ISSN 2237-0234

REDUCING PROCESS VARIABILITY, BY RETRACING EACH PRODUCT HISTORY AND BY DISCRIMINATING CATEGORIES OF PRODUCTS[1]

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Abstract

Process Variability impacts yield, product quality, environmental footprint, and consumption of energy and raw material. Better control on Process Variability requires enhanced means to investigate and follow-up influential Process parameters. To achieve our goal of reducing Variability, two pieces of software were designed: a Quick Data Delivery software. It gathers Process and Quality data from heterogeneous sources, and then retraces, for each product, the specific transformations it went through; and a Data Analysis software. It detects which Process parameters consistently changed from one category of products to another.
The key idea is to find what makes the difference between two or more categories of products (for example, "good" products vs "bad" products). We will base our presentation on the deployment of this software on the Mandrel Mill at Vallourec & Mannesmann do Brasil. The benefits to Production and Process Engineers will be illustrated: save investigation time, allow more frequent analysis, make discoveries easy to share and implement. Ultimately, anticipation of Process variations is in sight.
Key words: Process variability; Traceability; Data analysis software; Anticipation.

REDUZIR A VARIABILIDADE DE PROCESSO ATRAVÉS DA RECONSTRUÇÃO DO HISTÓRICO DOS DADOS DE PRODUTO (PROCESSO E QUALIDADE) E DA SUA CATEGORIZAÇÃO

Resumo

A Variabilidade de Processo causa impactos no rendimento, qualidade do produto, impacto ambiental e no consumo de energia e das matérias-primas. Para ter-se maior controle sobre a variabilidade do processo, são necessárias ferramentas sofisticadas para a investigação e acompanhamento dos parâmetros que exercem influência no Processo. Para se alcançar o objetivo de reduzir a variabilidade, dois *softwares* foram desenvolvidos: um software ágil de entrega de dados (*Quick Data Delivery software*), que reúne dados de Processo e de qualidade de fontes heterogêneas e que, em seguida , rastrea para cada produto as transformações específicas pelas quais passou; e um *software* de análise de dados (*Data Analysis Software*) que detecta quais os parâmetros de Processo mudaram, de forma consistente , de uma categoria de produtos para outra. A idéia principal é descobrir o que faz a diferença entre duas ou mais categorias de produtos (por exemplo, produtos de "boa" qualidade vs de "má" qualidade). Nós vamos basear nossa apresentação sobre a implantação deste *software* na área de Laminação Contínua com Mandris (*Mandril Mill*) da Vallourec & Mannesmann do Brasil. Os benefícios para os engenheiros da produção e do Processo será abordado: A ferramenta economiza tempo de investigação, permite a realização de análises rápidas e com maior freqüencia, torna as descobertas fáceis de serem compartilhadas e aplicadas no processo. Por último, mostra com clareza como se antecipar às variações de processo.
Palavras-chave: Variabilidade do processo; Rastreabilidade; Análise de dados; Antecipação.

[1] *Technical contribution to the 15th Automation and Industrial IT Seminar, September 20th to 22nd, 2011, São Paulo – SP, Brazil.*
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ISSN 2237-0234
ABM ASSOCIAÇÃO BRASILEIRA DE METALURGIA, MATERIAIS E MINERAÇÃO
20 a 22 de setembro 2011 - São Paulo - SP

1 INTRODUCTION

1.1 To Make a Good Cake

Remember when your grandmother made a cake. A nice chocolate cake. It was soft, tasty, slightly hot, and smelled wonderfully.
Now, imagine you want to make your own chocolate cakes. You took the cooking book. You read the recipe. You did exactly as it said. And your cake is good. But not as good as your grandmother's.

1.2 How Did She Do That?

What makes the difference between (her) delicious cakes and (your) good-but-not-great cakes? Well, your grandmother had a lot of experience. She knew her tools perfectly. And she knew the difference between theory and practice: she adapted the recipe to ingredients and cooking conditions.
This is also how it works on a steel mill.

