



EFFICIENCY THINKING

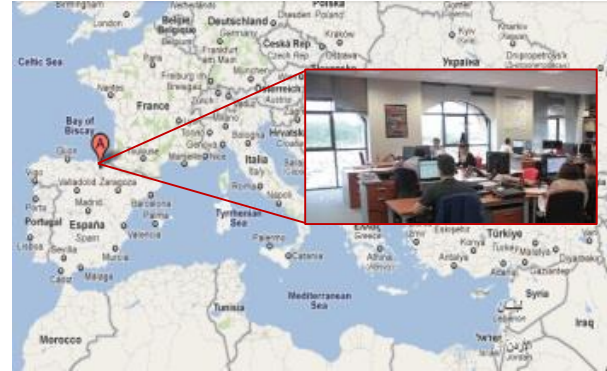
AI-based OPTIMIZATION SOLUTIONS

For Industrial Digital Transformation

REAL-TIME OPTIMIZATION 4.0 OF CEMENT FACTORIES Throughput, Energy & Quality

7/July/2020, Javier A. García – CEO & Founder

OPTIMITIVE



- Founded in 2008 in the Technology Park of Álava, Spain.
- 22 employees.
- Incubated and backed by TECNALIA - 5th largest European Research Institution with over 1400 Professionals.
- Strong collaborative R&D track in successful EC funded projects.



OPTIMITIVE has achieved AI-optimized decision making in **Industrial Operations**

