

Operational Intelligence for advanced process and asset monitoring

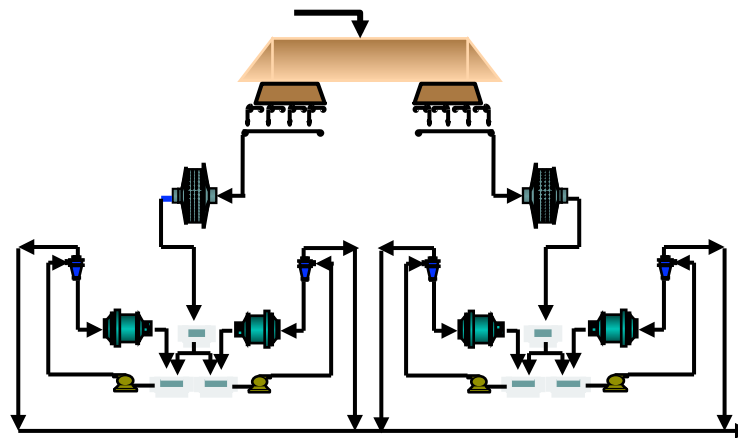
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Operational Intelligence challenge:

→ How to get actionable information from the process behavior?

Large number of process variables

- Complex cause-effect relationships
- Different (time based) Operation Modes: drift, noise, start-up, set point changes, disturbances, etc.



Large data bases for Real Time and Historical information about process variables and equipment vital signs.

Ol: an automated system capable to online analyze large sets of process data and generate context based meaningful information

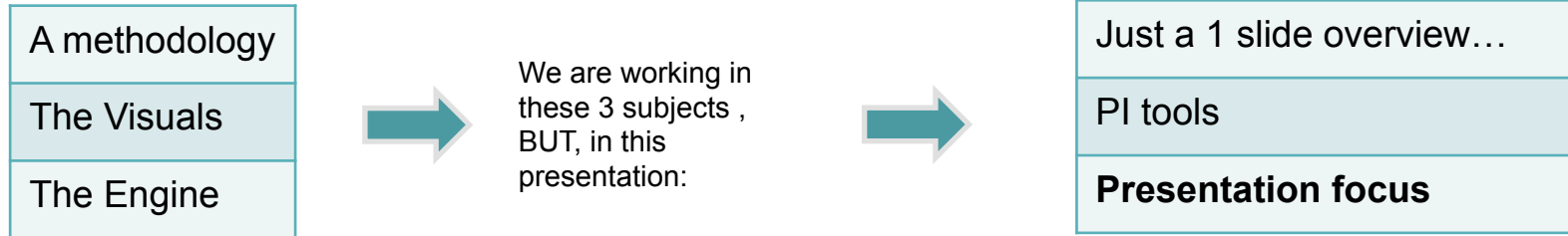
Operational Intelligence challenge:

→ How to get actionable information from the process behavior?

- How to determine early alerts if the process or equipment is deviating from a pattern or moving to a new one, being an “on quality pattern”, a “throughput pattern”, an “efficiency pattern”, a “malfunction pattern”, etc.?
- How to determine the “most influencing” factors that drives the evolution of a certain process variable or equipment vital sign KPI?

Scope

OI is a “multidimensional problem” by itself; it deals with:



Methodology, @ a glance

- ✓ An operational situation can be characterized (and measured) based on its primary function: GRIND, SEPARATE, RECLAIM, etc.. Characterization can be one or more KPI related to throughput, quality, availability, performance, efficiency, etc.
- ✓ Primary function deviations and sub-standard conditions can be categorized.
- ✓ An analysis can be done for the root causes of the deviations

Looks familiar?

...Primary function, failure mode, root cause, all of them are the basis for FMEA, FMCA.

...These basics concepts can be smoothly extended and applied to process analysis and monitoring.