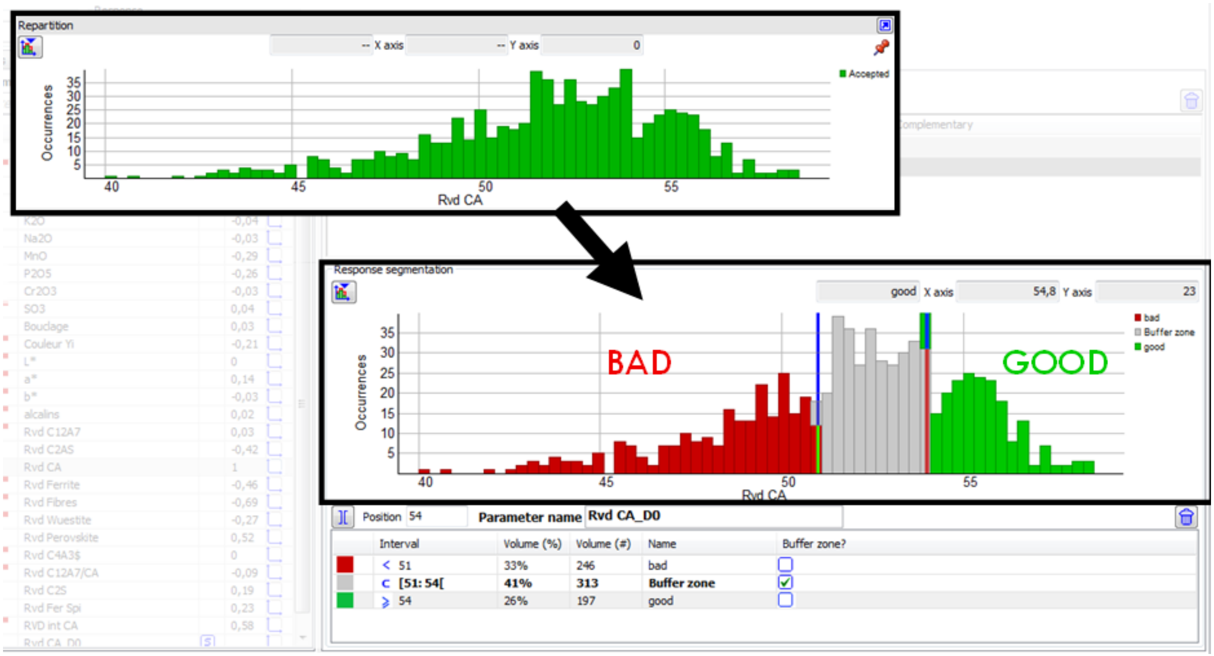

Figure 1. Asking the software what made the difference between "good" products (green) and "bad" products (red). Telling what we look for is an important step.

1.3 What Is at Stake Is What Variability Takes

A steel mill faces changes in its conditions of production: changes in the iron quality, changes in machines configurations, changes in the final requirements (steel quality, geometry). With hundreds – or even thousands – of process parameters, the cake is not easy to make: there is variability in the final products.
Process Variability impacts yield, environmental footprint, product quality, and consumption of energy and raw material. To control it, Steel industry players were soon aware of the value of making Process data available for Process monitoring, and good progress was achieved like this. However, there is still room for improvement.

ISSN 2237-0234

Process Variability depends on upstream operations (variable input) and current operations (complex process, involving many parameters that may interact). Everyone is well aware of that. However, it is common to see downstream areas working without detailed process information from upstream areas. It is like driving a car without knowing where you come from.
This is particularly true in the steel industry, both for historical reasons and because the process is long and complex.
This is why the first question is: “what is each product story?”

