REPRESENTATION LEARNING FOR INFERENTIAL SENSOR DEVELOPMENT IN AN ELECTRIC ARC FURNACE

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Abstract Overview

Stable smelter operation is critical for successful production of base metals from particulate ore. This work studies the operation of an industrial direct current electric arc furnace that operates as a smelter in a large-scale metallurgical process. Specifically, unexpected loss of the plasma arc is an important unresolved problem with a significant impact on production efficiency and profitability of the mining operation. To address this faulty operation a predictive inferential sensor is proposed to identify high risk operating regimes. Once a high risk situation is identified the alarm instructs operators to take corrective actions to avoid the loss of arc. A comprehensive representation learning framework involving latent variable methods is proposed in this work for preliminary development of the inferential sensor. Large quantities of historical industrial process data are analyzed under the proposed framework to perform fault detection, diagnosis, modeling and predictive classification.

Keywords

Process Monitoring and Diagnostics, Process Control, Applications

Introduction

This work focuses on the operation of a direct current (DC) electric arc furnace (EAF) as a smelter to refine ores into base metals. Ore is transported from the mine and passed through a series of hammer mill grinders, flash dryers, preheater cyclones, calciner combustion chambers and fluidized bed reducers. The upstream processing provides a fine particulate feed that is dried, heated and reduced to maximize the efficiency of the energy intensive twin electrode DC EAF, illustrated in Figure 1.

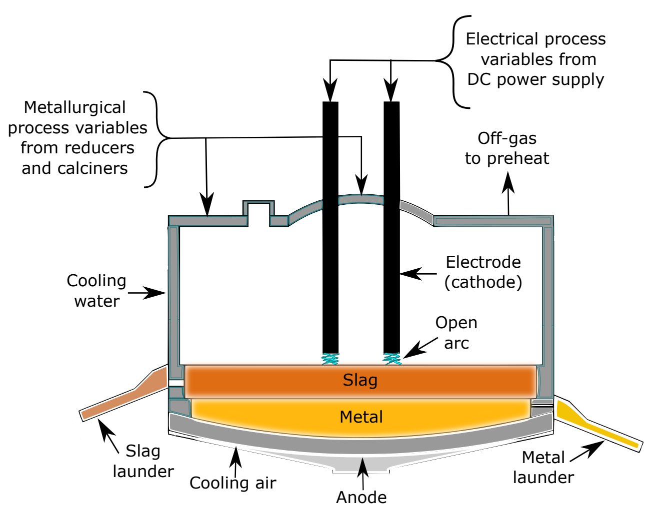

Figure 1: Direct current electric arc furnace

An open plasma arc spans from the hollow graphite electrodes (i.e., the cathode) to the surface of the molten slag (i.e., the anode) providing the energy required to maintain the slag and alloy at target temperatures over 1400°C depending on the slag composition (Lagendijk and Jones, 1997). As shown in Figure 1 the roof and side walls of the furnace are water cooled whereas the bottom anode is air cooled to maintain safe structural temperatures (Hurd and Kollar, 1991). Hot off-gas released from the furnace is recycled to provide upstream preheating. The feed enters from multiple ports along the roof whereas the slag and alloy are tapped intermittently from launders (Kotze, 2002). This work is relevant to a variety of EAF operations including nine in the Canadian steel-making industry (NRCan, 2007).

Stable EAF operation is critical for maximizing production efficiency and profitability. Unexpected loss of the plasma arc is a recurring and unresolved fault that significantly impacts the production rate and the electrical efficiency of the furnace. Diagnosing the cause of arc loss is an open problem with two major potential mechanisms, i.e., electrical disturbances from the DC power supply and feed disturbances from the upstream metallurgical processes (e.g., distributors, reducers and calciners). Both mechanisms are considered as part of a comprehensive representation learning analysis over months of historical process data in the development of an inferential sensor.

The goal of the soft sensor is to provide operators with a warning five to ten minutes in advance of an event with a 75% or higher probability of inducing arc loss. Process analytics are adopted to perform diagnosis through representation learning with latent variable methods. Once a parsimonious feature representation is learned, a set of predictive classification models are trained, validated and compared

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with test data. Development of a reliable predictive alarm that alerts operators of the onset of arc loss so that preventative actions can be taken could have wide-spread applications and significant beneficial economic implications. Initially this alarm will serve as a tool for engineers and operators but the ultimate goal is to implement an advanced controller that can automatically take corrective action.

