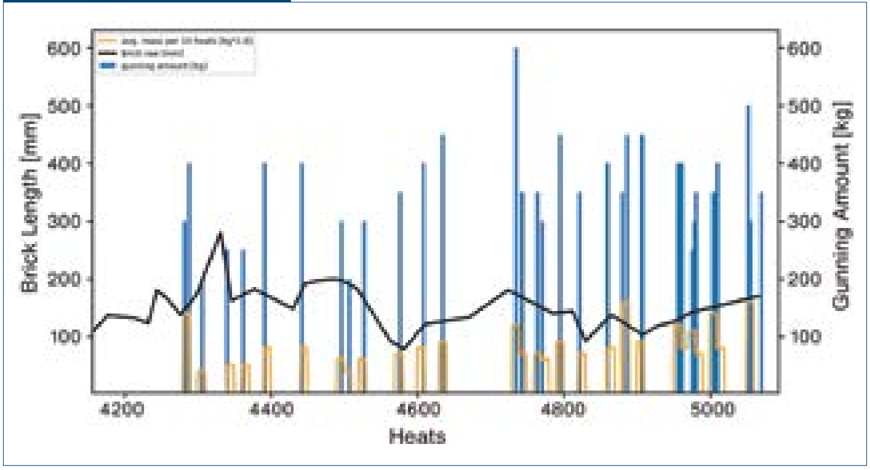
Figure 2



Basic oxygen furnace (BOF) laser scan visualization.

Maintenance Data — Maintenance data is provided as the amount — i.e., the mass in kg — of gunning material applied to a specified area, together with the heat number to indicate when the maintenance was performed. Further parameters such as material grade, feed pressure, and proportion of water and dry mass were not available for this work, despite the assumption of a notable influence of these parameters on maintenance efficiency. Fig. 3 shows gunning events and average gunning mass over intervals of 10 heats together with lining thickness measurements for a single hot spot. Note that there is no intuitively recognizable relation between applied gunning amount and lining thickness measurements.

Figure 3

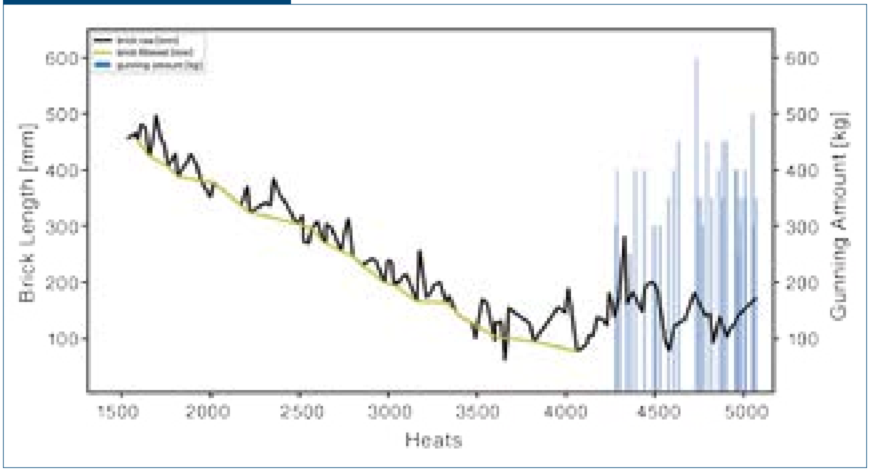


Gunning mass and thickness measurements.

Wear Model

In order to make meaningful suggestions for maintenance operation, it is crucial to monitor the condition of the vessel lining and its remaining brick length. Ideally, this is subject to precise

Figure 4



Raw and smoothed evolution of lining thickness.

and frequent surface scans. If such scans are not available, estimates of current lining thickness based on a refractory wear model can be used as substitute.