2 MATERIAL AND METHODS

2.1 What Is Each Product Story? A Matter of Traceability

Remember that you want to know why THIS group of products went wrong. Or why THAT group of products was great. The difference is in the way you made them. So, you need to know what happened to them.
Each product has a story. Retracing this story in the mill’s databases is a long and tricky job. So long and so tricky that it is rarely done. This “data gathering” work is traditionally done when the mill faces a big Process issue (such as an expensive defect that lasted for a long time). This very restrictive approach impedes Continuous Improvement.

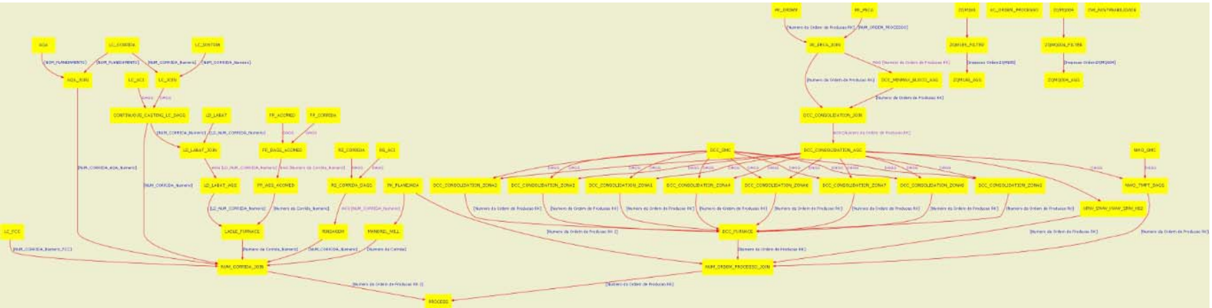

Figure 2. Retracing each product story can be a long job.

Our goal was to provide mills with means to look frequently at their data, without wasting time in gathering data from heterogeneous information systems.
To industrialize this “data gathering” and “data preparation” work, the system had to be able:

- get data from different databases (process and quality data);
- retrace the story of each product (with the specific transformations it went through);
- automate data cleaning;
- give everyone an access to information that is ready-to-use in real-time.

It is with this clear vision that this system was installed from november 2010 to april 2011, at Vallourec & Mannesmann do Brasil, Barreiro (MG).
Once we had each product story, we were able to compare each product with the others, and see what made the difference.
But how can I explain the difference between two products, when so many parameters constantly move?

ISSN 2237-0234

2.2 What Made the Difference? A Matter of Sorting Influential Parameters

When trying to find the root cause of a phenomenon within a great number of moving parameters, two approaches are possible:

- the top-down approach will tell which parameters have the greatest influence on the whole situation (ex: to grow a tree, you need ground, sun and water). A wide variety of techniques belong to this top-down approach, among which Statistics. These approaches are efficient to find big trends. But when coming to exceptions (why do pine trees do not grow as well here?), these approaches are no longer efficient;
- the bottom-up approach will focus on each specific situation (pine trees, eucalyptus, oaks, etc. growing in SP, MG, ES, etc.) and will tell what are the parameters whose value range changes from one group to another. This approach is very efficient to sort locally influential parameters, and interactions between parameters, without any *a priori*.

We chose to implement a specific bottom-up "graphically inductive" algorithm, fit for spatial investigation. This algorithm stands noise in data and missing values, and is also able to analyse non-numerical information (such as "blue", "red", "yellow" or "supplier A", "supplier B").