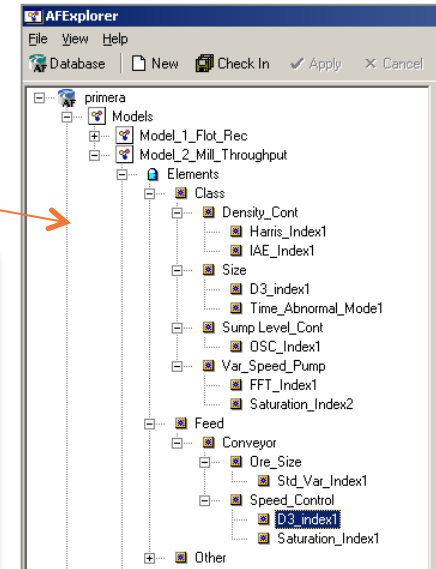
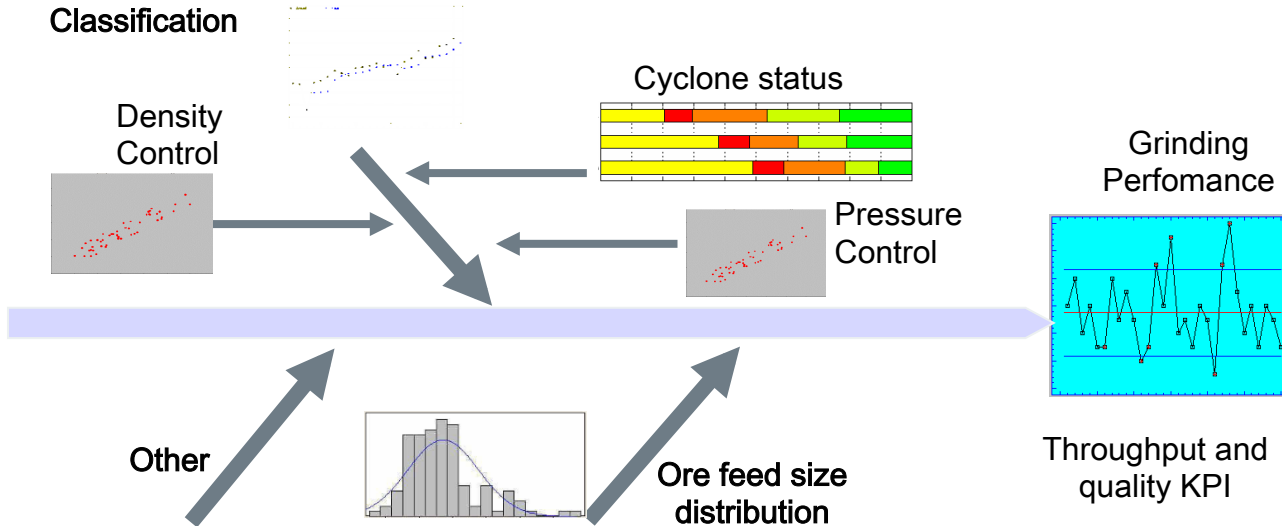
The methodology is already there....

1. Identify and characterize the primary function. Also the modes and “failure modes” among them. Whenever possible the measurements, calculations, status that best represent the primary function and mode.
2. Make a conceptual analysis of the “causes” that may affect, deviate or bias the operating mode.
3. For every root cause analyze how manageable is (ore characteristics in the grind feed is not, cyclone feed: yes).
4. For every root cause analyze its behavior that may affect the Primary function. Analyze how to characterize and measure this particular behavior, looking for: a) an explanation and hopefully: b) an anticipation on its effect.
5. If a better insight or anticipation can be obtained: repeat the process for the root causes.

Methodology, @ a glance

- For every behavior (Causes and Effects), a specific RtKPI is selected.
- RtKPI are structured and managed in PI-AF
- Model implementation: a context based representation of the cause & effect relationships and its related measurements,

