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Data Analysis of the Hot Rolling Process in a Stainless Steel Factory for Predictive Maintenance

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Abstract. This work presents the data analysis stage of the SiMoDiM project, an innovative project aiming at developing a predictive maintenance system for the stainless steel industry. The project focuses on the hot rolling process, one of the core steps in the manufacturing of steel sheets. Concretely, we have studied which parameters and variables can be employed in modeling the degradation of the coiler drums: critical components that operate under mechanical and thermal stresses. This study is the first step towards an intelligent system performing a predictive maintenance of such machinery.

Keywords. Data Analysis, Predictive maintenance, Intelligent prognostics tools, Condition monitoring, E-maintenance, SiMoDiM project

1. Introduction

In today's global competitive marketplace, there is intense pressure for manufacturing industries to continuously reduce and eliminate costly, unscheduled downtime and unexpected breakdowns. An important factor contributing to these breakdowns is the task of maintenance (that ultimately involves replacement of spare parts), which in the last years has suffered an important transformation to evolve from traditional *fail-and-fix* practices to *predict-and-prevent* ones, commonly referred as e-maintenance methodology [1].

E-maintenance addresses the fundamental needs of predictive intelligence tools to monitor the degradation of the machinery rather than detecting the faults in a networked environment and, ultimately, to optimize asset utilization in the facility. It relies on the fact that machines usually go through a measurable process of degradation before they fail, hence enabling a prediction of when a preventive maintenance must be carried out.

In this work we present the initial steps towards the implementation of this predictive maintenance methodology in a stainless steel factory from *ACERINOX Europa S.A.U.* (`http://www.acerinox.com`), one of the most competitive groups in the world

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in stainless steel manufacturing. Concretely, we focus on one critical process for manufacturing stainless steel sheets, the multipass *Hot Rolling*, a mill process which involves rolling the steel at a high temperature, enabling an easy shaped of it. The e-maintenance related to this rolling process is part of the challenging and innovative project *SiMoDiM*, which aims at developing a novel monitoring and diagnostic system for the stainless steel industry, seeking the digital transformation of the production processes in order to achieve intelligent, more efficient, competitive and flexible factories.

After a review of the hot rolling process, we analyze the collected dataset (a vast set of data about the hot rolling process from the ACERINOX factory in Cadiz (Spain)). Then we perform a visual and numerical data analysis to extract candidate variables and features that, in a future work, can be used to develop an intelligent prognostic tool, objective of the SiMoDiM project.

2. Steckel Hot Rolling Process

In metalworking, rolling is a metal forming process in which metal stock is passed through one or more pairs of rolls to reduce and uniform the thickness. Hot rolling refers to the case when the rolling process takes place employing metal that is preheated above its recrystallization temperature, typically over 1700 °F [2].

The starting material are large pieces of metal (like semi-finished casting products), which, after being heated, are worked to reduce their thickness. For that, the material may need to pass one or several times through the mill, reducing iteratively the thickness and increasing its length. Fig. 1 shows a schema of the Steckel hot rolling mill [3], where the steel sheets run along the roller conveyors to be worked in the roll stand. If more than one pass is necessary, the metal sheets are coiled around the drum, and the process is repeated in the inverse direction (left-to-right, right-to-left).

Due to the high temperatures of the process, degradation of the machinery is common and a proper maintenance plan is mandatory to avoid costly and long production downtimes. In this respect, the coiler drum is the part of the mill that fastest degrades because of the high temperatures and the friction against the material being rolled, therefore being the spare part which replacement we want to predict before it breaks.

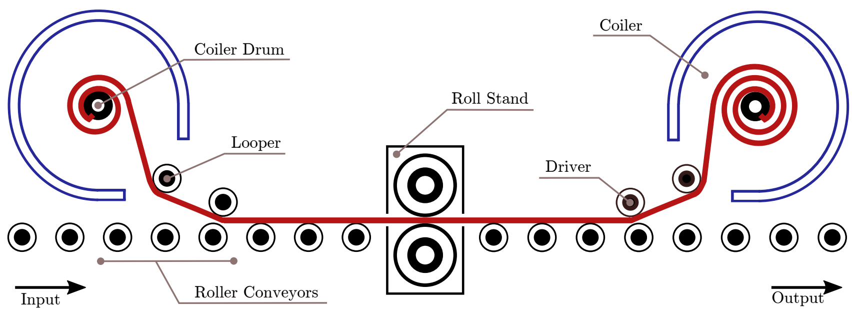

Figure 1. Schema of the Steckel hot rolling mill. The stainless steel sheet (in red) is heated and worked in the mill through one or multiple passes, until desired thickness is obtained.