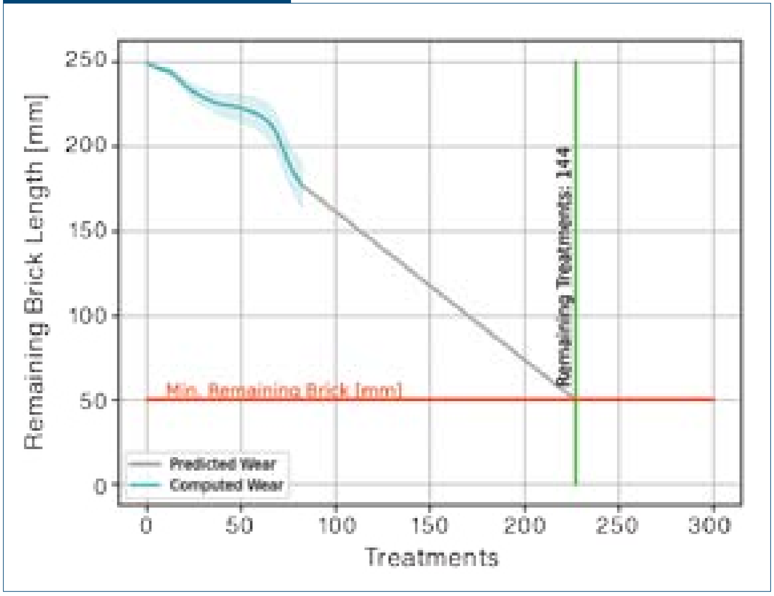
Measurement-Based Refractory Monitoring — Ideally, accurate measurements are available for every production heat. In practice, the lining surface is scanned in irregular intervals. As common practice, the scan frequency is increased in advanced lining age. Furthermore, the measurements are prone to noise and are often shifted against each other due to inaccurate positioning of the measuring device. This means that the available thickness measurements cannot be used in their original form and have to undergo filtering and correction procedures to increase the data reliability.[5]

Filtering — Unreliable measurements perturb the modeling of refractory wear as well as inferring maintenance action based on the current lining thickness. To overcome this, data pre-processing aims to increase the data quality and subsequently to achieve a higher reliability. Outlying scan points are removed in a local neighborhood, e.g., by discarding a lower and upper percentile of the data in the area of interest. Furthermore, applying aggregation methods such as mean or median on the data aims to increase the measurement's robustness against noise. Moreover, filtering is also applicable across a series of measurements, e.g., by discarding untrustworthy scans given their preceding and succeeding measurements, or by applying further smoothing, e.g., by using a moving average filter. Fig. 4 depicts raw and filtered thickness measurements, where filtering was only applied on heat intervals without maintenance events. Note that in this case, maintenance is started after 4,300 heats.

Linear Fit — An intuitive approach is to assume a linear refractory wear behavior. Under this assumption, the brick thickness can be determined by taking the average wear over all available measured intervals, or by using linear regression (i.e., fitting a line to the measurement series). Therefore, the calculated decrease per heat is constant and calculating the current remaining brick thickness is straightforward by multiplying the wear ratio by the number of heats. This approach also allows for the extrapolation of the thickness decrease into the future. Such an extrapolation is depicted in Fig. 5. At heat 80, the prediction provides an estimate for the remaining treatments (e.g., 144 in this case) of an RH degasser.

Wear Prediction Based on Process Parameters — A more sophisticated way of estimating the refractory wear is to model the wear behavior as a function of (available) process parameters. Such an approach was recently successfully established for an RH degasser unit.[3] In this approach, a linear regression model is used to relate process parameters that were pre-selected

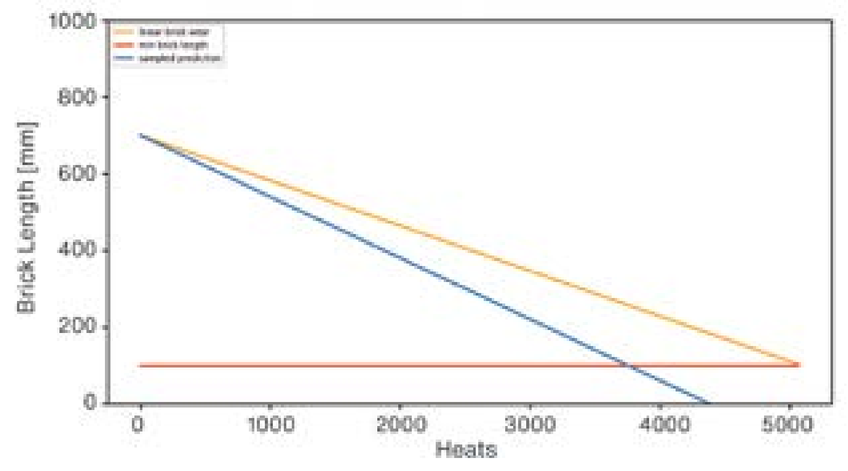
Figure 5



Wear prediction at heat 80.