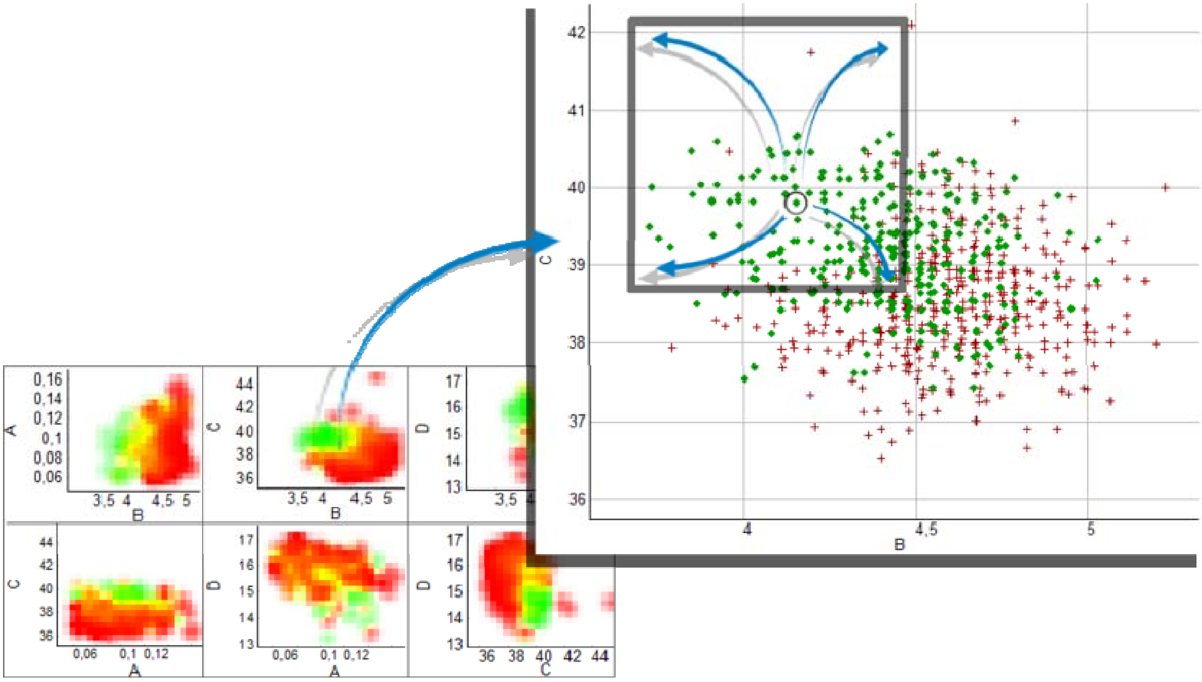

Figure 3. The "graphically inductive" algorithm works by growing groups with the same characteristics.

Investigating a great number of parameters, 1 by 1, then 2 by 2, then 3 by 3, etc. to investigate potential interactions involves an explosion of the number of combinations. This issue was addressed with an algorithm that stops the spatial investigation when it is not adding anything to previous discoveries.

ISSN 2237-0234

3 RESULTS

3.1 Autonomy Makes Continuous Improvement Faster

Fruit of 7 years of investigation and software development, this data analysis technology is substantially easing the work of Process Engineers:

- getting ready-to-use data is a matter of seconds. For some users, it made a change from several days of work to only a few seconds. This is engineer time saved;
- having ready-to-use data in one click allows reacting much faster to any situation that requires analysis. This represents days, weeks of months of production defects or over-consumption spared;
- having ready-to-use data in one click brings the possibility to make many more investigations than previously. Time saved on data preparation is spent to improve the Process much more frequently. This brings agility. Agility means ability to deliver products quicker;

