M Watson

gmented Intelligence – Towards Plant
eration Excellence (Mill Advisor for
ment Plants)

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enda

- Problem Statement
- Mathematical Solution
- Architectural Solution
- Results

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blem Statement

Cement Major operates 1000s of cement mills around the world.
All are highly standardized and largely automated.

However, there is **40% variance in many KPIs between the 'Best' and 'Worst'.**
Key KPI is Energy Consumption.

We are applying statistical and cognitive methods to **find out why**.

Our goal is to build a system that advises the operator on how to conserve energy.

Approach

- Based on 1.5 years of high-frequency operating parameter history from 2 plants, apply
  - **Statistical methods** looking for correlation
  - **Cognitive methods** looking for impact of non-structured data
- Identify parameters and operator behaviors that optimize mill operations
- Make recommendations to optimize long-term – goal is "one recommendation per day"
- …and then do this continuously to adjust to changes to environment

→ Mathematical Solution in 3 Steps….

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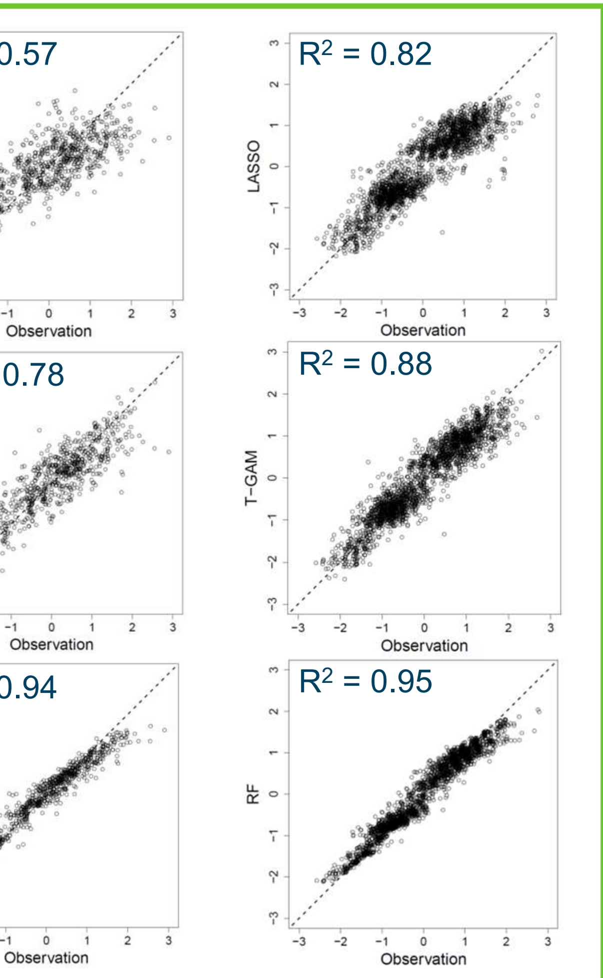
p 1: Mathematical models were built that explain and predict mill behaviour

Fit of model

Mill 2



Influence of variables

Mill 1

Control	
Total feed	0.18
Grinding aid	**0.44**
Separator speed	0.16

Observed	
Mill E. Energy	0.39
Mill Temp.	0.07
Clinker Temp.	0.08
Separator Temp.	0.07
Sep. fan current	**1.00**
Mill fan current	0.16
Free lime	0.02
Belite	0.04
Total E. Energy	0.61