Classification



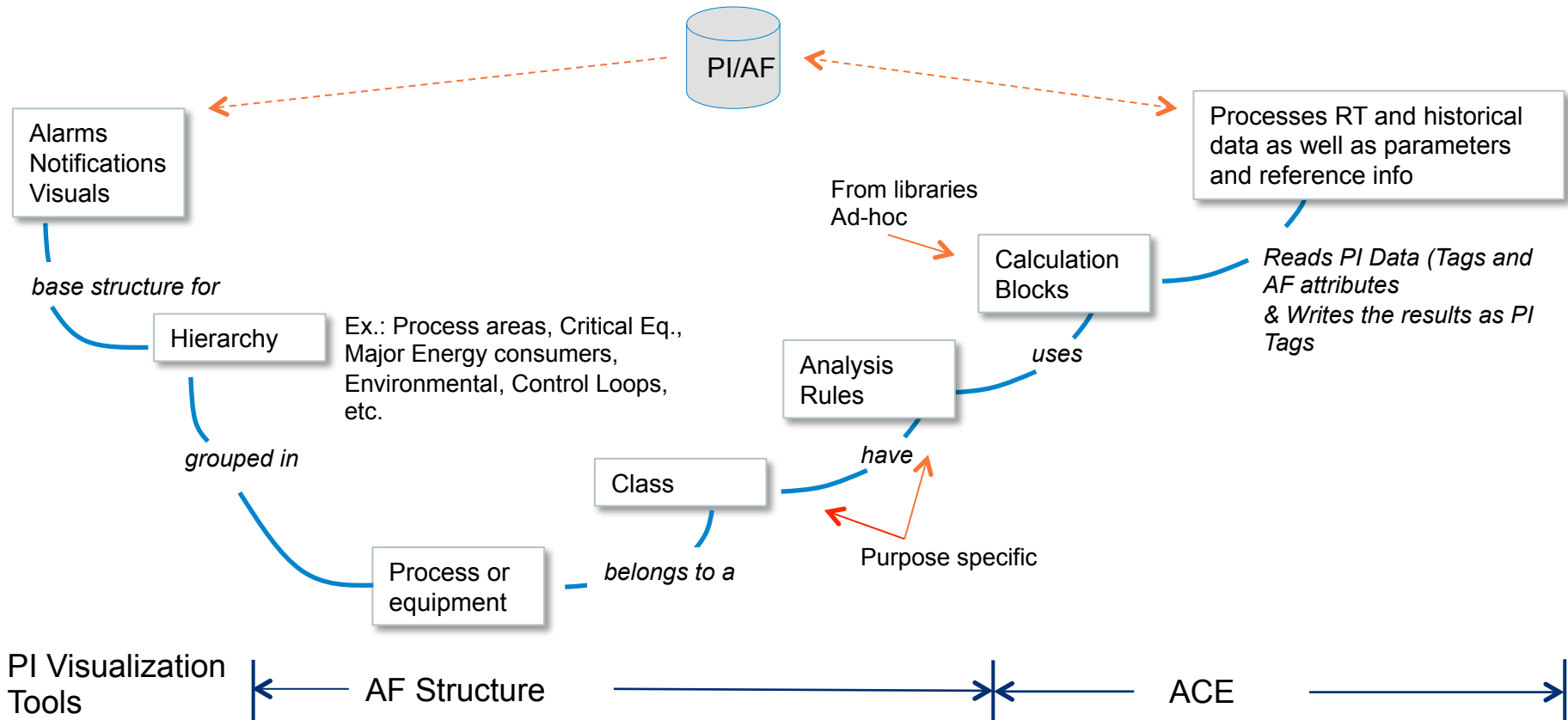
- The C-E model being managed in PI-AF.
- A set of templates for the calculation libraries that runs on PI-ACE.

The Engine

- ✓ The OI Model Runs in PI-AF, calculation block in PI-ACE
- ✓ OI model defines
 - The process or equipment decomposition tree for the C-E modeling
 - At any level the RtKPI evaluation blocks are assigned
 - Tree hierarchy can be used in case of roll-up KPI calculations
- ✓ The OI model is purpose specific, ex.: operational performance, equipment monitoring, energy efficiency, environmental, early alert of malfunctions, critical condition evaluation, variability monitoring, control loop assessment (*).
- ✓ There are two “calculation blocks families”: single variable and multivariable.
- ✓ The overall architecture allows for the inclusion of specialized calculation blocks
- ✓ OI model “reads” data from PI Tag’s and “writes” RtKPI as PI Tag’s.
Visualization is made using the standard PI tools, as well as the related ones, such as PowerPivot or similar.