OPTIBAT is our product, operational since 2011

MAIN MARKETS



Power generation



Cement production



Oil and gas



Chemical



Paper production

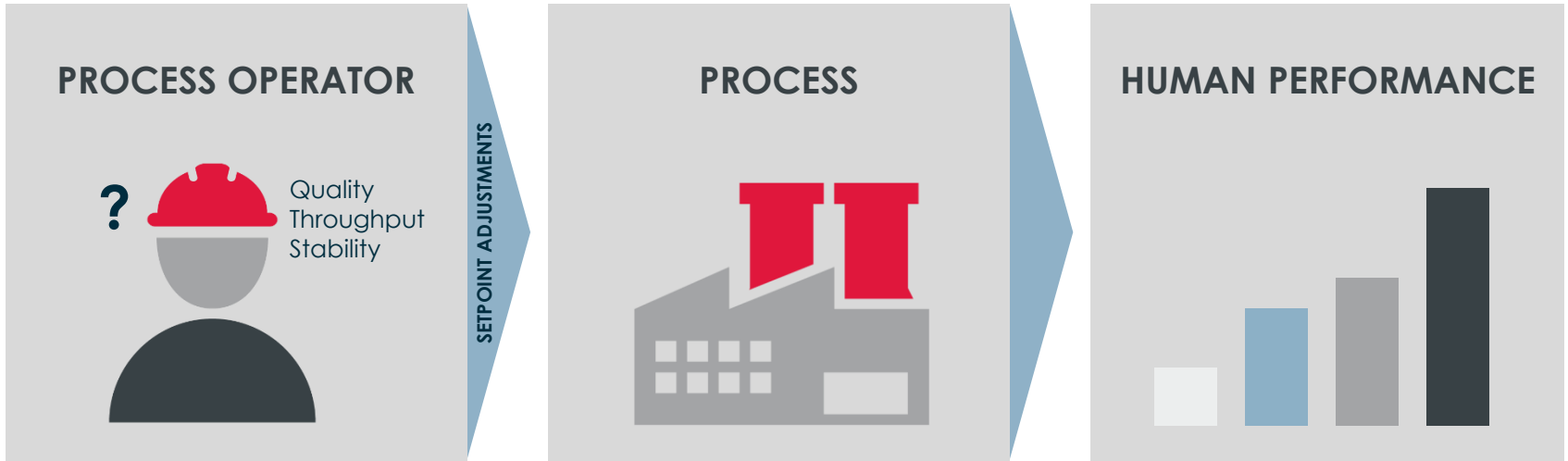
OPTIBAT



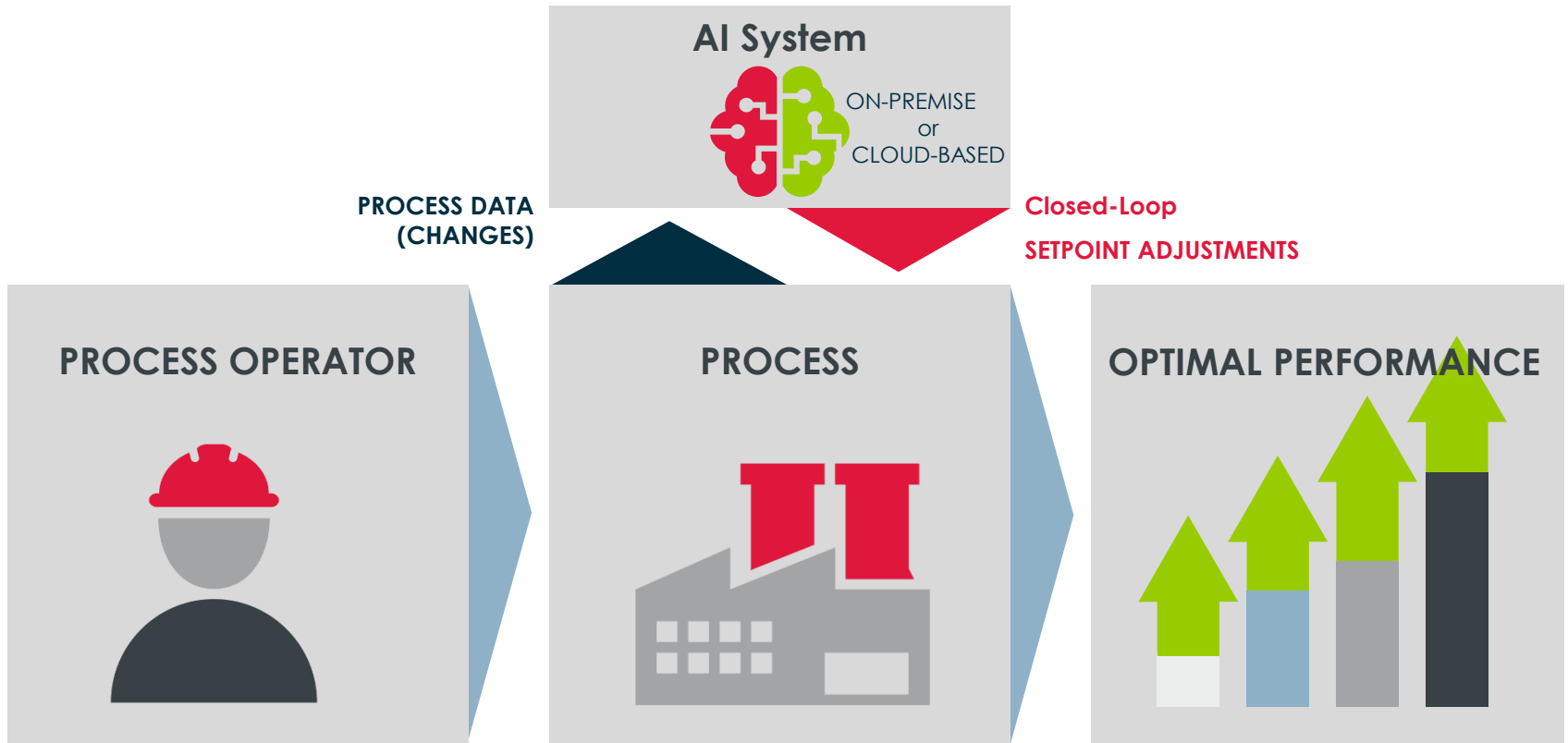
MARKET DRIVERS

- Digital Transformation
- Industry 4.0

Challenge in process industries

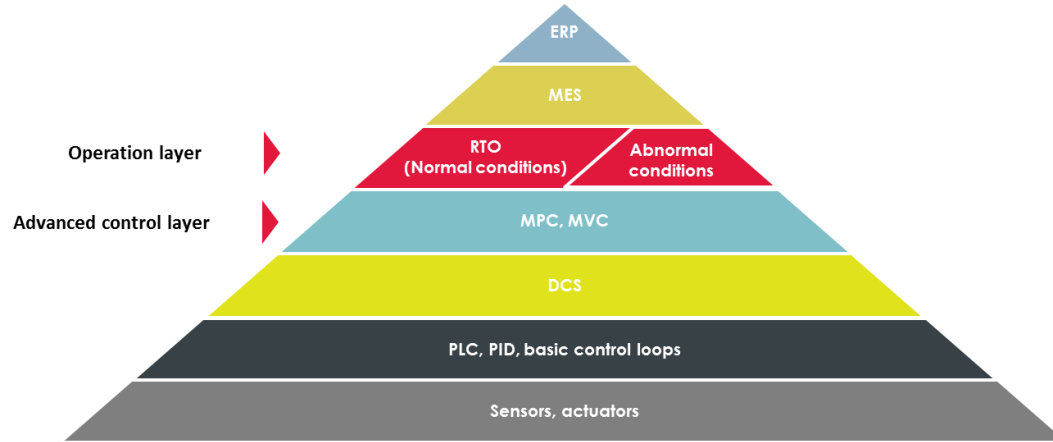


Solution: AI in closed-loop



OVERVIEW OF MPC AND RTO SOFTWARE LANDSCAPE

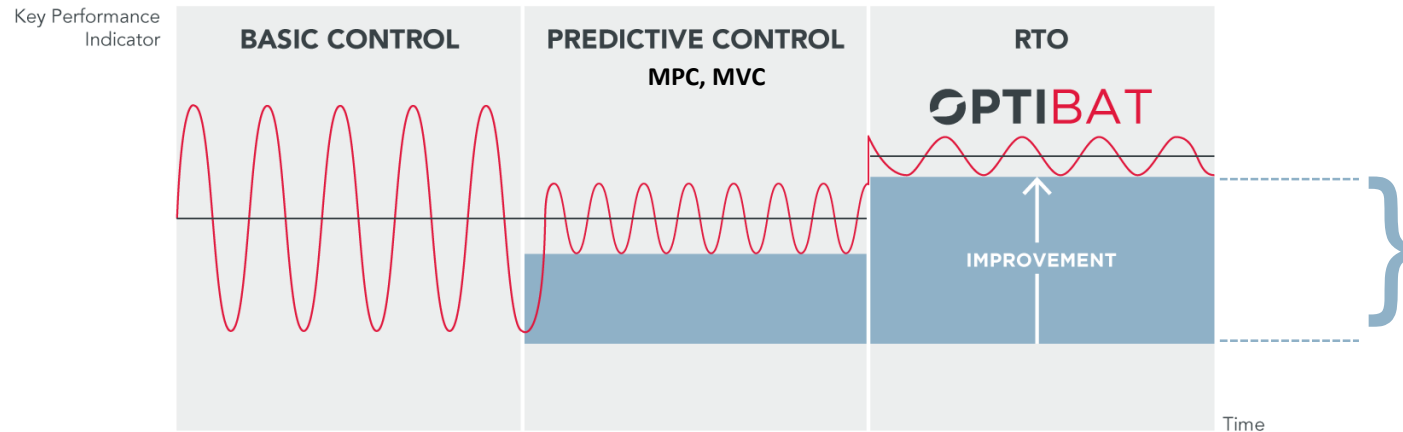
Process Automation Panorama



- RTO (Real-Time Optimization) is applied since the late 80's
- It sits on top of the Multivariable Process Control (MPC or MVC) or directly over the DCS. It proposes setpoints for controllable variables that must be reached by the underlying controls.
- Those setpoints make optimal some KPI (throughput, quality, energy cost), while preserving plant constraints.

RTO Vs MVC

- A RTO provides setpoints that optimize target KPI's while ensuring constraints satisfaction. It works on top and supported on existing controls (basic control or advanced control).
- MVC (Multivariable Control) or MPC (Model-Based Predictive Control) is in charge of making controllable variables reach their setpoints accurately, in minimum time and with minimum standard deviation.



RTO approaches and examples

- Their level of presence depends mostly on the industry. Only in large Chemical industries, O&G and partially in Cement industry they have a relevant adoption level.
- They depend largely on costly fine-tuning works.