While developing the inferential sensor, this work simultaneously aims to evaluate and compare both traditional and advanced data-driven methods for process analytics. Process analytics and latent variable techniques are employed for both the representation learning and the predictive classification. However, prior to any feature selection or model validation the raw data must be pre-processed into a structured form that is amenable to statistical analysis. Moreover, before any supervised learning techniques can be used the arc loss labels must be generated which necessitates a quantitative definition of what constitutes arc loss. In what follows the data pre-processing is first described after which the definition of arc loss is presented and the training data is labeled. Finally, techniques for representation learning and predictive classification are presented before concluding remarks and future directions are provided.

Data Preprocessing

The raw data used in this work involves one year of daily exports from a real industrial process historian. Over one hundred different measured variables throughout the process are taken into consideration including categorical data such as valve positions and numerical data such as furnace temperatures. Each daily export contains as many as thirty thousand rows for densely sampled variables and as few as ten rows for sparsely sampled variables. The raw data contains errors such as missing values, bad inputs and not a number (NaN) values. Systematically removing the corrupted data is one of the first stages of pre-processing.

As illustrated in Figure 2, each measured variable in the raw data has a corresponding time stamp with sampling rates varying significantly among variables. To provide structure while condensing the data the most densely sampled variable from each day is identified and its corresponding time stamp is used as a unified time stamp (blue bars in Figure 2) for all process variables. The strategy for pre-processing is to clean the data in a manner that preserves as much information as possible. Furthermore, given the abundance of available data it is not desirable to insert synthetic data through interpolation, extrapolation or advanced imputation. Instead the less frequently sampled variables are resampled according to the unified time stamp by using a simple forward fill or zero order hold operation.

Once the data is cleaned and structured it is in a suitable format for generating the arc loss labels. Additional preprocessing tasks include removing irrelevant variables, removing data that corresponds to plant shutdowns and setting outlier limits based on process knowledge. The definition of arc loss and the generation of these labels is described in the following section.

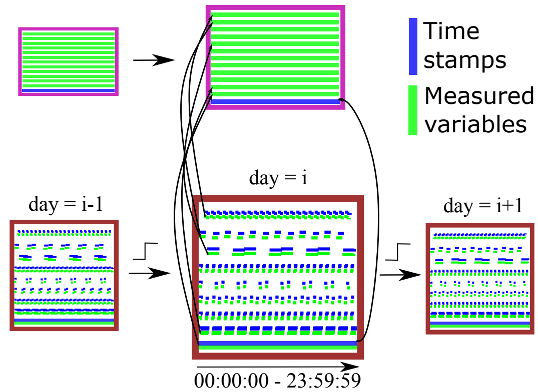

Figure 2: Preprocessing one year of historical process data

Detection and Defining Arc Loss

The electric arc provides the energy required to drive the separation of base metals and slag from the particulate ore. If the arc is lost that energy is no longer available and the separation process ceases. Potential causes of arc loss include disturbances to the power supply, impurities creating higher resistances in the slag and disproportionate feed mechanisms. In order to label the structured data the quantitative definition of arc loss shown in Figure 3 is applied.

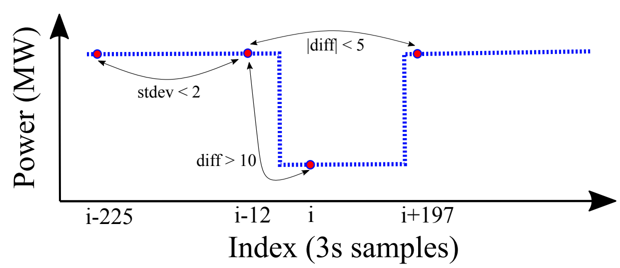

Figure 3: Satisfy all three conditions to define arc loss

All three conditions in Figure 3 regarding the measured power of a single electrode must be met in order to constitute a loss of arc in that electrode. Specifically the power must be stable within a standard deviation of 2 MW for approximately 11.5 minutes, then there must be a power drop greater than 10 MW within the past 36s and finally the power must recover to within 5 MW of the original stable power within a period of approximately 10 minutes. These conditions help to avoid mislabeling plant shutdowns as arc losses. By applying these three conditions new columns are added to the structured data that indicate whether or not arc loss occurs in an electrode at each index of the unified time stamp. Past and future conditions require calling from both the previous day and the next day as shown in Figure 2.

