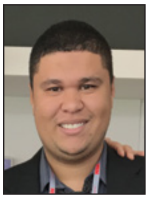
A Revised Concept of Quality Performance Measurement

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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It is common in the steelmaking industry to measure a product's quality performance using the metallic yield concept: [input/output]. As iron mass tracking basically links the highest costs from upstream processes to the losses in the downstream phase, this concept is widely applied but presents some limitations in assessing overall quality performance in downstream operations, such as forming.

For instance, in the rolling mill, the geometric distribution of the mass of steel along the rolled body does not impact the metallic yield but might have a high influence on the business result, because the price paid by the customer can be based a geometric characteristic instead of weight (thickness, length, etc.).

Specifically in the pipe industry, customers often pay by the geometric characteristic of length, which can cause the so-called "latent" quality losses in relation to the traditional metallic yield model.

The tube quality loss model is a data-driven model that proposes the process optimization, not only by avoiding weight loss, but by enhancing the geometry of the product to maximize profit.

By highly intensive pipe-by-pipe measurement and tracking systems, the model describes — in terms of variance leverage — how and where the company's profit is impacted through the production flow. It is also possible to update physical specialist models for rolling geometry with actual production results, reducing variability on the production planning operations.

Discussion

The Problem — In the pipe and tube industry, the client request can be made in terms of both the length and weight of tubes, so there can be ineffectiveness that is invisible, because they are not direct weight losses like length cuts or material burns, but geometric losses.

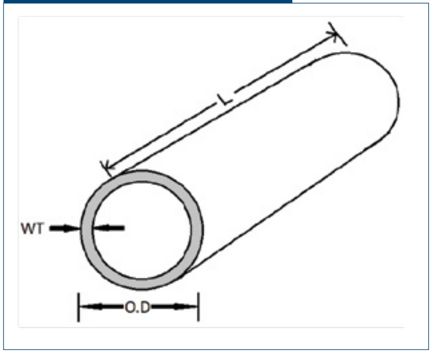
The principle of mass conservation states that in any system closed to mass and energy transfers, the mass of the system must remain constant over time as the system's mass does not change,[1] as mass can neither be created or destroyed a slight change on the tube's wall thickness can have a big impact on the length or weight of the tube.

$$kgm = \frac{(OD - wt) \cdot wt}{k} \qquad \text{(Eq. 1)}$$

where

kgm = kilogram per meter,
OD = outside diameter,
WT = wall thickness,
L = length and
K = coefficient related to material's density (carbon steel = 40.55).

Figure 1



Tube dimension.

$$\frac{(339\,mm - 13\,mm)\cdot 13\,mm}{40.55} = 104.51\frac{kg}{m}\cdot 30\,m = 3135.4\,kg$$

(Eq. 2)

$$\frac{(339\,mm - 12\,mm)\cdot 12\,mm}{40.55} = 96.77\frac{kg}{m}\cdot 30\,m = 2903.1\,kg$$

(Eq. 3)

In the equations shown, if one aims to produce a tube with 339-mm outside diameter, 13-mm wall thickness and 30-m length, a 1-mm change in wall thickness represents the need for 232.3 kg more steel to produce the same tube maintaining the length.

The Model — Depending on how the client makes their request, it is possible to optimize the geometry of the tube in order to avoid geometric losses. The model proposed describes how rolling geometry behaves along the process steps and shows how the exact processes contribute positively or negatively to the final pipe geometry and, consequently, how each step affects the company's dispatched volume in the same terms of the unit sold pricing. Moreover, the model provides the necessary information to optimize, with actual production results, the rolling mill process in order to deliver the requested quantity with minimum asset occupation.

As the market buys rolled pipes in dollars per length, the first step is to change the rolling geometry recursive formulas, which are usually written in terms of mass conservation to their equivalent geometric conservation. These formulae were applied in modeling the actual industrial database, which is obtained by massive automation and measurement systems installed through the Vallourec Soluções Tubulares do Brasil S.A. (VSB) state-of-the-art premium quality finishing (PQF) rolling mill, located at Jeceaba in Brazil (Fig. 2).

The Formulae — By studying the variation between the planned production standard on each measurement system, it was possible to determine the impact on the final tube length, which created a concept called "Effect (E)," the contribution or ineffectiveness to the final tube variation, so the sum of each effect represents the tube's deviation from the planned length.

$$\Delta L_{\substack{final\\tube}} = \sum E = E_{Billet} + E_{PQF/EM} + E_{Crop\,EndSaw} + E_{SM} + E_{Scale} + E_{BeamSaw}$$

$$E_{Billet} = \Delta L_{Billet} \cdot \lambda_{Billet}$$

$$E_{Scale} = \left[L_{PQF} - \left(L^{\circ}_{PQF} + E_{PQF} \right) \right] \cdot \lambda_{PQF-NDT}$$

$$E_{PQF} = \left\{ L^{\circ}_{PQF} \cdot \left[1 - \left(\frac{A_{PQF}}{A^{\circ}_{PQF}} \right) \right] \right\} \cdot \lambda_{PQF-NDT}$$

$$E_{CropEndSaw} = \left[\frac{(L_{NDT})}{\left(\frac{A_{PQF}}{A_{NDT}} \right)} \right] - L_{PQF} + L^{\circ}_{CropEndSaw}$$

$$E_{SM} = L^{\circ}_{NDT} \cdot \left\{ \left[\frac{\left(\frac{A_{PQF}}{A_{NDT}} \right)}{\left(\frac{A^{\circ}_{PQF}}{A^{\circ}_{NDT}} \right)} \right] - 1 \right\}$$