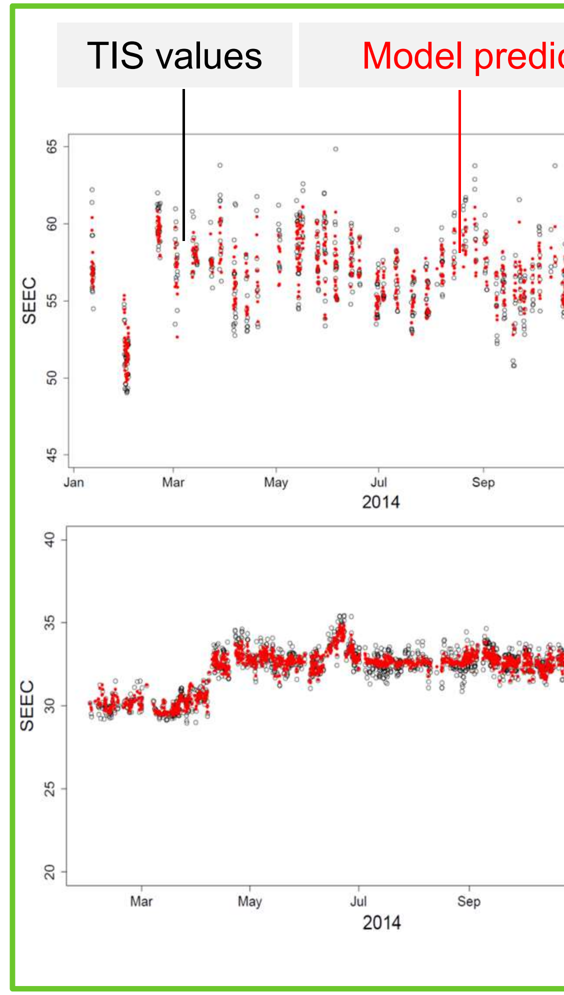
Mill 2

Control	
Total feed	0.17
Grinding aid:HER60	**0.39**
Grinding aid:TDAN	0.01
Separator speed	**1.00**
Water injection	0.21
Mill fan speed	0.21
Separator fan speed	**0.48**

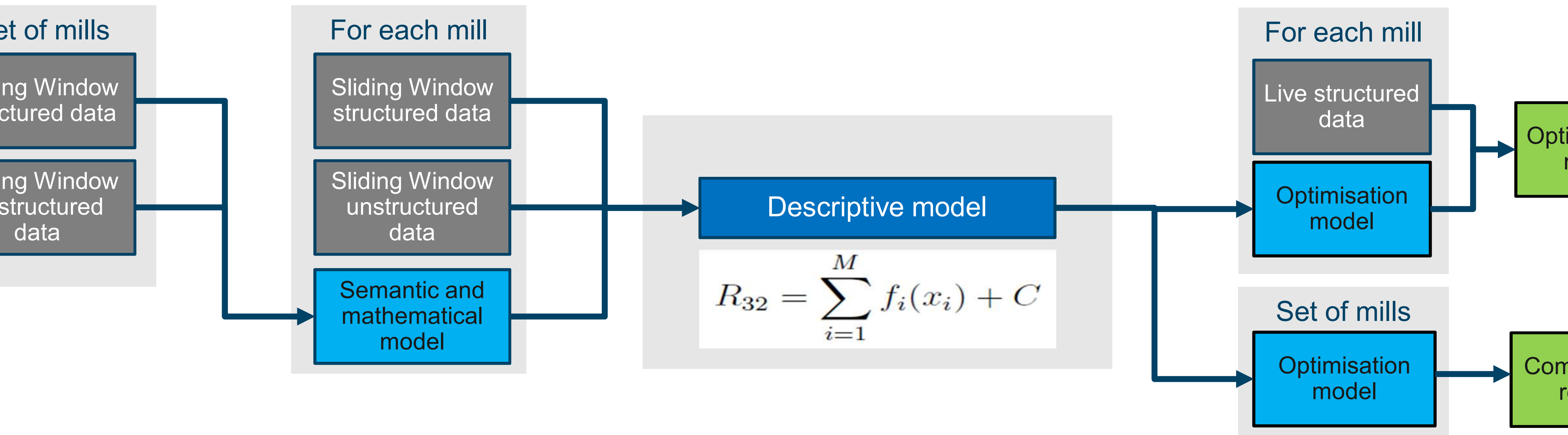
Observed	
Mill E. Energy	0.17
Temperature	0.16
Filter pressure	0.31
Free lime	0.15
C2S (Belite)	**0.56**
Total E. Energy	0.53