by experts to the refractory wear of neuralgic areas of the vessel's lining. A wear prediction based on this model is depicted in Fig. 5. Despite the differences across liquid steel vessels and aggregates from a metallurgical point of view, the problem of estimating refractory wear is similar for most vessels from a data modeling perspective. Since the available data usually consists of process parameters and (possibly sparse) thickness measurements, the approaches and methods can be adopted to different vessel types. This work utilizes the methodology and findings of the RH model for refractory wear prediction. Fig. 6 shows the desired lining wear behavior (assumed linear in this example) together with the predicted decay of refractory based on sampling of production parameters. The gap in heats between predicted and desired lining life at the level of minimum thickness states the number of additional heats that is required to reach the target lining life (i.e., 1,300 heats in this example).

Figure 6



Desired and predicted refractory wear behavior.

Production Plan Sampling — Naturally, estimating the refractory state based on production parameters requires the availability of those parameters for each heat where the wear should be determined. This is often the case for past heats, but regarding the future, the production is often planned on short term and on demand, and therefore process parameters of future heats might be unavailable. This is true for parameters that become available only during or after a heat, such as temperature measurements. When it comes to predicting the refractory wear to take appropriate maintenance measures in advance, the expected production parameters can be estimated statistically. This can be achieved by estimating the distribution of production data of the past and sampling a series of process parameters from this distribution. In practice, the individual process parameters are not independent, since steel is produced by following particular "recipes" in order to achieve the desired steel quality for a given heat. Therefore, production plan sampling is performed on all parameters simultaneously rather than sampling the parameters individually.

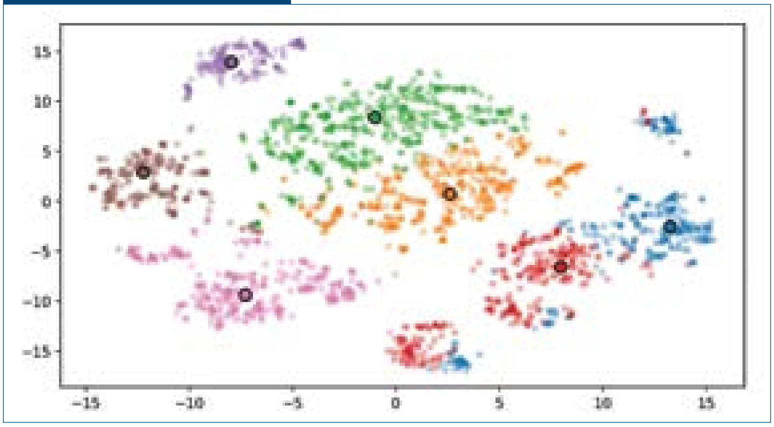
Discrete Probability Distribution: In order to identify a finite number of representative production data vectors, clustering algorithms, such as k-means clustering,[6] can be used to determine groups of heats with similar production conditions. Taking the cluster centers, i.e., the average over all samples assigned to a cluster, results in a set of archetypical production data vectors. Each real parameter vector is assigned to the cluster with the most similar cluster center. The euclidean distance can be taken as similarity measure. A discrete probability distribution is then established by counting the number of samples assigned to each cluster and their portion with respect to the total number of samples. Production data vectors can be sampled from such a distribution by fitness proportionate selection such as roulette wheel sampling.[7] The probability of selecting a cluster center c is given by:

$$p(c) = \frac{N_c}{\sum_{j=1}^{C} N_j} \forall c \in \{1 \ldots C\} \quad \text{(Eq. 1)}$$

where C is the number of clusters and N_c is the number of heats assigned to cluster c, respectively. Alternatively, data grouping can also be subject to given categories instead of statistically determined clusters, such as steel product families. The group archetype is determined analogously by taking the group's average. Such an approach may be closer to reality, but selecting meaningful categories can be a challenge on its own, e.g., if there is a large number of categories (product families) relative to the available data samples.