(*) A dedicated set of KPI libraries is available for this purpose

The Engine, schematically



The Engine, calculation blocks and methods

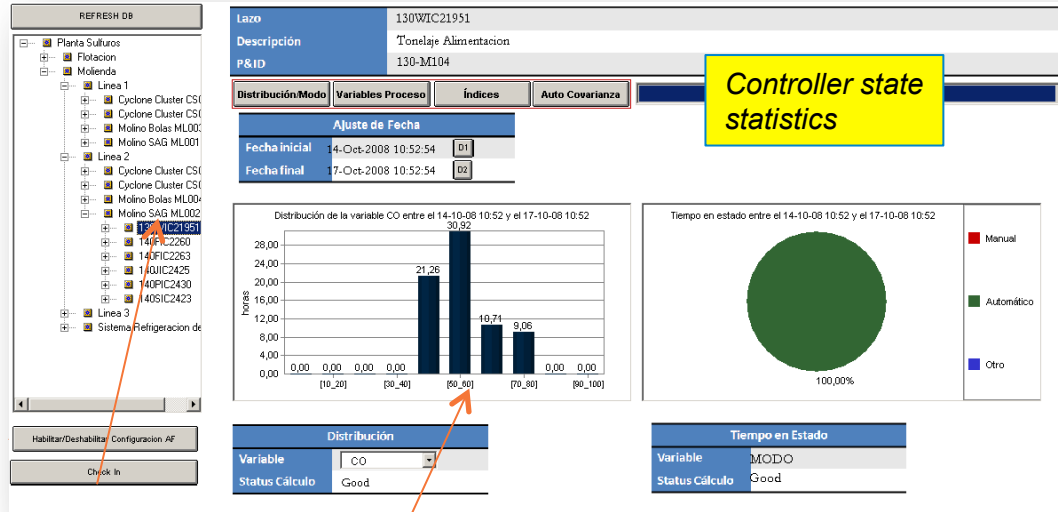
Single Variable	Description
Harris	Evaluates error variance
IAE (ITAE, ISE, ITSE)	Absolute error total (integral)
Miao Seborg	Oscillation index based on auto covariance.
Forsman Statting	Oscillation index. Computes the areas whenever the variable is crossing "zero"
D3	Scheffe's test, detect behaviour changes.
Time on state	State histograms
Distribución	Time on range, for selected ranges
General Statistics	As available in PI AF

Variability
indexes

Mostly
used for
control
loop
monitoring

Multi Variable	Description	Purpose
VFA	Variability Factor, evaluate the most influencing factors for a specific behavior.	Process analysis- Data Mining
PLS	On line estimation of selected variables.	Process Modeling
SBM	Similarity based Method; evaluates if the current behavior corresponds to a recorded pattern. Also a self learning method for new patterns	

The Engine, calculation blocks and methods, app. Example, single variable RtKPI



PB Visualization of RT calculation blocks results.

Example: Control loop monitoring

Controller selection

Variable values distribution histogram

Forsman Index (Oscillations)

IAE Trend

Miao Seborg Index (Osc.)

The Engine, Multivariable Analysis, Variability Factor analysis

From “n” process variables, generate a set of “m” new variables or “Variability Factors” that:

- $m \ll n$ (reduction in the complexity of the interpretation)
- The VF's are expressed as a linear function of the original “n” variables (linear on the parameters, the variables can be preprocessed, ex.: squared, log, etc.)
- The VF's are selected as those that explains “most” of the variability of the original “n”.

THEN

The process behavior can be characterized using the reduced set of new variables, specifically: using statistical indexes to evaluate patterns.

USES

- Deviation from a pattern can be related to a process sub-standard condition or equipment failure.
- Belonging to a pattern can provide an insight about the most influencing factors at a certain time.
- A new generation of “process visualization” for operator empowering, beyond trends.

The Engine, Multivariable Analysis, Variability Factor analysis examples

SAG liners wearing analysis

- Flujo de Mineral en la alimentación
- Flujo de Agua en la Alimentación
- Potencias en los motores del molino (Nº1 y Nº2)
- Velocidad del Molino
- Presiones en los Descansos de Alimentación y Descarga
- Flujo de Pebbles
- Ruido
- % de Llenado, Molino SAG
- % de Llenado con Bolas, Molino SAG
- % de Llenado con Mineral, Molino SAG
- Mediciones de Granulometrías D90, D75, D50, D25 y D10

Data reduction from 15 to 4 (pseudo variables) that explain more than 80% of the variability.