Forecast of values

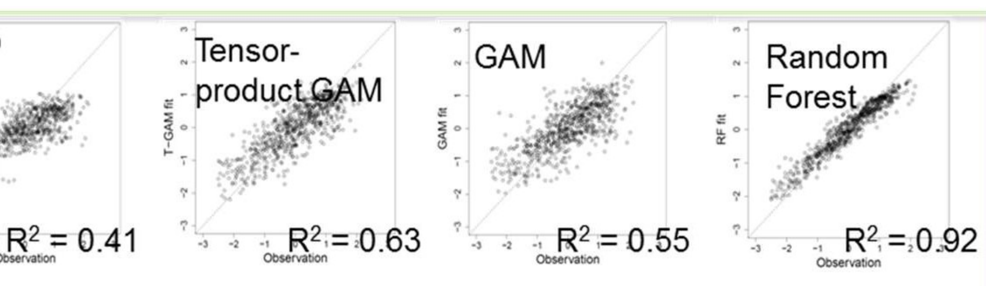
Mill 1



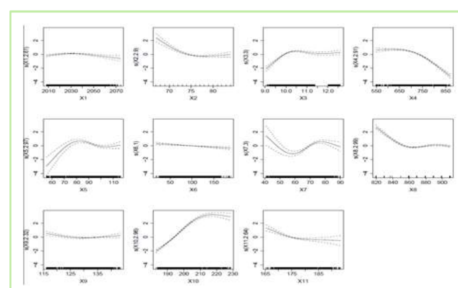
o 2: Models & Operator behavior were combined to built an optimization strategy



dentify best fit among 6 models (2 linear, 4 non-linear).
ingle random forest as best non-linear model with high R^2
or all mills in scope now



Apply generalized additive model to model each mill individually.



- Perform stochastic hill climbing to identify loca maxima (or minima) fo optimization
- Apply periodically usin window to adjust to ch in mill and operating conditions.