Continuous Probability Distribution: Sampling sets of production parameters from a continuous feature space requires knowledge of the underlying — also continuous — probability distribution to draw the samples from, e.g., multi-variate Gaussian or a Gaussian mixture model,[8] where the latter is a combination of single multi-variate Gaussians. Fitting a multi-variate Gaussian to an available set of samples, i.e.,

Figure 7



Production data clusters.

the production parameters, can be done by using the expectation-maximization (EM) algorithm and is closely related to k-means clustering. Fig. 7 shows production data clusters (dimensionality reduced to two dimensions) with their respective centers.

Maintenance Model

The goal is to determine the effect of maintenance measures on extending the lining life. Therefore, the relation between the applied amount of gunning material and the resulting gain of lining thickness, and subsequently the gain of additional heats per unit of applied mass, must be determined. This relation can be set by expert's knowledge, by empirical examination in field trials, or statistically based on maintenance records and lining thickness measurements. The latter approach is discussed in the following. Further constraints, such as desired maintenance interval, limitations for the applied amount of gunning material or number of heats before first gunning can be incorporated as well for adaptation to operational conditions and requirements.

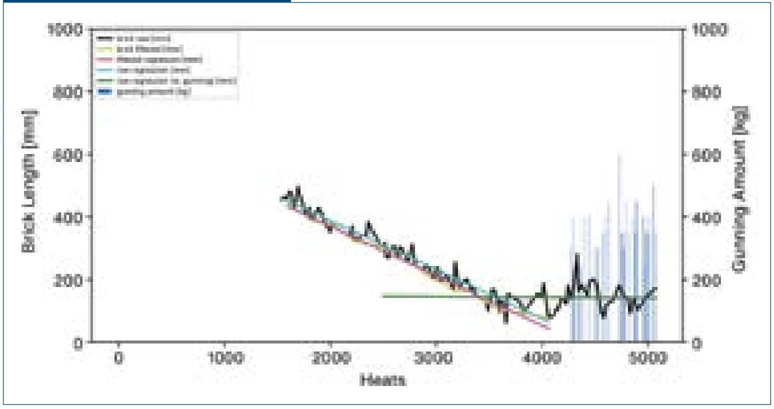
Impact of Gunning on Lining Wear — Next to monitoring the current state of the refractory lining, it is crucial to know the effect of maintenance procedures on the refractory life. The impact is formulated as the ratio of wear reduction over the amount of refractory mix per area per heat. Once this impact is known, it can be used to determine the amount of repair material required to close the gap between predicted and desired number of remaining heats in terms of refractory life.

Determining the wear reduction empirically requires accurate thickness measurements. Provided that, the average wear reduction can be calculated by dividing the thickness of the gunning layer by the number of heats it takes for the applied gunning material to erode and by the applied amount. If the measurements lack acceptable accuracy, or the wear of gunning material is not explicitly measured, a more general approach can be applied. The maintenance impact is estimated by observing the wear behavior over a sequence of heats that contains multiple gunning events. Fitting a regression line to the available measurements of that sequence gives the combined wear of brick and gunning mix. The result can potentially state a negative wear rate as well. Analogously, the average wear rate is determined for a (sufficiently long) series of heats without maintenance. Subtracting this from the combined wear rate results in the average effect of maintenance per heat. Fig. 8 shows approximated wear rates for sequences with and without maintenance measures. The straight lines in the segment with no gunning (up to 4,000 heats) represent a linear regression fitted to the raw and smoothed thickness measurements, respectively. The nearly horizontal line shows the linear regression fit to measurements in the segment where gunning is applied. The gradient of the latter represents a combination of wear rate and counteracting gunning effect.

Given an acceptable measurement accuracy, as discussed, the gunning consumption can also be incorporated in a wear model along with other process parameters. In the case of a linear model, the gunning effect can be determined directly from the model weights.

