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# Inferential sensor-based adaptive principal components analysis of mould bath level for breakout defect detection and evaluation in continuous casting

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ABSTRACT

This paper is concerned with a method for breakout defect detection and evaluation in a continuous casting process. This method uses adaptive principal component analysis (APCA) as a predictor of inputs–outputs model, which are defined by the mould bath level and casting speed. The main difficulties that cause breakout in continuous casting are, generally, phenomenon related to the non-linear and unsteady state of the metal solidification process. PCA is a modelling method based on linear projection of the principal components; the adaptive version developed in this work uses the sliding window technique for the estimation of the model parameters. This recursive form updates the new model parameters; it gives a reliable and accurate prediction. Simulation results compare PCA, APCA, non-linear system identification using neural network (NN) and support vector regression (SVR) methods showing that the APCA gives the best Mean Squared Error (MSE). Based on the MSE, the proposed approach is analyzed, tested and improved to give an accurate breakout detection and evaluation system.



## 1. Introduction

Soft sensors are virtual instruments based on analytical models. They give an estimation of the process states parameters based on modelling and identification techniques. An inferential model can be obtained using first principles (i.e. mechanistic modelling), or by using grey or black box identification methods. However, in continuous casting the breakouts propagation, which is due to complex effects and high interactions between different variables, makes the process hard to model. It is, then, strongly recommended to use a data driven empirical model. Such model is based on the analysis of interactions between variables, data exploration, and modelling.

In continuous casting, the main measured directly affecting the breakout are the casting speed $v(t)$, the mould bath level $h(t)$ and the control input $u(t)$, see Fig. 3.

As known by the theoretical aspects and practical standards, procedures and methods are applied in continuous casting to control the interactions between metallurgical process elements. In fact, chemical composition, casting temperature, casting speed and other parameters should directly or indirectly be taken into account to obtain a reliable soft sensor for breakout detection.

The objective of this work can be summarized in two tasks:

- Firstly, breakout detection,
- Secondly, the breakout is evaluated according to the importance of the deviation of the model from its normal behaviour: This amount is quantified with MSE. A breakout with a little deviation from the normal MSE value is not as important as a breakout with a large deviation.

There are many related works in the field of soft sensor for quality prediction and evaluation applied in different systems and processes, the following are some of them:

- The prediction and evaluation of the key factors characterizing the product quality in various processes using soft sensing based multivariate statistical process control, fuzzy means and multivariate identification [1–10].
- Soft sensing methods including support vector machine, data driven and data mining [11–19].
- Mechanistic modelling based energy and mass balance [20,23]. This aspect is very complex to model particularly in a dynamic way.

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Nomenclature.

| | |
|---|---|
| PCA | principal components analysis |
| APCA | adaptive principal components analysis |
| PLS | partial least square |
| PCs | principal components |
| MSPC | multivariate statistical process control |
| MSE | mean squared error |
| MSEA | acceptable mean squared error |
| SVD | singular vector decomposition |
| Std | standard deviation |
| $C$ | covariance matrix |
| eig($C$) | eigenvalue of the covariance matrix $C$ |
| $\Re$ | real space |
| $\Phi$ | ideal correlation function |
| $\gamma$ | output space |
| $\chi$ | input space |
| $y$ | real model output |
| $X$ | vector of input data |
| $\varepsilon$ | modelling error |
| $S_x$ | estimated value of std |
| $u(t)$ | control input |
| $h(t)$ | mould bath level |
| $v(t)$ | casting speed |
| $T_{\text{cast}}$ | casting temperature |
| $N(0, \sigma)$ | normal distribution with zero mean and a std ($\sigma$) |
| $NN$ | neural networks |
| $f$ | modelling function |
| $D^{\text{Hist}}$ | historical domain of real data |
| σ | standard deviation |
| $T$ | score matrix of PCA algorithm |
| $R(f_{t-1},X_t^R)$ | model of the adaptive function used by PCA procedure |
| $[x_t, \ldots, x_{t-Nx}]$ | input data |
| $X_{\text{scaled}}$ | scaled vector of input data |
| $X_{\min}$ | minimal value of input vector ($X$) |
| $X_{\max}$ | maximal value of input vector ($X$) |
| $X_{\text{Meas}}$ | measured value of input vector ($X$) |
| $P$ | loading matrix of PCA algorithm |
| $E$ | residual error obtained from PCA |
| $V$ | eingenvalue matrix |
| $B$ | proportional coefficients of the estimated linear model using (PCA) |
| λ | eigenvalue of the covariance matrix |
| $N_x$ | number of the element of the input vector ($X$) |
| $N_y$ | number of the element of the output vector ($y$) |
| $N_\varepsilon$ | number of the element of the modelling error ($\varepsilon$) |
| $\beta$ | proportional coefficients of the estimated linear model using (APCA) |
| $l$ | number of the significant eigenvalue |
| $m$ | number of global vector |
| $\rho$ | volumetric mass of the liquid steel |