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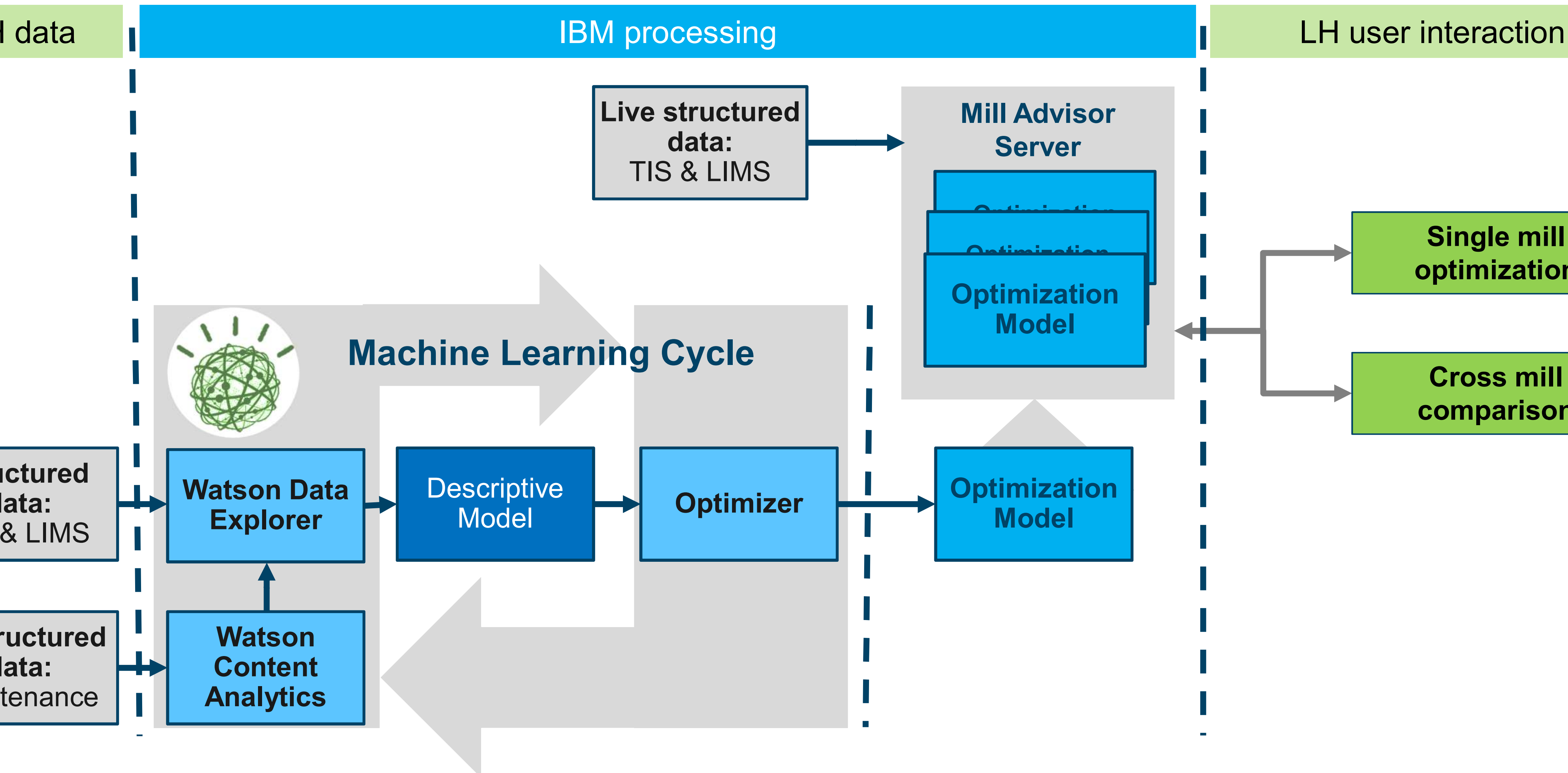
p 3: An automated machine learning process can be assembled to make prediction dels available to broad range of users at Global Cement Major



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Components

dvanced Analytics
achine Learning
uemix Dash DB
ockers
ustomized modeling and optimization
rategy

Unique Solution

The actual value contribution of the solution for the companys users:

Instead of a pure control cycle based on minutes or hours, this system is self-learnin
with the continuous data input – and displays data in a way which is both

- ✓ **Easy to digest (variables explained and range displayed in trends)**
- ✓ **Understandable for each party invovled (advice is given)**
- ✓ **Available as a unified view on the data all across the company (cloudplattfo**

r interface

Processing data for display

- Prediction (script)
- Recommen-dation (script)

Mapping to database scheme in Bluemix

- Changing name convention
- Mapping to columns

Dash-DB

Data extraction from database through a once per day

- Alignment of data f
- Extract data (no er

Daily extraction
production monitori

Bluemix- IBM hosted

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tinct User Scenarios show target users and quantifiable business benefits

Use Case 1: **Optimization**

Urs, the local PPE, advises the Production & Quality Manager and Operator for energy efficient operations.

Role:	**Process Performance Engineer**
Main Interest:	Bring energy consumption to an optimum and run mill close to proces quality limits
Use of Mill Advisor:	• Fact based advisory for optimized energy consumption • Ability to predict different key performance criteria
His main benefits:	- Mid-term optimization for set points of Mill Master & control loops - Create long-term efficiency by detection of improvement potential

Use Case 2: **Benchmarking**

Dirk, a Corporate Mill Expert, consults for the best use of grinding technology.

Role:	**Corporate Mill Expert**
Main Interest:	Perform A- & B-Level assessments with mills for anomaly detection ar performance consulting
Use of Mill Advisor:	Mill data analysis for Assessment and view of x-mill performance for advisory in an automated, standardized way
His main benefits:	- Detect anomalies faster with a time efficient analysis - Enable timely assessment of performance and facilitate target settir - Enable cross-mill analysis and clustering of mills

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Case 1: Single mill optimization – Electricity cost control

Monday, 7.30 am: Analysis of optimization potential

Urs is about to meet the Operator in the daily meeting: He takes a look at the long-term dashboard for the separator speed and R32 values.