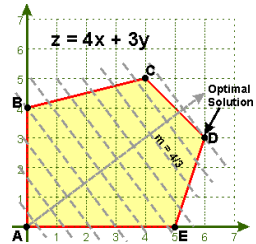
Linear Matrix Model	RTO based on a Matrix-based linear MPC control model	▶	Aspentech DMC, Honeywell Profit Optimizer, Rockwell Pavilion8, ABB Expert Optimizer, Shell SMOC
Rigorous Models	RTO based on Rigorous Physical/Chemical Models of the process	▶	Schneider Romeo, Sotetica (Yokogawa) Visual Mesa, Aspen OnLine
Fuzzy Rules	Pseudo-RTO based on Fuzzy Control rules	▶	FLSMIDTH's Process Expert (PXP) - only in cement industry -
AI-based Models	RTO based on non-linear Models Learned from Process Data and automatically updated	▶	OPTIBAT RTO by OPTIMITIVE

Matrix-based linear MVC control RTOs

Linear Matrix Model

RTO based on a Matrix-based linear MVC control model

It makes use of the MPC model to optimize economic KPIs.

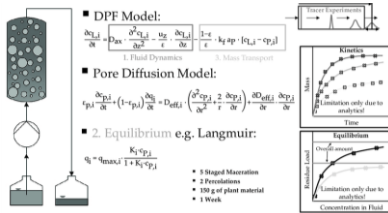


Linear Optimization

- They are based on Linear relations (gains) among Controlled Variables (CV) and Manipulated Variables (MV) - rough approximation to complex dynamics.
- They depend on the costly execution of Step-tests
- A Linear Programming (LP) algorithm is normally used to find optimal settings. This limits the chances of finding the real optima.

Rigorous Model based RTOs

Rigorous Models



RTO based on Rigorous Physical/Chemical Models of the process

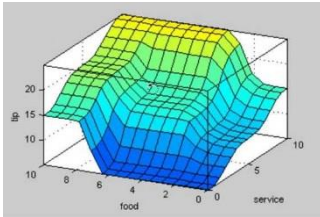
Once fine-tuned, models achieved can be accurate while the equipment is not modified.

- They require the definition of equations of the physics and chemical reactions of the process. This can never represent the complexity of real equipment status.
- They demand a costly work of modelling, of ca. 1 to 1.5 years. Implementation cost is very high.
- Models are static and difficult to maintain. Any change will mean that models are not valid anymore.

Fuzzy rule based RTOs

Fuzzy Rules

Not really an RTO. Pseudo-optimization based on heuristic human-created rules

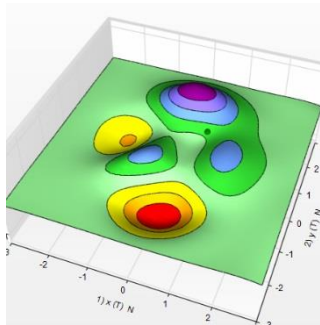


This kind of Expert System gives process engineers the feeling of controlling exactly what the optimizer will do in each situation.

- **They require the definition of many fuzzy control rules to specify how to act in every process condition.**
- **Models are not accurate; they define rough tranches of behavior**
- **Models are difficult to maintain**

AI-based non-linear RTOs

AI-based
Models



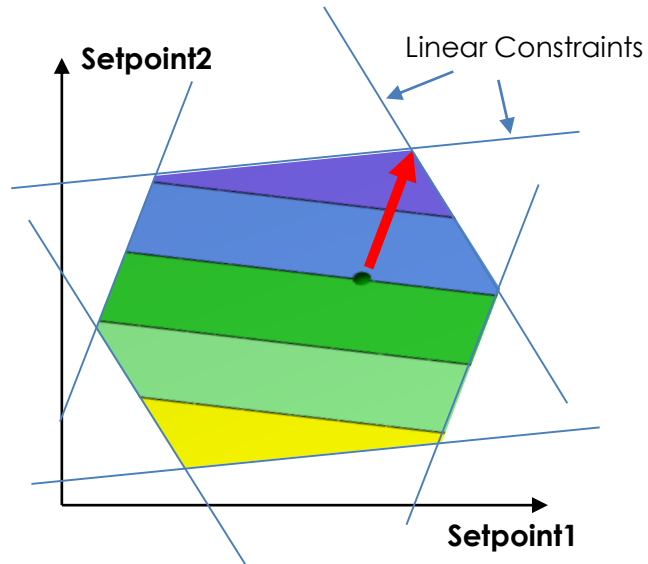
Non-linear AI models

RTO based on AI-based non-linear models

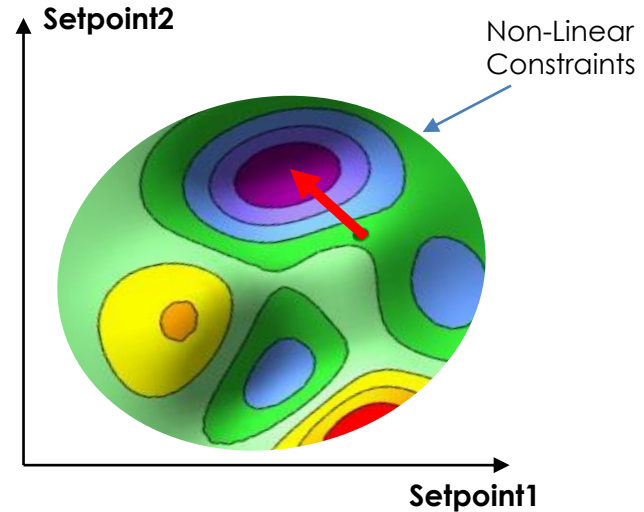
This is the most advanced and innovative approach. It makes use of Machine Learning (ML) Algorithms to achieve highly accurate non-linear models to optimize economic KPIs.

- They are based on highly non-Linear relations.
- AI-models are fast to setup and only depend on the availability of process data
- Models remain continuously updated thanks to Machine Learning.