Simpler XY plots can be used for the process monitoring

A single Index, named "Hotteling" can be used to evaluate the operation (belonging to a pattern)

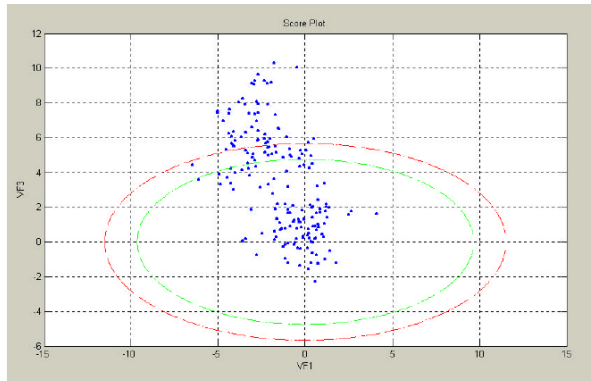
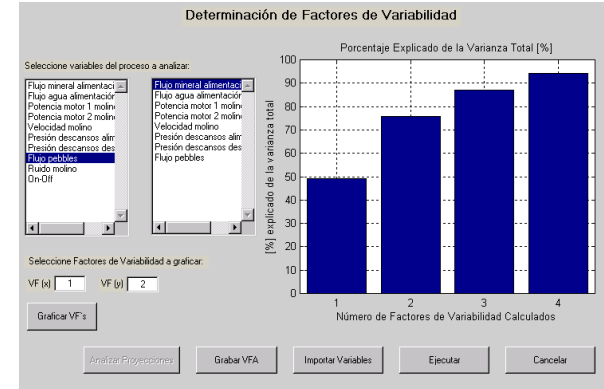
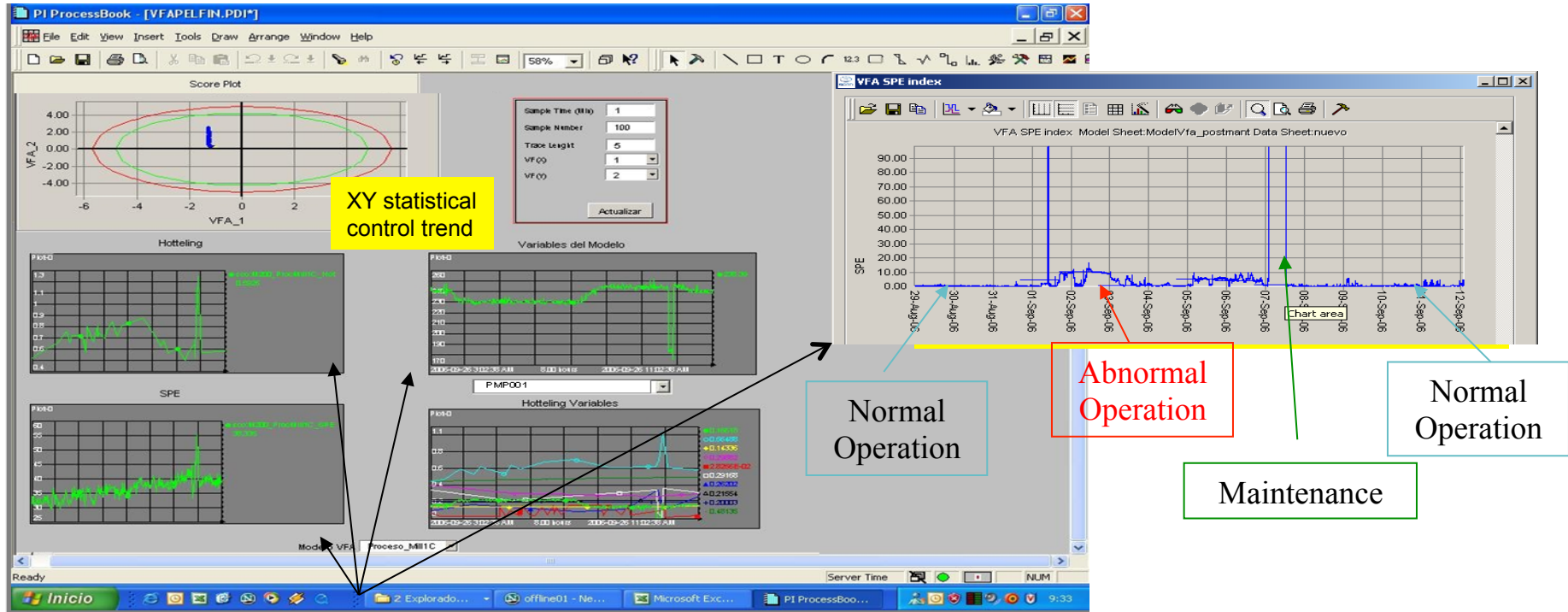