Monday, 8.00 am: Solution recommendation

Depicting the shift in R32 and separator speed, the Advisor tells him to adjust the latter. Urs discusses recommendation with Production & Quality Manag

f mills

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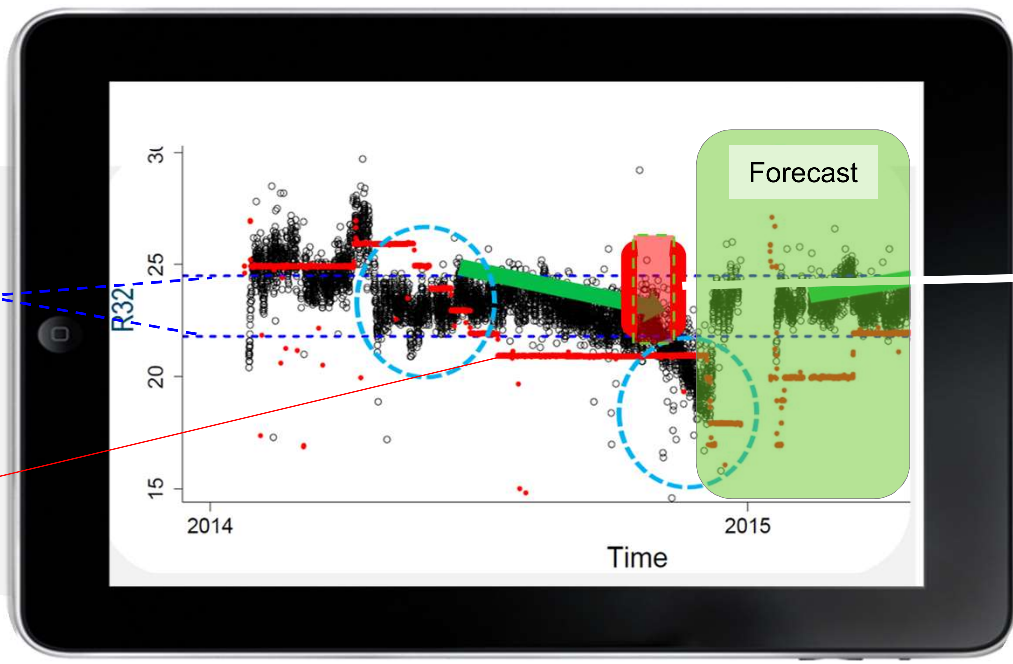
Quality limits

Sepa-rator speed



Undiscovered savings: CHF 50'00
quarter for this mill

Attention! The mill is not runnin
efficiently. **Recommendation:** Se
separator speed to new paramete

Case 2: Cross-mill comparison and improvement potential

Monday, 9.30 am: Analysis of optimization potential

Dirk is preparing A-level assessments for the European mills and selects the geography, the mill and product in the Mill Advisor. For DACH, he finds one is higher, one lower performing mill.

Monday, 10.00 am: Discussion on optimization potential

He benchmarks them and gets a quick impression SEEC trend over the probability density distributior plans to talk to the PPE about their operational stra to make the SEEC more evenly distributed.