Traditional Vs AI-based Optimization



Traditional Optimization
with Linear Model and Linear
Constraints

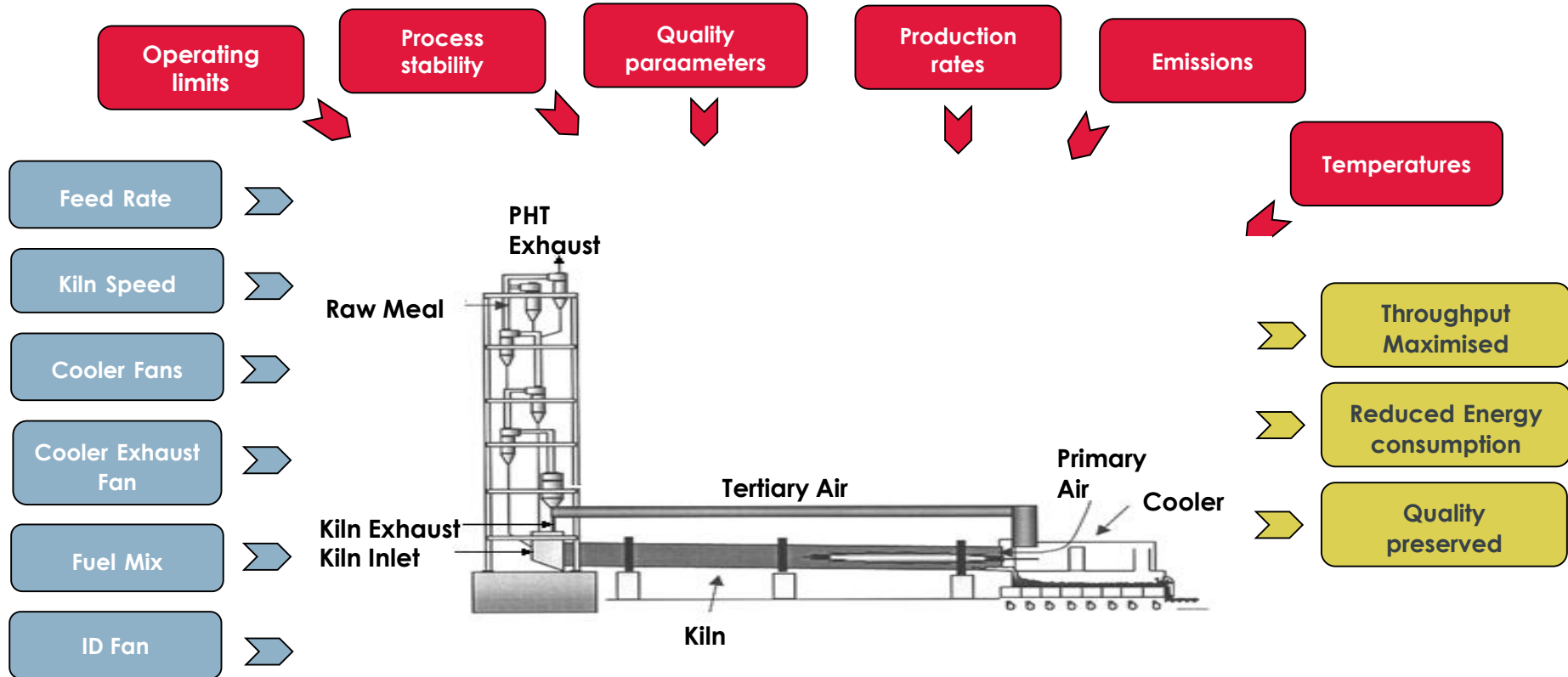


AI-based Optimization
for the same problem, with non-Linear
Model and non-Linear Constraints

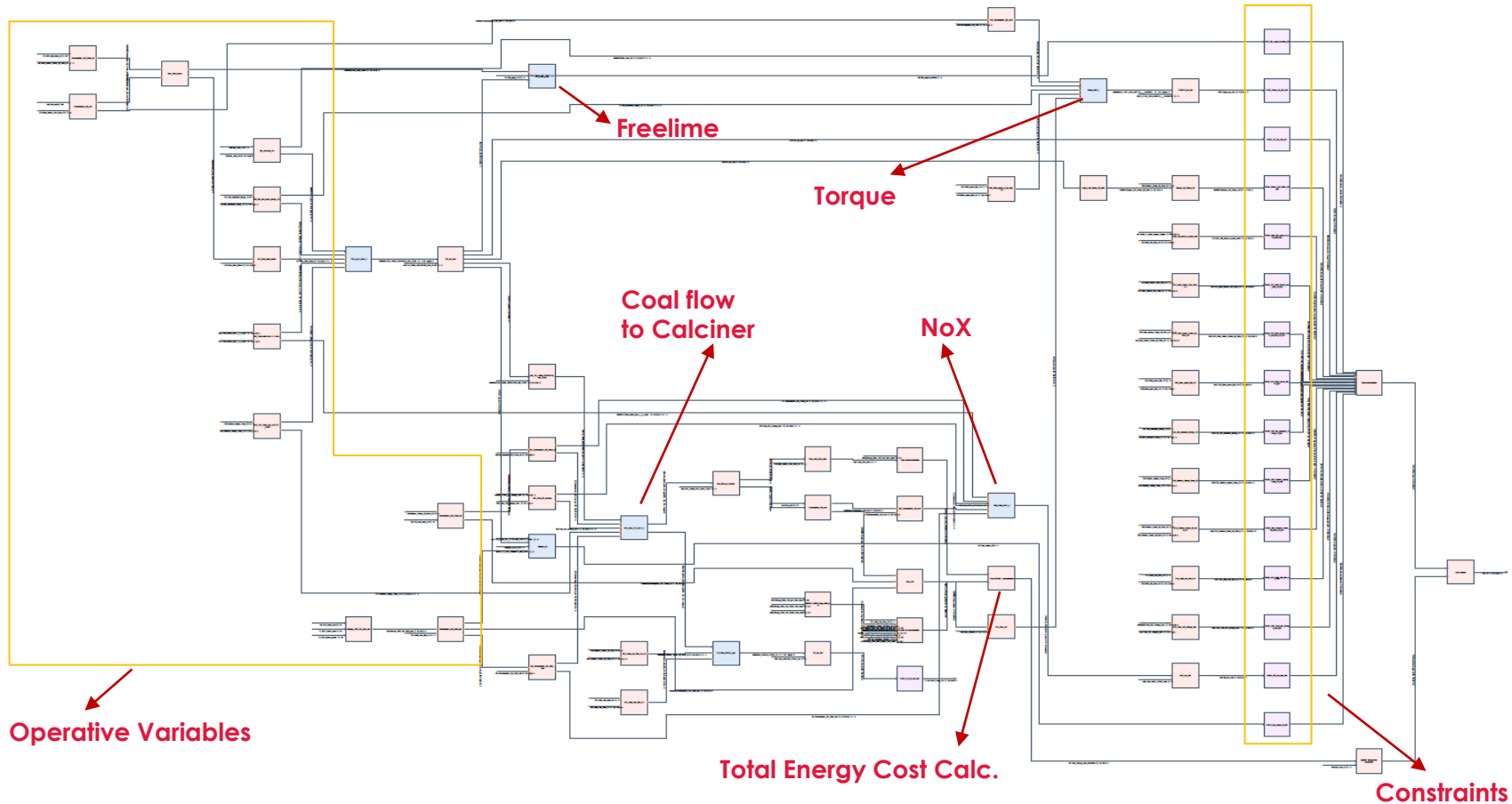
CASE STUDY 1

ROTARY KILN - CLINKER FURNACE OPTIMIZATION

Kiln Optimisation at a glance



Overall Strategy - Kiln optimization



RTO Setup



The Process:
Vertical Raw Mill

Receives As-Is process data

Constantly monitors, learns, analyses, improves



OPTIBAT®

Standards:
TCP/IP, OPC,
SQL, OCR, XML,
ODBC, ...