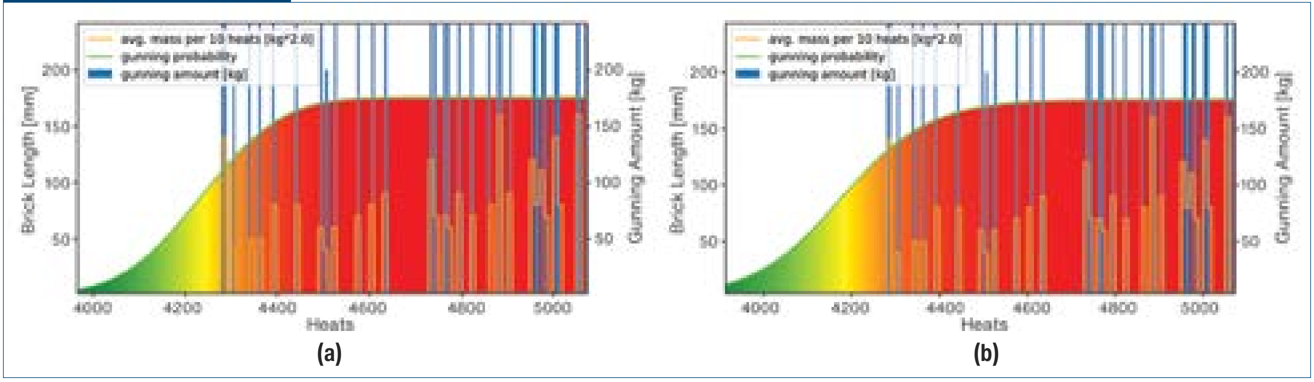
Gunning Probability — In order to reflect customary maintenance practice in a recommendation strategy, the probability of

Figure 8



Approximation of refractory wear with and without maintenance.

Figure 9



Gunning probability: cumulative density function (CDF) of Gaussian fit (a) and sigmoid fit (b).

maintenance events during a running campaign is estimated. For this purpose, the heat series of a campaign is split into fixed and equal-length segments and the frequency of gunning events and average amount of gunning material is calculated for every segment. The probability of gunning events having happened is then assumed to be proportional to a cumulative density function (CDF) fitted to the data. A sigmoid function can be used as proportional CDF. Common curve fitting and optimization methods such as least squares are applicable. For facilitating the fitting process, the gunning amount of every heat is set to be the amount of the slice to which it belongs. Alternatively to directly estimating a CDF, a probability density function (PDF) such as a normal distribution can be estimated for the available data. The CDF can be subsequently calculated by integrating over the PDF. The probability of a maintenance procedure given the heat number is illustrated in Fig. 9.

Gunning Plan — Planning maintenance operations requires a desired wear behavior to be defined. In the simplest case, this requirement is met by providing a minimum value for the lining thickness and a target lifetime (expressed as number of heats). Such boundary conditions will assume a desired linear wear behavior, but any curve of refractory decay is potentially possible.

Required Gunning Mass — The amount of gunning mix m that is required to close the gap between target lifetime h_l and its current estimate h_c can be easily calculated. Given the estimated refractory wear rate r_t for heat t and the counteracting effect of maintenance g, the necessary amount of gunning mix for extending the lining's life by one heat, and subsequently the overall amount to reach the target life is modeled as linear relationship, i.e.:

$$m[kg] = \frac{\sum_{t=h_c}^{h_l} r_t[mm]}{g[mm/kg]}$$

(Eq. 2)

If a uniform wear rate r is assumed (see the Impact of Gunning on Lining Wear section), this simplifies to:

$$m[kg] = \frac{r[mm/heat]}{g[mm/kg]} * (h_l - h_c)[heats]$$

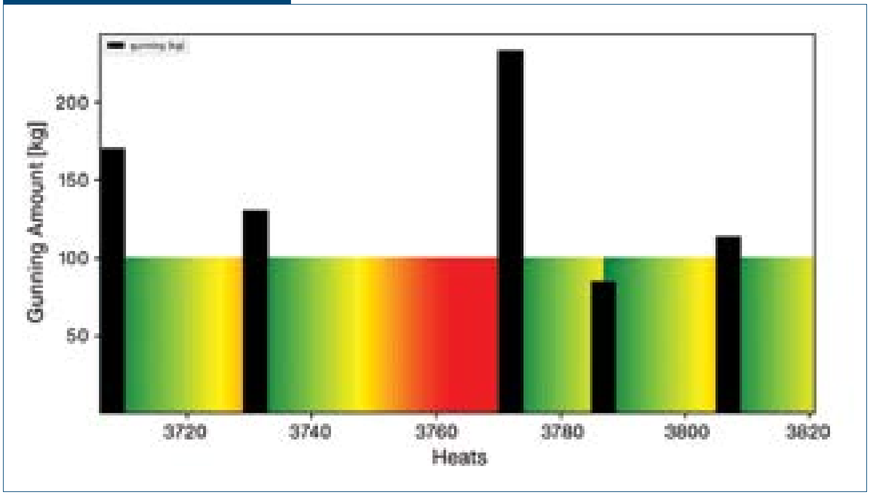
(Eq. 3)