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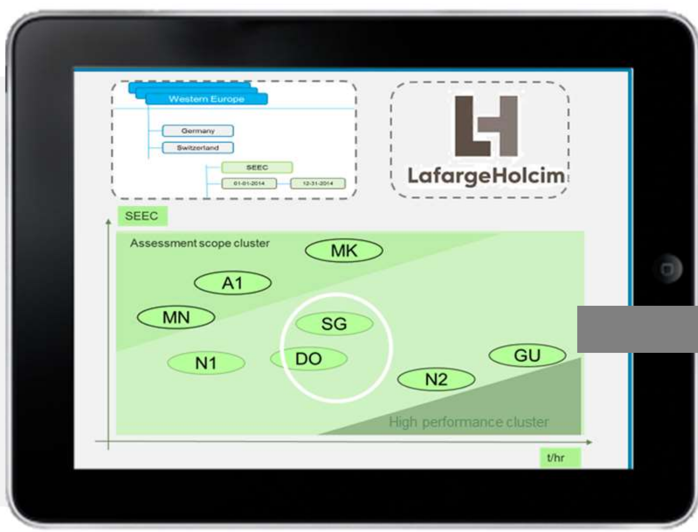

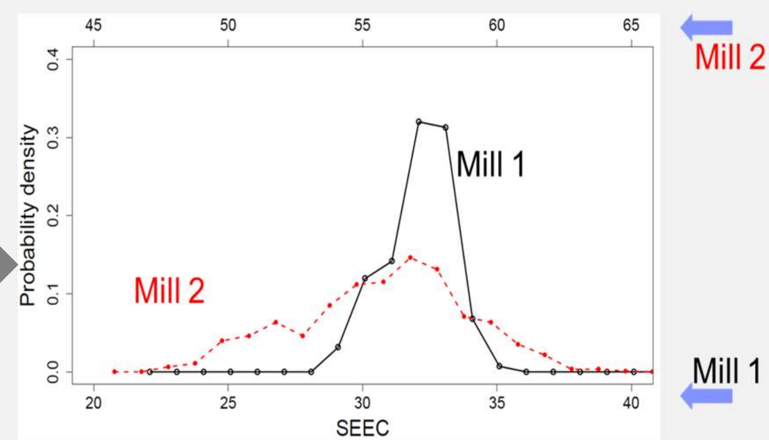

Set of m

Mill 2
Drill Do

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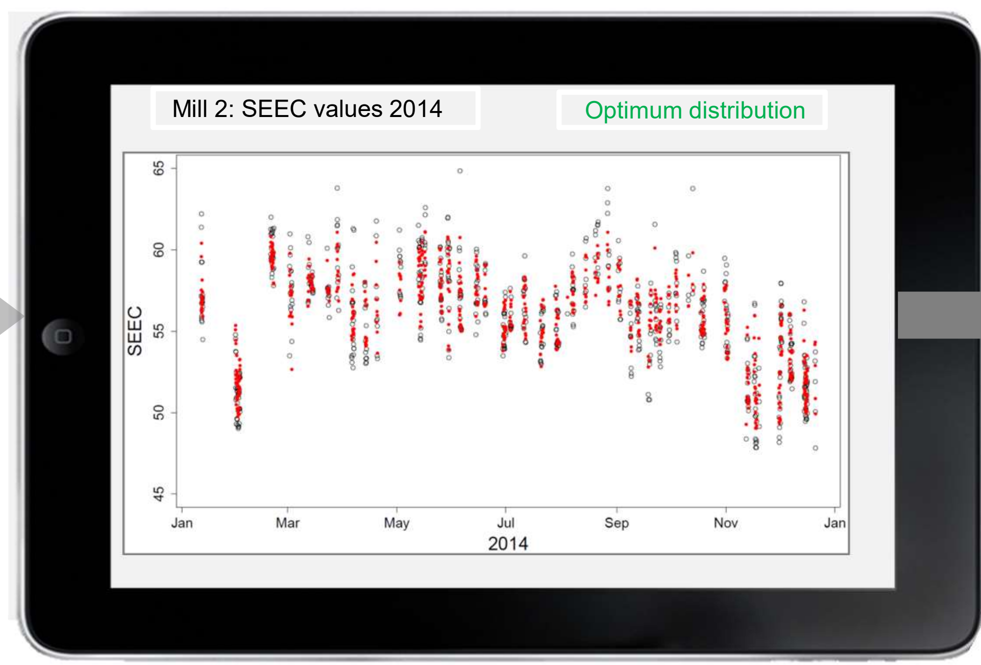
Case 2: Cross-mill comparison and improvement potential