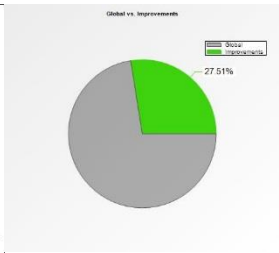
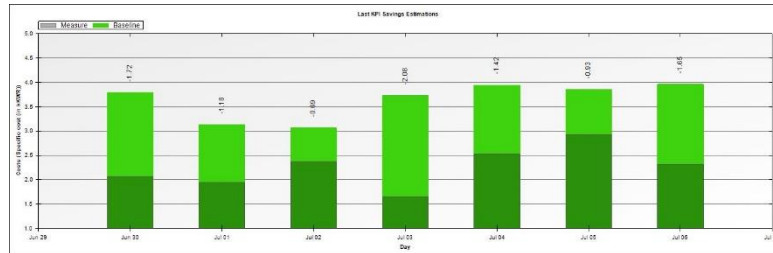
Sends back improved set-point data

Working Strategy in Real Time



New setpoint recommendation to optimize the Objectives

Improvement analysis dashboard

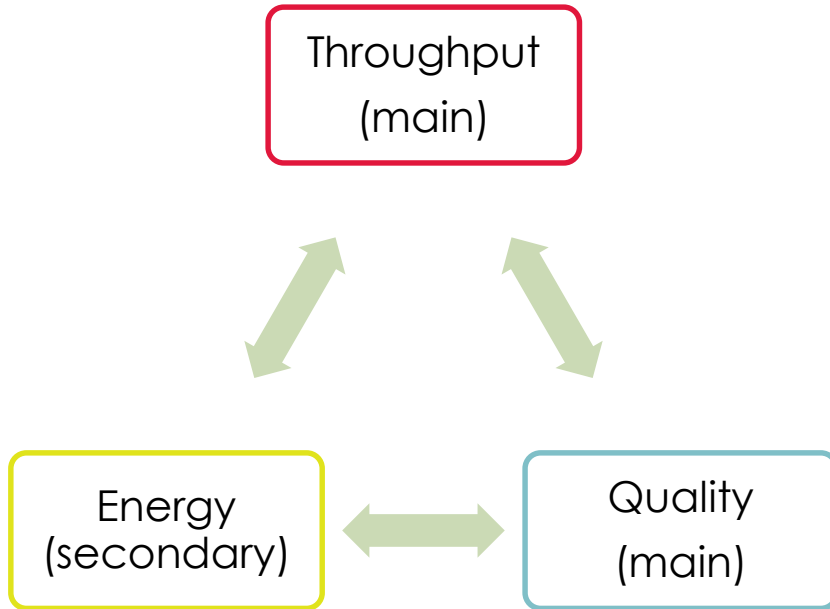


CASE 1: KILN + COOLER OPTIMIZATION

Location	→	USA
N° of assets	→	1 KILN
Capacity	→	400 tph
Objectives	→	Throughput + Quality + Energy
Operative variables Controlled by OPTIBAT	→	Calciner temperature, Preheater O ₂ , Kiln fuel, Dust %, Kiln feed, Kiln hood draft, cooler fans, undergrate pressure.