3. The Data

The available data span over the years 2013-2016. For each month within that period, a number of files are provided describing each hot rolling process carried out in the factory. These files contain the value of 19 different variables measuring the processes' state after each 0.5 meters of rolled steel, including for example steel densities, coiler temperature, engines power or pressure and forces in the roll stand. The resultant dataset is vast, containing a total of 118,484 hot rolling processes, divided into 7,351 with one pass, 6,523 of 3 passes, 65,704 processes with 5 passes, and 38,906 of 7 passes or more. In order to design a successful predictive maintenance system, it is necessary to find out the variables that best reflect the coiler drum degradation and can turn into good indicators for deciding a preventive drum replacement.

4. Analysis

To analyze the data we built a toolbox written in the Python language, a trendy option within the *data analysis* community. Exploiting the insight and knowledge provided by experts from the factory, we considered four candidates for reflecting the drums' condition: *input* and *output-tension*, which measure the traction forces in both coilers, *leveling* that indicates the slope of the sheet being processed, and *bending* that measures its curvature. This feature selection process, is later verified both visually and numerically.

4.1. Visual analysis

A first analysis of the data was visually performed with the aim to detect changes in the behaviour of the four studied variables during the coiler drums lifetime. Also, we looked for likely correlations between these variables and other parameters of the hot rolling process that could interfere in their behaviour. In this way, it was detected a strong correlation between the observed variables and the length of the sheets being processed. Fig. 2-left illustrates this for the case of the *input-tension* and *output-tension* variables, where we can clearly see that the shorter the sheet, the higher the tensions. Since the number of passes in the rolling mill directly affect the sheet length, we also used that

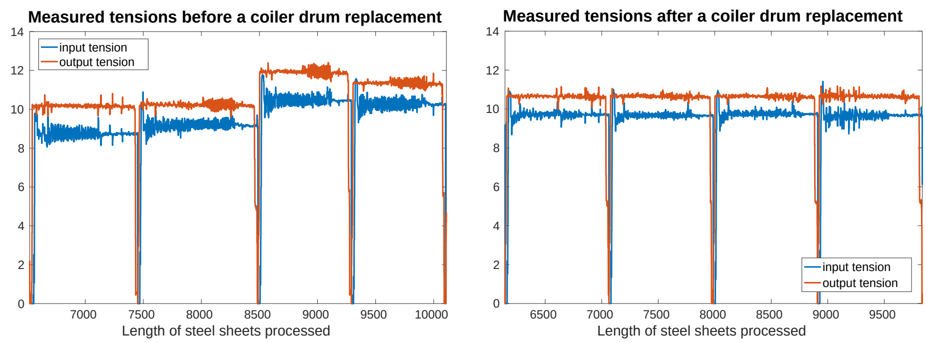

Figure 2. Measured tensions from the 4^{th} pass in four 5-passes processes just before (left) and after (right) a replacement of both coiler drums. Vertical axes are kilograms, and horizontal ones accumulated length of sheets processed in meters. Notice how tensions become more *stable*, and how lengths directly affect them.

parameter to cluster the processes, being the resultant groups individually studied. This drastically reduced the data dispersion.

The visual inspection also served to perform a first validation of the directions from experts. For example, Fig. 2 shows the input and output tensions measured during 4 processes (with sheets between 300 and 320 meters and 5 passes) just before (left) and after (right) the replacement of both drums. We can see how the tensions become more *stable* and reach faster a value close to their final one after the maintenance operation, which supports the expert's intuition that these variables can indeed be used to predict the drum's deterioration.

4.2. Numerical analysis

To validate the previous insights, the variables were characterized according to their different nature, and then numerically analyzed. The *Pearson* correlation coefficient r was used to check the influence of the sheets' length on the observed variables. The obtained values were -0,79 and -0,75 for input and output tensions respectively, indicating a strong downhill relationship, 0.62 for bending, setting a strong uphill relation, and of 0.32 for leveling, that reflects a weak-moderate linear relation. These coefficients came with a reduced *p-value* in all cases.

To verify that there is a significant/meaningful change in the values of the observed variables over time we analyzed them in the surroundings of four drum replacements. For that, we employed a window of 50 processes just after and before such replacements, selecting only processes with sheet lengths between 300 and 320 meters. From each data window, we extracted a number of features (including among others: average and variance of each variable, oscillation value or FFT coefficients), and numerically analyzed the variability/discrepancies before and after the replacements. For example, in the case of the first studied replacement, the average values of the leveling and bending variables decreased considerably (*e.g.* from 1.01 to 0.82*mm.* and from 93.46 to 72.61*Ton.* respectively). They also oscillated less, which was checked counting the number of times that these measures took values out of a certain range.

5. Discussion

The findings drawn from the visual and numerical analysis, suggest that the development of a predictive tool for inferring the drum's degradation seems possible. In this way, our next milestone is to select a suitable model for that tool, which being fed which such variables, allows us to detect the *optimum timing* for a preventive maintenance.

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