f mills

l 2:
Down

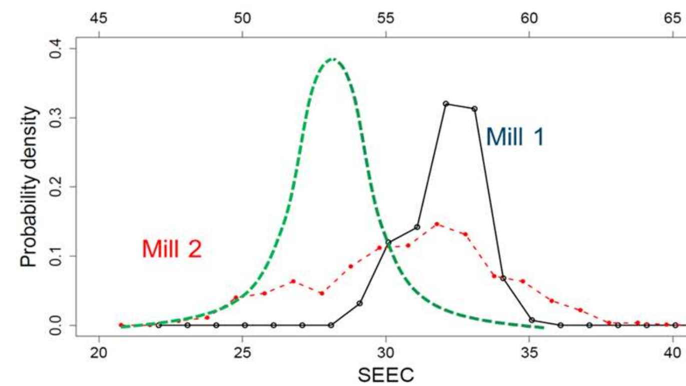
Monday, 10.30 am: Detail analysis of optimization potential

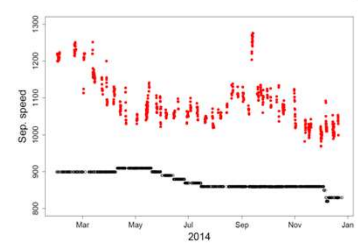
Dirk has a short call with Urs: They look at the values of the SEEC in Mill 2 to discuss the optimization potential. They drill down in the data to see the optimimum distribution.

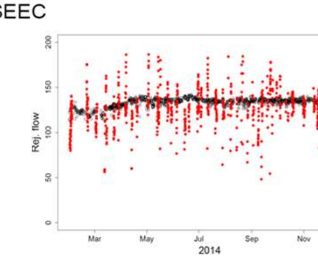


Monday, 11.00 am: Solution recommendation

Urs and Dirk discuss briefly: As Mill 2 uses the M
Master to support their operations, they agree to
the fresh feed settings to minimize SEEC.







ult 4: Mill operations can be optimized as there are quantifiable business benefits

Challenges for the rrent mill operations	Limited insight into	Requirements for a resolution	Target	Global targ group
Electricity cost CHF 2.8 mio for 850 kt cement p.a.	**Cost drivers PPE**	Optimization suggestions as 40% of electric energy consumption is from grinding	**Local: Optimize operational cost**	**PPE Operator**
25 mill experts, >400 mills Today, <20% of ball mills are covered	**Long-term optimization**	• Leverage existing data • Find approach for comparability of mills	**Local, Regional & Corporate: Performance control**	**PPE Mill Expert**
Numerous influence factors >300 signals in TIS	**Mill Expert knowledge**	• Help Mill Expert to identify underperforming mills • Ability to run a long-term benchmark	**Corporate: Define optimization potential**	**Mill Expert**