KILN: Project Objective and main KPIs



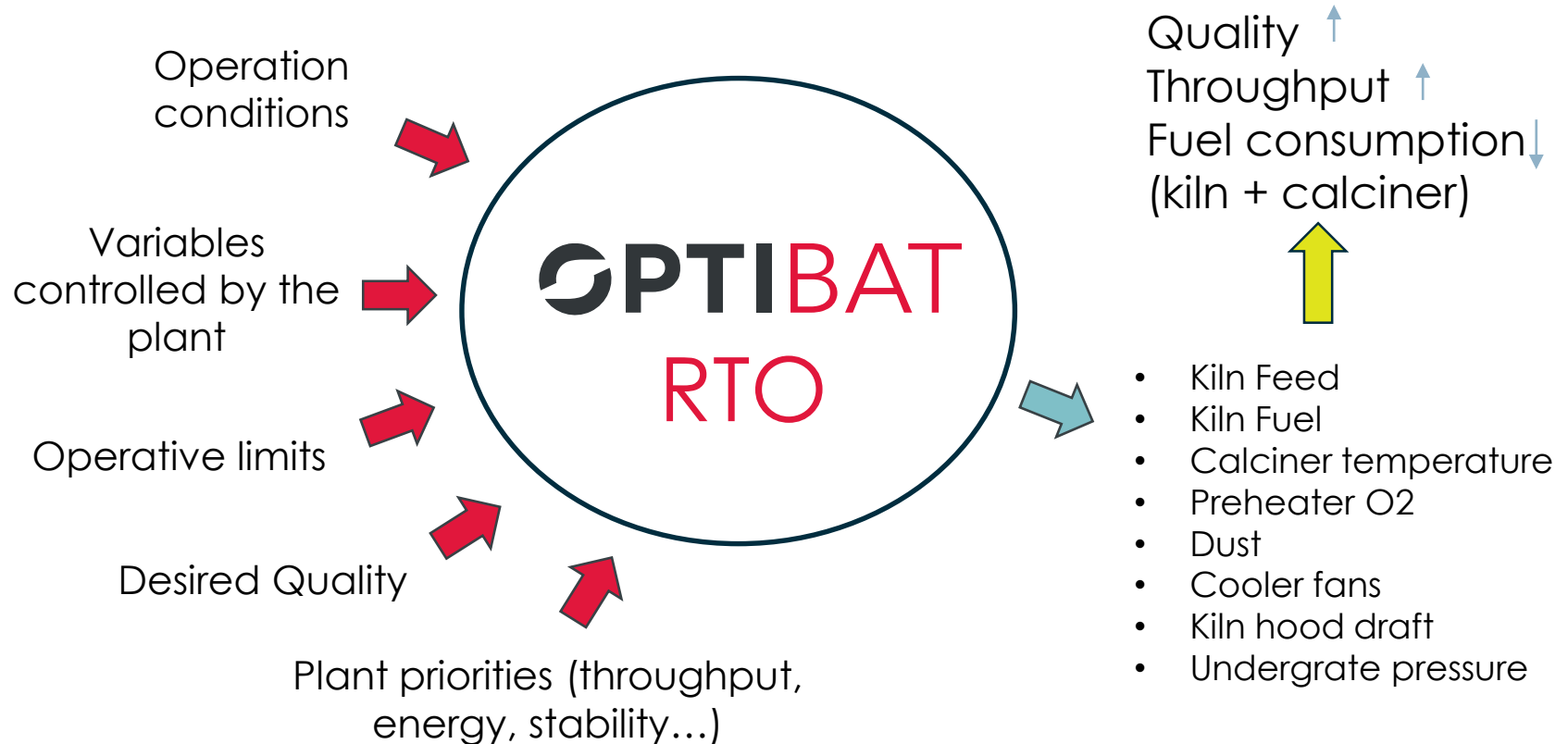
Optimization target

- Increase average kiln throughput (keep it in allowed maximum as much as possible)
- Maintain or increase quality (FreeCaO)
- Maintain or decrease the fuel consumption

Other Constrains

- KILN stability
- KILN equipment's limits
- Easy to use
- Minimum attention needed from operator
- Operate kiln and cooler independently

KILN: Optimization process



KILN: Project results in closed-loop

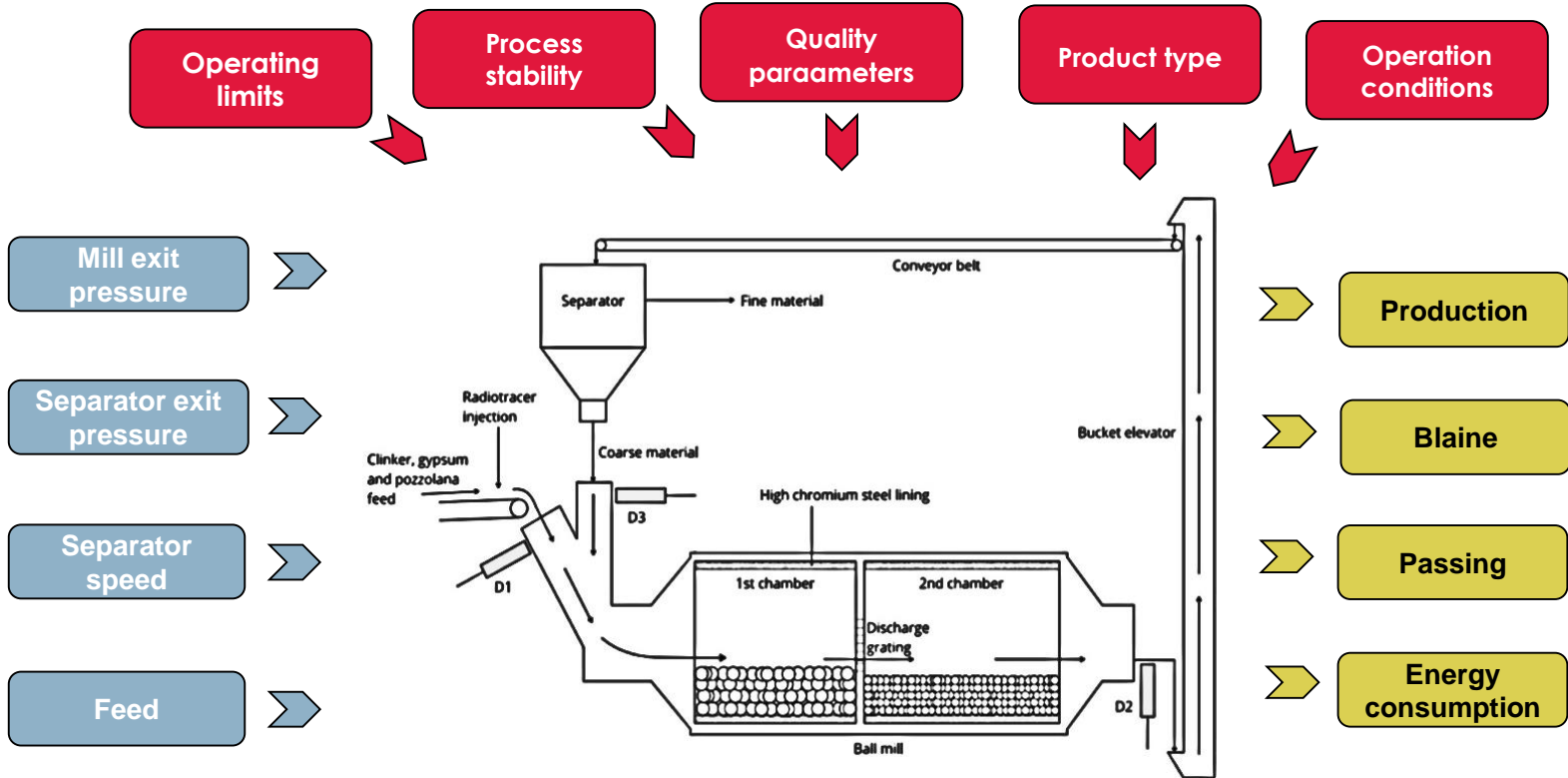
- Quality → **FreeCaO withing desired ranges 97% of the time.**
- Throughput → **Kiln in maximum allowed (by plant) throughput 99% of the time.**
- Specific energy consumption → **4% reduction***
- Process Constrains → **Main constrains fulfilled**