Figura 3. Score Plot. Visualización del cambio de Revestimiento en SAG 1

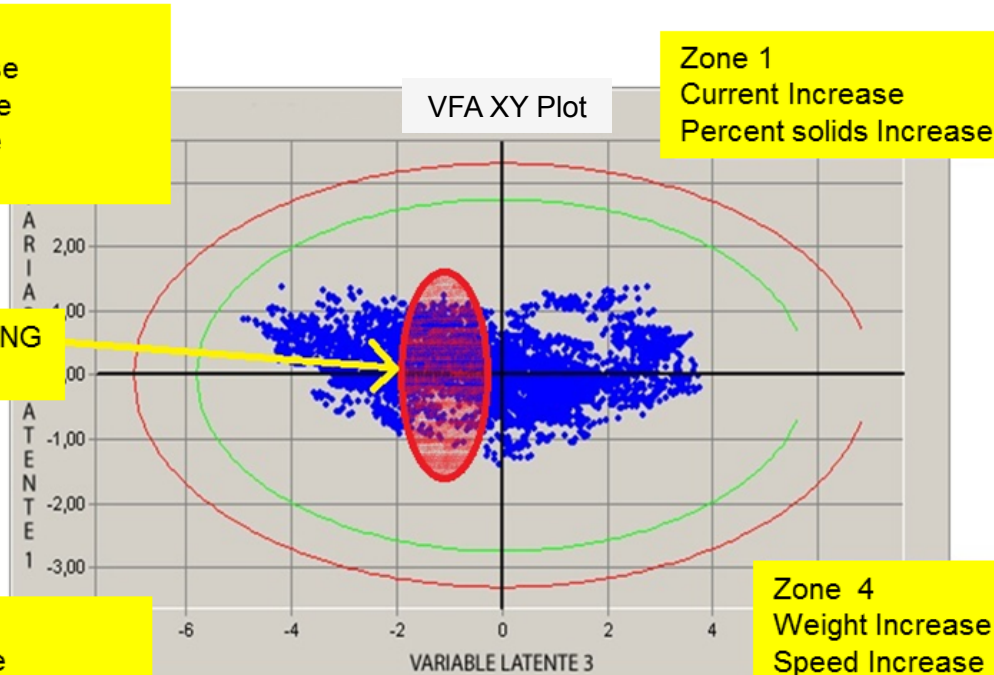
Excursions on the XY plot can be related to changes in Mill Liners, conversely, to Mill Liners wearing

The Engine, real time evaluation of a cyclone pump operation



Simple RtKPI evaluates if the Pump operational variables (15) belongs to a "normal" pattern

The Engine, Process and Equipment Modeling, the PLS technique



Zone 2
Weight Decrease
Speed Decrease
Power Decrease
TPH Increase

Zone 1
Current Increase
Percent solids Increase

PREFERRED OPERATING
ZONE

Zone 1
Current Decrease
Percent solids Decrease

Zone 4
Weight Increase
Speed Increase
Power Increase
TPH decrease

Using the historical data a VFA analysis was done, being the goal to determine a pattern model for the SAG mil operation as well as the relationship of the Pattern visualization with the process variables

The Engine, Process and Equipment Modeling, the PLS technique

For a set of “X” input variables and “Y” output variables, applying similar statistical technics as described, it is possible to determine a reduced set of variables that:

- represents the variability of the original ones
- with a much less quantity of variables
- AND: are “orthogonal” or “independent” variables
- Then a model can be developed, that calculates the relationship of the “new” set of I/O. And using the “reduction” equations, the model that relates the original X and Y variables.

USES

- Evaluate difficult to measure process variables, ex.: when the “Y” can be measured by offline sampling and analysis only.
- Similar, but using the model to provide information between lab analysis
- Compare the actual operation against selected behavior models.
- Run the model online, if the output fits the actual operation, it is reasonable to infer that the influencing factors of the model are representative of the real operation. This provides actionable information for the operator

The Engine, Process and Equipment Modeling, the PLS technique example.