Representation Learning and Predictive Classification

Once the data is processed and faults are detected a high-dimensional analysis enables systematic elimination of irrelevant features. Traditional dimensionality reduction techniques such as principal component analysis (PCA), partial least squares (PLS), Fisher discriminant analysis

(FDA) and canonical variate analysis (CVA) have been successfully implemented in many process industries (Russell et al., 2012). Extension of these methods to non-linear associations and on-line applications is achievable through the kernel trick and dynamic variants, respectively (Chen and Liu, 2002; Choi et al., 2005). Finally, state of the art methods such as t-distributed stochastic neighbor embedding (t-SNE), uniform manifold approximation and projection (UMAP) and variational autoencoders (VAEs) are implemented (Lv et al., 2016).

An example of using PLS for dimensionality reduction with a subset of the metallurgical process data is illustrated in Figure 4. The red cross indicates the optimum number of

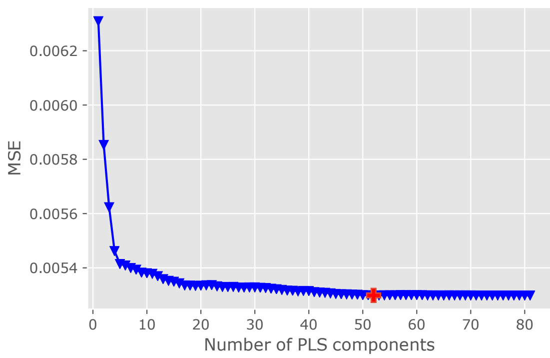

Figure 4: Dimensionality reduction example with PLS

PLS components (i.e., 52) in terms of mean squared error (MSE) and the remaining thirty components are candidates for dimensionality reduction. A random forest classification is performed and feature importance scores are determined as shown in Figure 5. The fifteen most important features are ranked in Figure 5 according to the mean decrease in accuracy with a random forest.

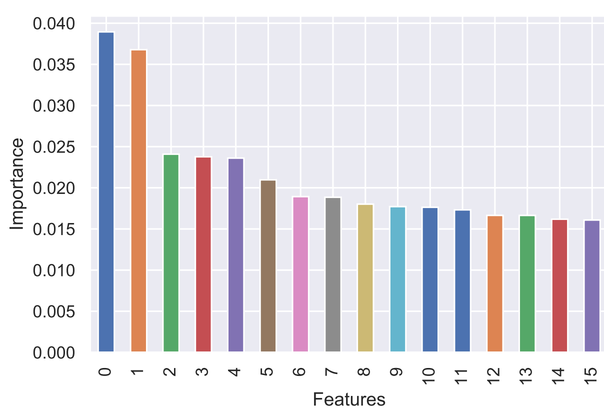

Figure 5: Feature importance in a random forest classifier

Ultimately the evaluation of the dimensionality reduction techniques will be directly tied to the predictive classification accuracy. In terms of the predictive classifier a similar comparative analysis will be adopted with traditional methods such as random forests, logistic regression, k nearest neighbors (kNN) and support vector machines (SVMs) as well as advanced techniques. In particular we will present the use of a long-short term memory (LSTM) recurrent neural network (RNN) with a deep convolutional architecture. Training data can be procured in the form of heat map images or time-series to leverage the cross-correlation and auto-correlation among features. Candidate models will be tested on new process data and evaluated according to the previously stated prediction objectives.

Conclusions

The use of representation learning algorithms for process data analytics is an emerging research area that offers significant benefits to the process industry. This work is a small part of a larger movement to migrate advanced data analytics techniques from statistics and computing sciences to process industries. Successful completion of this work will yield a predictive alarm that can improve EAF operation and increase production. Moreover, this work will explore and develop state of the art methods for predictive classification and dimensionality reduction. A comprehensive evaluation of the various techniques will be provided.

Acknowledgments

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