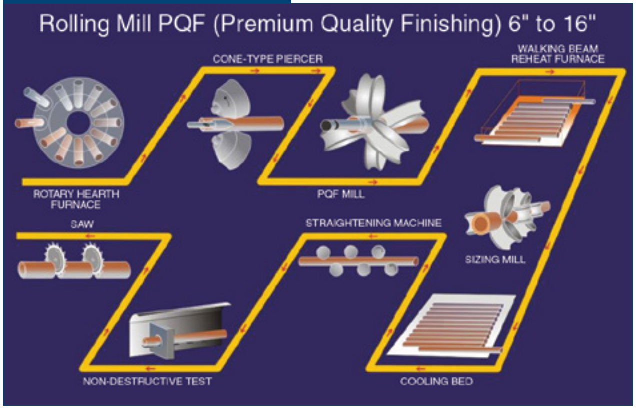
ΔL = Pipe's length deviation from the plan,
λ = Pipe's elongation until the final tube,
L = Pipe's length,
L° = Pipe's planned length,
A = Pipe's cross-section area and
A° = Pipe's cross-sectional area

Statistical Model Fitting — By exploring the process data, it is possible to define which equipment had more variability and therefore more impact on the performance. The sources of variability were enumerated and their respective effects were estimated, and so defined which systems should be monitored closer.

Analysis of variance (ANOVA), as shown in Table 1, was applied to describe the volatility of the pipe net length, whose associated generalized linear model (GLM) described how each process step contributes to the response variable "length deviation:" either on its mean or on its variance.

Each term of the length conservation recursive formulae was considered as a covariate in the statistical model,

Figure 2



Rolling mill's production flow at VSB Jeceaba.

Table 1

Model Fitting — Analysis of Variance (ANOVA)

Source	DF	Adj SS	Adj MS	F-Value	P-Value	%Variability load
Crop end finishing saw effect	1	2,366,903,077	2.37E+09	1,238,509.00	0	57.62
Conti mill effect	1	933,626,615	9.34E+08	488,530.90	0	22.73
Scale effect	1	510,953,028	5.11E+08	267,362.10	0	12.44
Sizing mill effect	1	169,502,083	1.7E+08	88,693.92	0	4.13
Crop end hot saw effect	1	89,129,922	89,129,922	46,638.26	0	2.17
Billet effect	1	573,830	573,830	300.26	0	0.01
Groove	3	325,200	108,400	56.72	0	0.01
Error	19,245	36,778,930	1,911			0.90
Total	19,254	4,598,025,234				100

Table 2

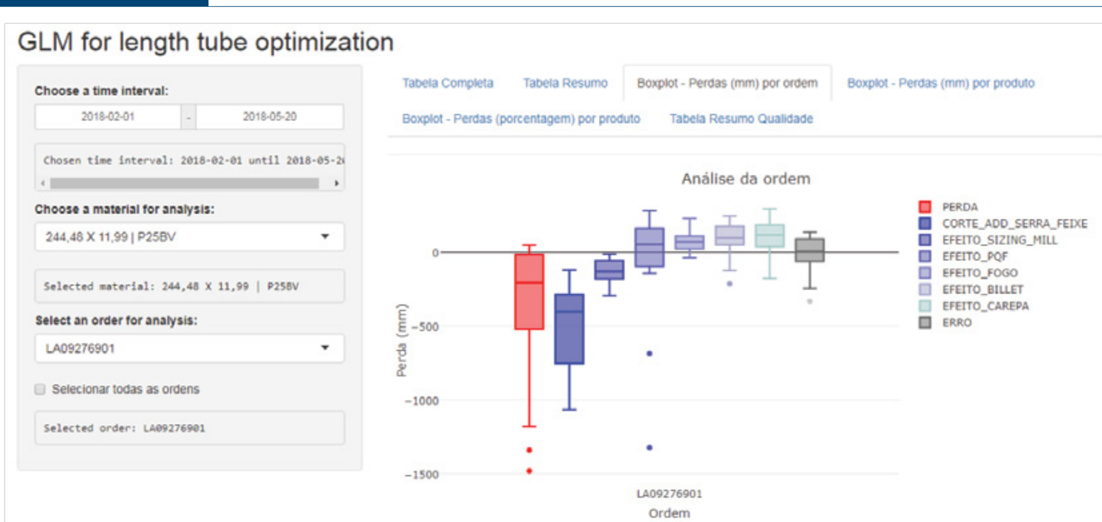
Model Fitting — Estimated Coefficients

Term	Coef	SE Coef	T-Value	P-Value
Constant	106.77000	1.04000	102.53	0
Billet effect	0.06897	0.00398	17.33	0
Scale effect	0.88924	0.00172	517.07	0
Conti mill effect	1.07979	0.00154	698.95	0
Crop end hot saw effect	0.80397	0.00372	215.96	0
Sizing mill effect	0.74432	0.00250	297.82	0
Crop end finishing saw effect	1.03808	0.00093	1,112.88	0
Groove				
1	10.2230	0.8740	11.96	0
2	–1.1260	0.8800	–1.28	0.201
3	–1.2210	0.8800	–1.39	0.165