Gunning Schedule — Once the amount of gunning material is estimated, a schedule for maintenance operations can be established. A direct approach is to use historical statistics of maintenance events, e.g., by determining the average interval between gunnings and the average amount of mix applied per event. By incorporating this knowledge of best practice, a suggestion for a reasonable number of gunnings can be made.

Gunning Proposal — By combining the approaches discussed here, i.e., required amount of gunning mix (see the Required Gunning Mass section), reasonable intervals and maintenance probability (see the Gunning Probability section), the urgency for maintenance of the current heat can be presented as "traffic light" color code, meaning (i) green: no maintenance required, (ii) yellow: maintenance should be performed and (iii) red: immediate maintenance action is required to fulfill the target lifetime. Fig. 10 shows the color-coded gunning urgency and applied gunning amount at every heat.

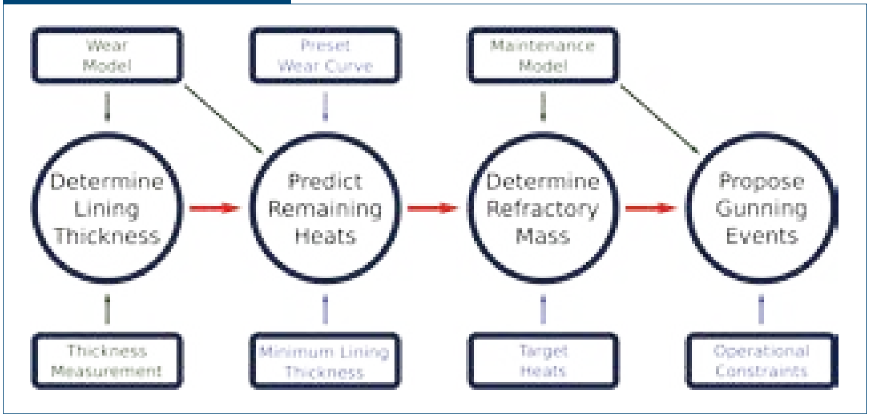
Furthermore, the amount of gunning mix to be used in the next maintenance procedure can be proposed. Fig. 11 depicts the processing diagram

Figure 10



Gunning urgency.

Figure 11



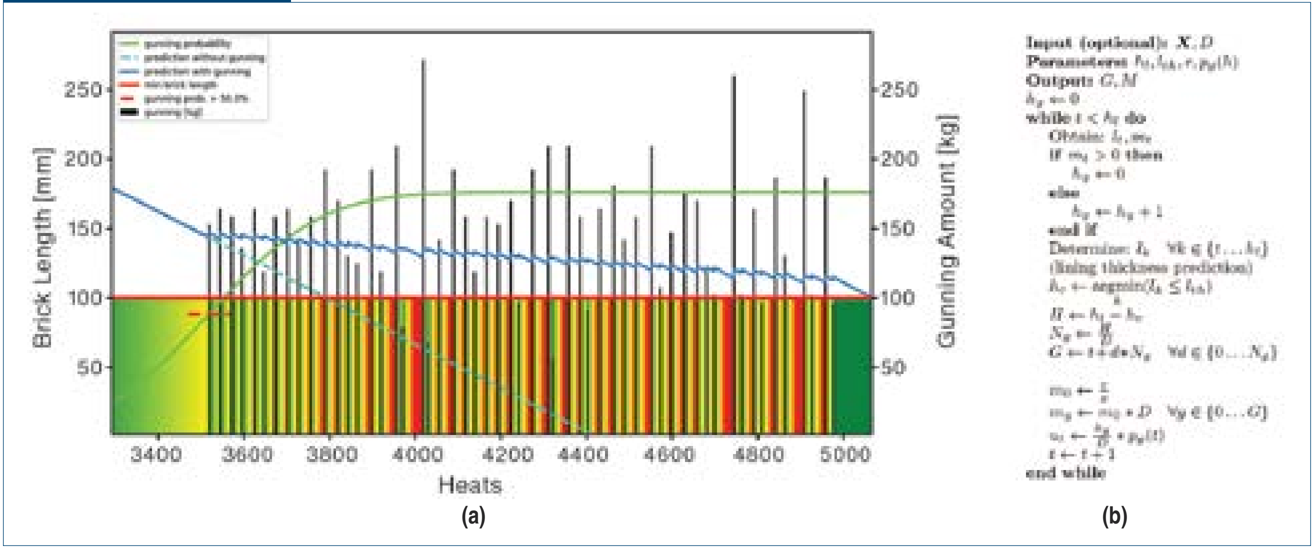
Maintenance proposal diagram.