For each SAG mill a model was developed. Based in a pattern analysis of the history, a model was built that correlates the “max throughput” with the current one, using Mill variables and Size distribution variables.

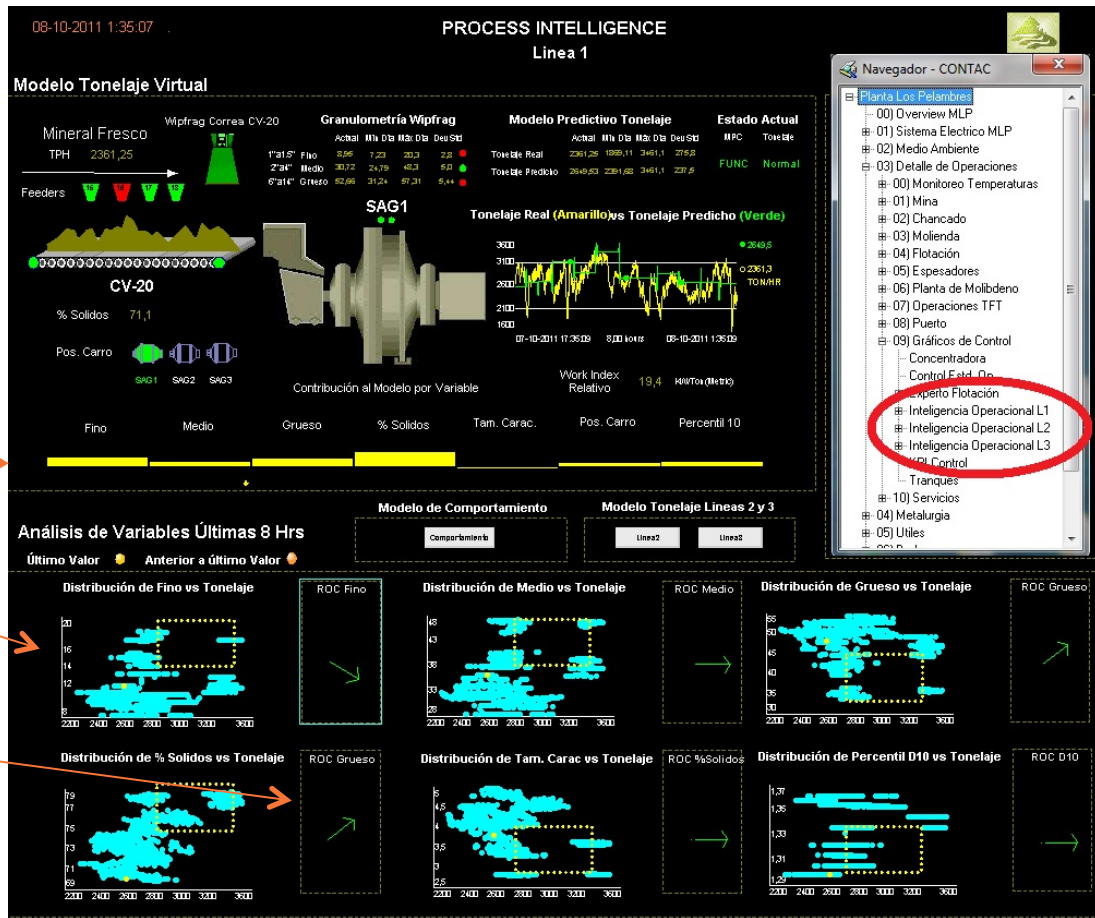
Also shows:

The individual weighing factors of the Key operational variables, as related to the throughput.

A set of XY plots with an indication of the preferred operating zone.

Also shows the “ROC” or rate of change of selected variables.

The goal of this application was to empower the operator by a new type of process visualization, giving a deeper insight about what to do and the consequences of its actions.



The Engine, Process and Equipment Modeling, the SBM technique @ glance

SBM is different from most of the modeling techniques we know. Most models relates through mathematical expressions and parameters the relationships between X and Y variables, namely: Inputs and Outputs.

SBM is quite different. The “model” is a set of selected process variable samples that represents the Equipment or Process Behavior.