and the product size families were formed and considered as factors in the model, as shown in Table 2. Finally, the random error of the model must be checked in terms of stability and normality, which are premises of this class of statistical model. In addition, the random error can be interpreted as the total sum of the measurement system's random errors, which is inherent in the process control.

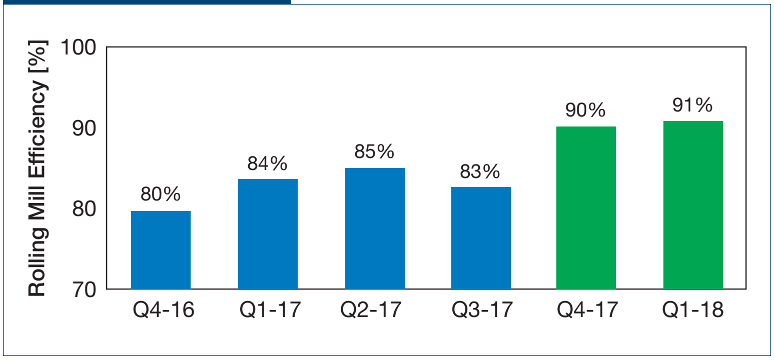
Therefore, these statistical tools help the analyst to answer questions about how each production step contributes to the final volatility of the company's revenue per product family, and then help him/her to prioritize technical actions to reduce the process variability and, consequently, revenue volatility.

Figure 3



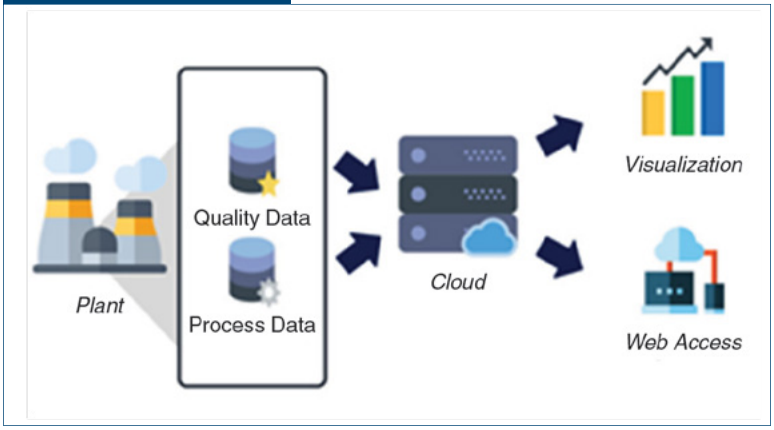
Published report on tube's performance.

Figure 4



Efficiency [%] for the reference product family of ϕ244.5 #47 lbs./ft.

Figure 5



Data flow for the model.

The raw data to feed the model was withdrawn by both Oracle and Postgres on a Cloud relational database and processed by Minitab® and RStudio®, producing comparative scatter and boxplot graphs to analyze process behavior and act on major causes of length loss.

The rolling mill's performance by material is shown in a web application based on calculations and measurements to represent the impact of each equipment on quality performance; therefore, this information is available for everyone interested, from the engineering to the shop floor team.

Results

After ranking the main causes of variability in net pipe length production, the process engineering and data sciences teams elected the main actions for improving the rolling mill productivity and, consequently, the entire downstream production flow. The actions were implemented in the second half of 2017.

To illustrate the quick wins of this model, Fig. 4 shows the trend of the indicator of line efficiency — which is the percent achievement of the theoretical productivity (in tons per hour) — for a specific standard reference product of size ϕ244.5 #47 lbs./ft. In green bars, the results after implementation of the actions related to the modeling analysis.

Next Steps

The implemented solution in the model demands high-capacity processing, since several tubes from multiple lots are analyzed. Moreover, the system's query demand varies over time, demanding a platform that is capable of being robust enough to scale resources in case of necessity. An advantage of this scalability is the fact that it's not necessary to maintain an expensive hardware without its full processing capability being used. Therefore, the next step of the project is to process the whole model in a cloud computing service, making it sturdy and favoring multiple accesses at the same time, all with a low operational cost (Fig. 5).

The model is used by the process engineer for analysis of the performance, but it can also be used for process target optimization to feed the production plan and be used by the supervisory system as an aim for real-time performance quality charts.

As the solution can be used on real-time applications and uses real-time information, a big disturbance on the residual error of the model means failure of the measurement system.

Reference

1. L. Okuň, "Energy and Mass in Relativity Theory," *World Scientific*, 2009, p. 2531. ✦