Soft sensing based principal component analysis (pca), and partial least squares (PLS), including its adaptive form have been widely considered as a promising approach for quality monitoring and data-based analysis and control from process history data. Its successful applications have been reported in numerous process industries [12,18]. Traditionally, PCA as a part of the MSPC takes an important place in monitoring methods. The PCA technique, characterized by its multivariate component, is strongly recommended to model a multi-input–multi-output system. Moreover, in some works, it was extended for quality prediction-based models [12,18,24].

Adaptive principal component analysis (APCA) is a relatively new method which is recommended for an accurate detection and evaluation of the breakout. Different factors such as metallurgical properties of the material, the solidification rate and the thermal operating conditions are then controlled.

The development of an accurate system to detect and to evaluate a breakout is a very complex task because the breakout cannot be directly measured by an instrument. The complexity of the breakout phenomena is due to a mixture of non-linear and unknown dynamics and parameters. There are many accomplished works in continuous casting technology field. However, they are limited, or have not dealt with a model correlation of key variables. Generally, the detection of breakout is based on processing of measured temperature profiles using the embedded sensors on the mould copper. This approach is detailed in [21–23], where some theoretical and applied aspects using neural networks are considered. In fact, the majority of published works on breakout prevention and detection systems deals with different methods of modelling using linear, non-linear system identification among others. Measurements of process parameters are done on main factors that influence the breakout, including temperature profiles.

Breakout detection and evaluation systems are generally based on the sticking phenomenon which is detected using thermal sensors located in the mould. The cooling–solidification process connected to breakout is considered as a thermal reactor where all process parameters as the mould bath level, the mould temperature field, the casting speed and other unsteady state parameters are considered.

In this paper, the idea of introducing an adaptive PCA connected to measurement of the above cited process parameters is somehow new. This approach is based on the analysis of the correlation between the mould bath level, casting speed and the tundish stopper. This approach consists in the following steps:

- The first step is modelling. A regression model is built using the input and output data, taking into account all dependencies. A residual is generated using the difference between the real and the computed data.
- The second step is an evaluation of the generated residual based on the MSE. Depending on the importance of the computed residual, the adaptive procedure reacts.
- The third step is a general evaluation of the detected breakout based on the MSE values. A classification of the breakout as significant and important is given according to the importance of the numerical value of MSE. This latter will be defined in Section 2.1.

The main motivations to use such an APCA-based approach are:

- The considered application is a multivariable system.
- The nature of the process application can present non-linear and unsteady state reactions; in such a case an adaptive form is needed.
- In many cases, the soft sensing approach does not require more than simple programming tasks. However, it may need some hardware tools. This approach is applied only in the case of the existing numerical control system i.e. modification of the existed software.
- The PCA algorithm is relatively simple to be implemented.

This paper is organized as follows. In Section 2, the proposed inferential model using data mining is developed, and then the PCA algorithm is presented. In this part, a matrix inversion procedure is needed and eigenvalues are computed. A particular focus is given to the numerical implementation of the proposed adaptive form of PCA. After that, the proposed computing scheme is implemented and tested. MSE would help to evaluate the residual importance. Section 3 gives a description of the continuous casting process and presents the process parameters as the main factors which the breakout is highly depending on. Simulation results and comments of the used adaptive and non-adaptive PCA forms are presented in this same section. Whereas, at the end of the paper, there is a comparative study between PCA, APCA, non-linear system identification using neural network (NN) and support vector regression (SVR). In this part, simulation results are shown in the corresponding figures and tables and an interpretation of the obtained results is given too. Finally, the developed