from determining the current refractory status to proposing maintenance measures. The circle nodes represent the steps of the algorithm and its inputs are stated as rectangles. Green inputs have a data-driven or statistical character, where blue inputs represent user-defined parameters, to be set as desired. The processing scheme consists of four stages. First, the current refractory state is determined, either by a thickness measurement or by an estimate using a wear model. Second, the remaining heats before the lining wears to its minimal thickness is predicted, e.g., by extrapolation of past wear behavior or by a prediction based on a (sampled) production plan. Third, the amount of gunning that is required for reaching the target lining life is calculated. In the last stage, a schedule for gunning events is proposed.

Fig. 12 shows a gunning proposal during a running campaign to extend the lining life to the desired number of target heats. In this example, the proposing algorithm is constrained as follows. Gunning events are allowed at a maintenance probability of greater than 50%. The gunning urgency is color-coded from green for low to red for high urgency, respectively. The urgency is based on an average gunning interval of 23 heats (calculated from historical data) and weighted by the gunning probability. The wear prediction is based on clustered production data. The gunning intervals are set with a small randomness factor around the average interval for the sake of a more realistic scenario. The target lining life is set to 5,100 heats with a minimum brick length of 100 mm.

The maintenance proposal algorithm shown in Fig. 12b states the procedure for calculating a gunning proposal that outputs a series $G = \{h_1, \ldots, h_g\}$ of gunning events together with the according gunning amounts $M = \{\mathrm{m}_1, \ldots, m_g\}$. Inputs of (future) production parameters $\boldsymbol{X} = [\boldsymbol{x}_c, \ldots, \boldsymbol{x}_l]^{\mathrm{T}}$, with $\boldsymbol{x} = [x_1, \ldots, x_m]^{\mathrm{T}}$ holding the single production parameters, and desired gunning interval D are optional. Required parameters are the desired lining life h_l in heats, the minimum lining thickness l_{th}, the refractory wear rate $r(x)$ and the gunning probability $p_g(t)$ for heat t, (whereas the latter two can also be constant, e.g., $p_g(t) = 1$). At every time step (i.e., heat), the current lining thickness l_t and applied mass m_t are determined. Subsequently, the lining thickness l_k for future heats is predicted and the heat h_c where the lining thickness will hit the minimum brick length is determined. From there, the number of required additional heats H is calculated as the difference of target number of heats h_l and h_c, followed by the number of required gunnings N_g and the corresponding gunning events G. The gunning amount m_g for every gunning event is calculated as the product of the required mass per heat m_0 and the gunning interval D. The current urgency u_t for gunning is set as the ratio of the number of heats since the last gunning event h_g and D, scaled by $p_g(t)$.

Figure 12



Maintenance proposal (a) and maintenance proposal algorithm (b).

Conclusion

This work presents an approach for suggesting maintenance operations based on historical data records. The individual data sources are described, and preprocessing steps like data filtering and aggregation are discussed. Models for refractory wear and gunning maintenance are developed in order to predict refractory wear behavior and to propose adequate maintenance activity for reaching the desired lining life. Methods for estimating currently unavailable data as well as predicting data of future events are presented. Statistical metrics are used for model building as well as incorporating knowledge from best practice routines applied in real-world operation. A strategy for planning and proposing gunning maintenance based on the established models is proposed, where both data-driven and user-defined boundary conditions are considered. Future work will include the adaptation of the discussed methods to other vessel types. Furthermore, setup data and parameters of the maintenance procedure can be incorporated to improve the maintenance model, as well as investigating the behavior of different compounds of the refractory lining.

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