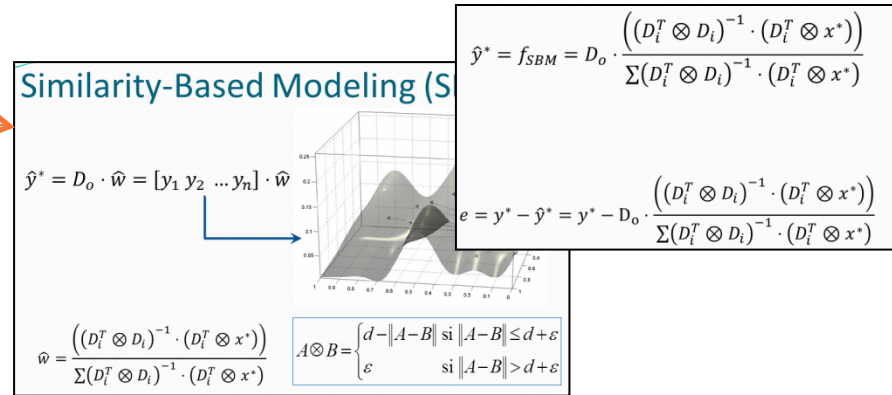
For a set of “input variables”, the algorithm compares with the Model Sample Data Set and calculates the estimated output as a result of a mathematical computation of the samples considered to be the closest ones.

Real world: not as easy...., But the explanation is enough to see its potential.

To “train” the model we just need “history”.
History that may represent more than one operational case or pattern.

USES

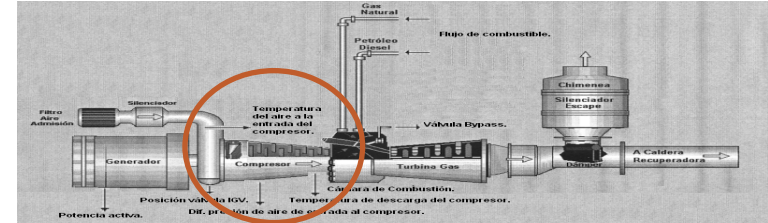
Belonging or deviating from a pattern provides actionable information, being a failure or a reference for an operation action



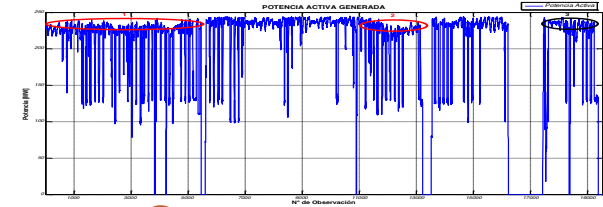
The Engine, Process and Equipment Modeling, example, Turbine Compressor → Dirt

Early detection of dirt in the compressor to avoid:

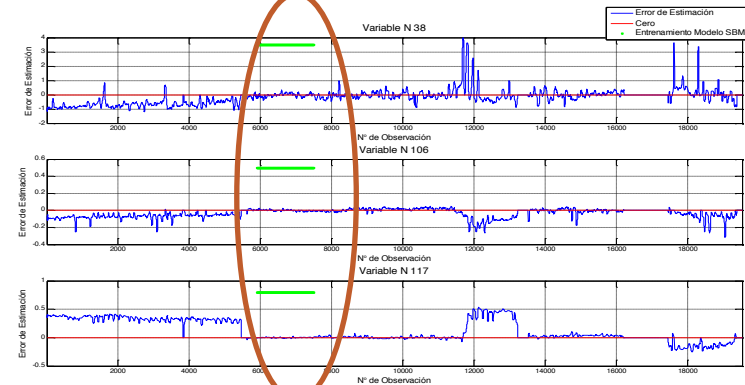
- ✓ Decrease on the turbine power because compressor dirt
- ✓ Increase on fuel consumption.



Turbine Power. In Red, Power decrease because of dirt



Initial selection of the training sample: In green, time interval of the operation considered as “normal” (only three variables are shown)



Final Remarks

Process and equipment history can be processed and structured towards the identification of patterns and cause-effect relationships.

Patterns and relationships can empower both, analysts and operators, providing a deeper insight of the process and equipment behavior, early alert of deviations or failures as well as the consequences of its actions.

AND

All of this can be implemented using the PI-AF-ACE infrastructure, in an modular, comprehensive and manageable manner.

Modeling tools and online deployment framework exists. Not needing to be an expert mathematician, just have a deep knowledge about the process.

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THANK

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