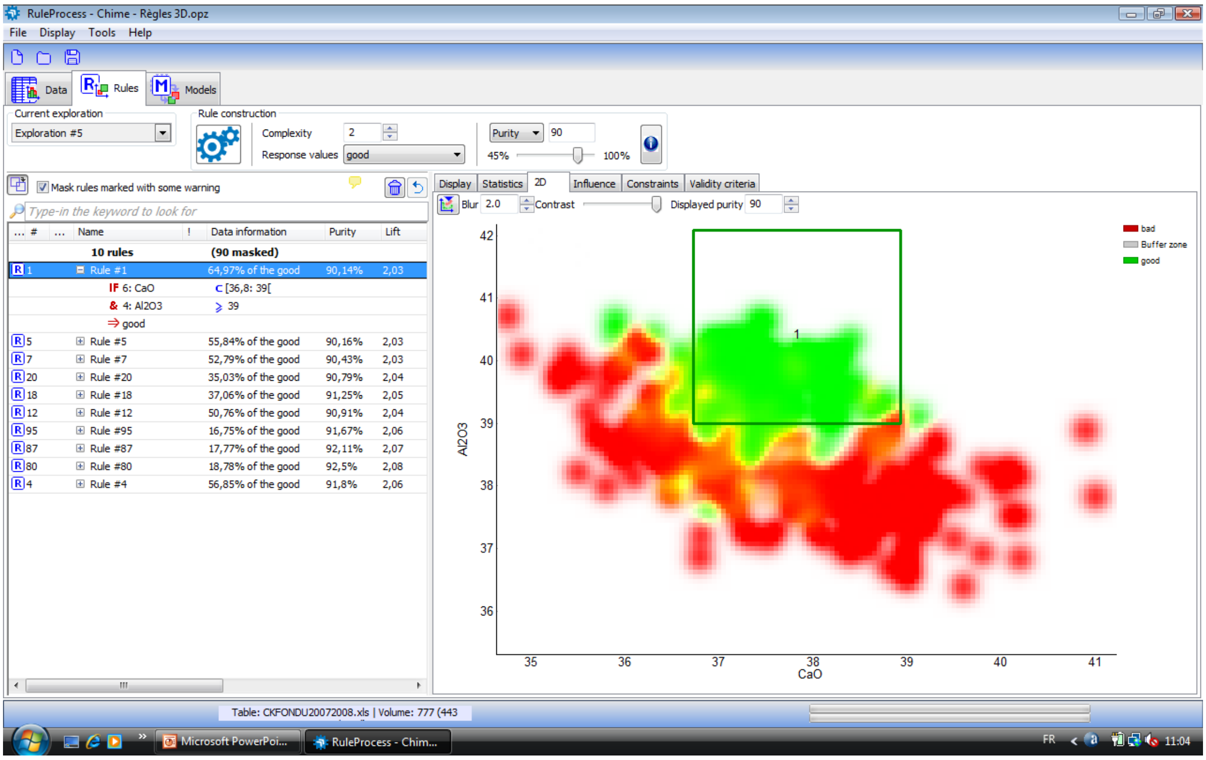

Figure 4. Finding what makes the difference between "good" Process Windows (green) and "bad" Process Windows (red).

- analyzing data with the "graphically inductive" algorithm allows to investigate up to 3 000 parameters, and the algorithm will sort a handful of significant parameters in a given situation, as long as the information is recorded. It allows finding best practices, ready for implementation (influential parameters, and exact values, that will improve the Process). Results are so clear, that they can be shared with everyone: acceptance by Process operators is key to Process improvement;
- analyzing data with the "graphically inductive" algorithm allows using raw data: noisy data, aberrant values, missing values, and symbolic (non-numerical) data. Also, such algorithm can be used on discrete or continuous phenomena

as well. Clearly, it allows analyzing data that could not be used before, thus widening the scope of investigation: the odds to find a solution to a given problem are greater.

Resulting from this, Process Engineers get an opportunity to gain autonomy in their Process analysis. The mill protects and capitalizes on its know-how.

4 CONCLUSION

4.1 Beyond Technology, Process Intelligence Depends on People

As any data analysis technology, this approach is limited by data availability and data accuracy. The steel industry clearly has great maturity, in this respect.

However, gathering data from one end to the other end of a steel mill is not an easy task. Beyond technical ability, there is a crucial issue in animation. This Continuous Improvement animation requires clear organization, skilled workforce, and appropriate culture. In this respect, our experience is that steel players in Brazil are a step forward, and they have a clear opportunity to maintain a competitive advance. By sharing Process information from upstream areas to downstream areas, a steel mill can significantly improve its Process Intelligence.