(*) Provisional results by June/2020

CASE STUDY 2

HORIZONTAL FINISHING MILL OPTIMIZATION

Horizontal Finishing Mill Optimization

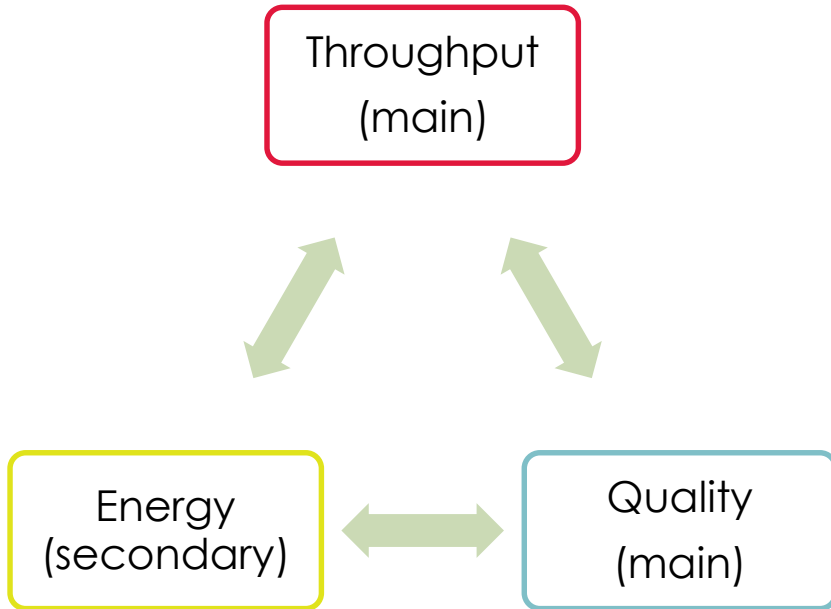


CASE 2: HORIZONTAL FINISHING MILL

Location	→	USA
N° of assets	→	3 FM
Capacity (per asset)	→	100-140 tph
Objective	→	Throughput + Quality + Energy
Operative variables Controlled by OPTIBAT	→	Feed, Separator speed, Mill pressure, Separator pressure



FINISHING MILL: Objective and main KPIs



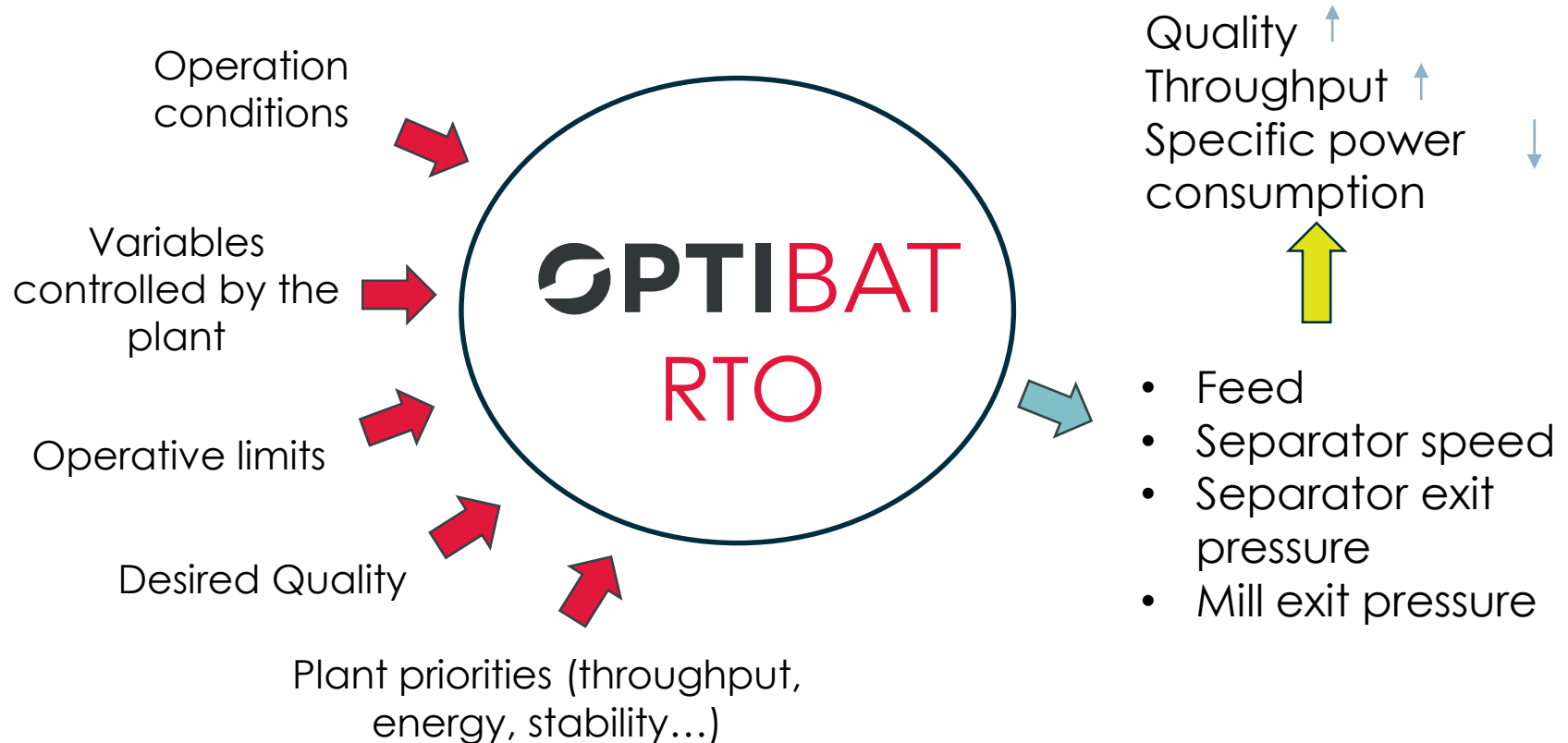
Optimization target

- Increase average mill throughput
- Maintain or increase quality (blaine + passing)
- Maintain or decrease the specific energy consumption

Other Constrains

- Mill stability
- Mill equipment's limits
- Capable of working with different cement types
- Easy to use
- Minimum attention needed from operator

FINISHING MILL: Optimization process



FINISHING MILL: Project results in closed-loop

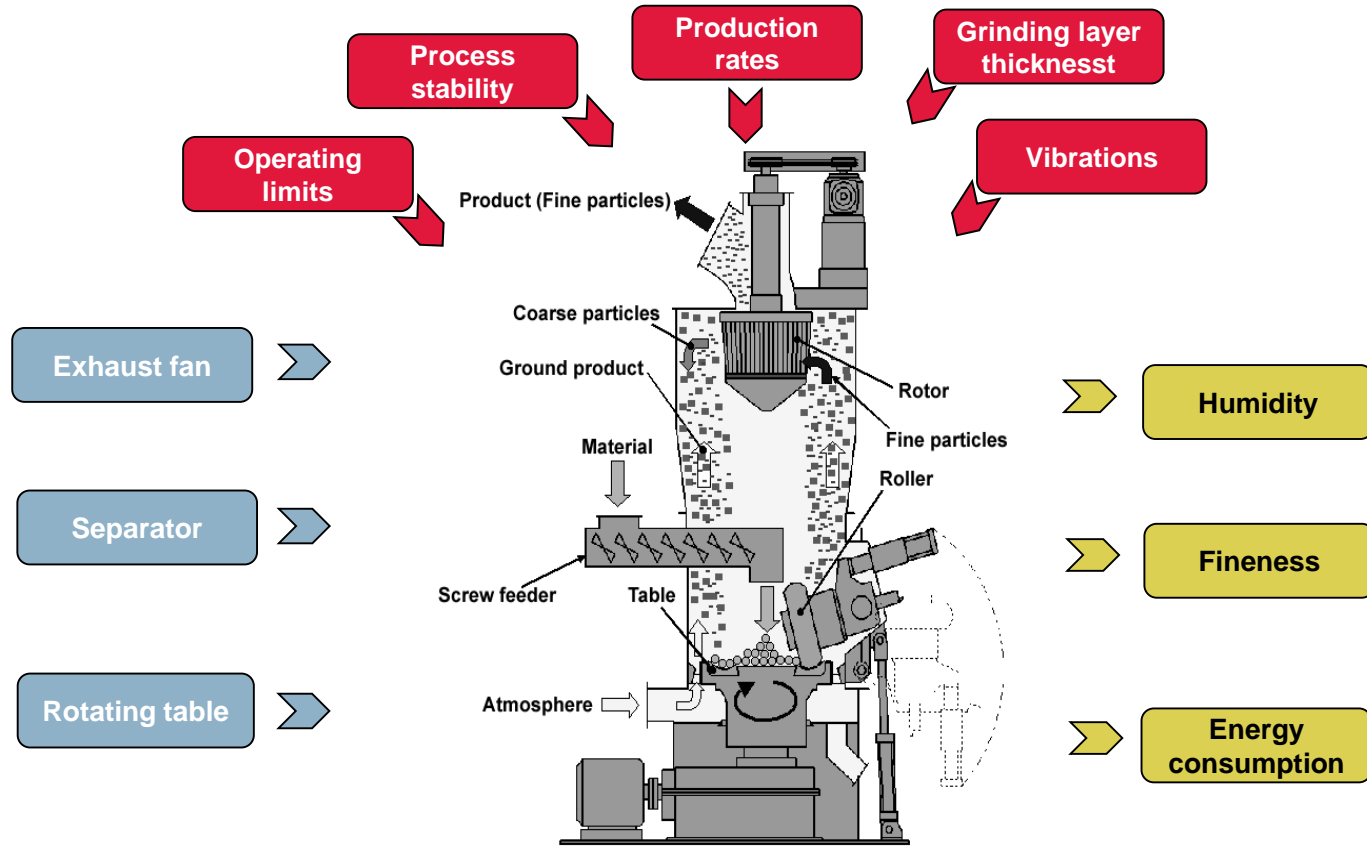
- Quality → **10-50% increase in Passing and Blaine***
- Throughput → **Increase in 5-9% (dep. on product)**
- Specific energy consumption → **Decrease up to 5% (dep. on product)**
- Process Constrains → **Main constrains fulfilled**

*First 3 months of 2019 vs First 3 months months of 2020

CASE STUDY 3

VERTICAL RAW MILL OPTIMIZATION

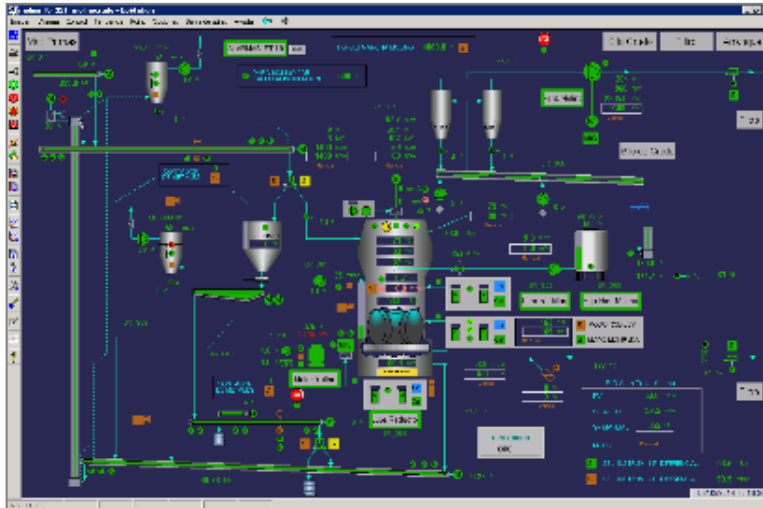
Vertical Raw Mill Optimization



CASE 3: VERTICAL RAW MILL

CEMENTOS MOLINS in Sant Vicenç dels Horts, near Barcelona.

- Vertical Raw Mill, brand FLSmidth.
- Production capacity of 340 tons/hour.



VERTICAL RAW MILL: open loop operation



Quality parameters have improved, and are always kept inside acceptable ranges.

A minimum of energy cost in KWh/t is achieved.

Average productivity also increased thanks to OPTIBAT.

Operators follow closely the recommendations (yellow lines). In "Automatic Pilot", OPTIBAT carries out directly the recommendations.

VERTICAL RAW MILL: Solution installed

OPTIBAT is connected to the existing control system, learning from data, reporting actual savings and recommending in real time the optimum set-points values for 3 main operating variables, carefully chosen with the customer's process engineers:

1. Power of air exhauster fan
2. Inside differential pressure
3. Pressure of grinding rollers

Constraints that determine the stability of the process are strictly respected:

- Vibrations of the cement mill
- Thickness of grinding layer
- Fineness of Raw Meal
- Operating limits of the mill components
- Production rates
- Outlet temperature

VERTICAL RAW MILL: 1-year results

Results obtained quarterly in one year of service at a typical cement mill have shown sustained improvement of:

Energy Consumption → **5% to 10% energy savings**

Throughput (feeding) → **2% to 9% increased productivity**

Quality (fineness) → **3% to 6% better quality**

DEMO



EFFICIENCY THINKING

THANK YOU!

More information:

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www.optimitive.com