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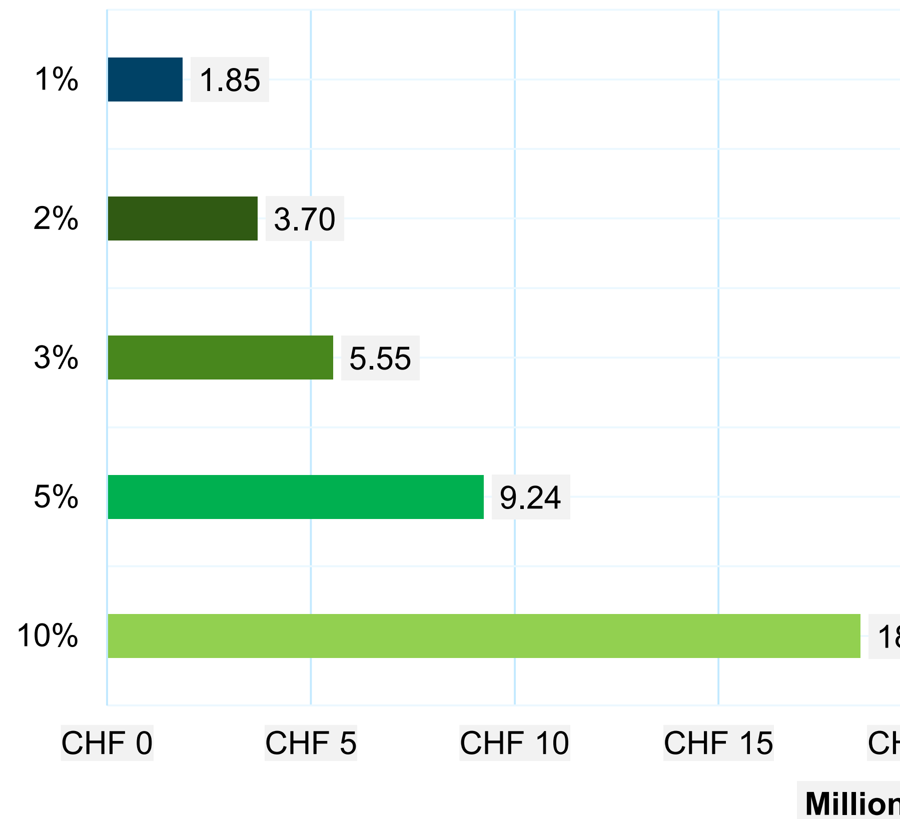
siness benefits in summary

Today	Future	
Manual set-point for Mill Master defined by experience	Set point for Mill Master based on fact analysis	Opera-tional
No precise forecast for electrical energy cost in grinding (40% of all EEC)	Forecast control for savings in SEEC	Tactic
2 days of manual analysis per mill, only <20% of ball mills covered p.a.	1 hour instead of 2 days for a simple analysis of a mill	Strategic

Savings across selected ball mills p.a.
(energy cost only, given LIMS&PIMS data are available
200 mills in scope from Global Cement Major only)



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pendix

agement Summary

approach

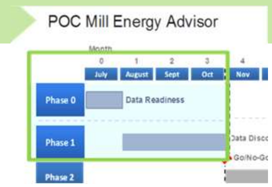
ta concept
all, scale quickly”

- Statistical approach in a small scale sample
- Extension to further mills for optimization & comparability

ta in PoC for Mill Energy or
asibility, succeed quickly”

- Optimization potential and scenarios shown with quantifiable benefits
- Modeling strategy developed
- Data requirements for Cognitive approach agreed
- Analysis of 4th mill in progress

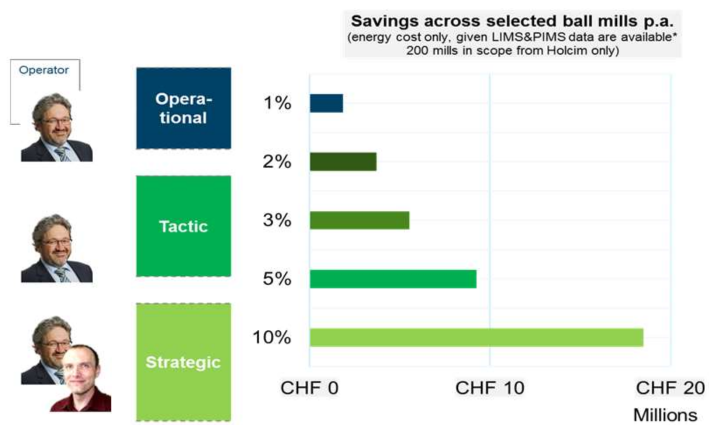
Results



Value proposition
“Enable users, scale expertise”

- Mill Energy Advisor for long-term analysis, forecast and traceability of anomalies
- Enablement of people and multiply access to expert knowledge (see user scenario)
- Potential value generation from structured and unstructured data (see benefit case)

User scenarios & benefit case



Outlook

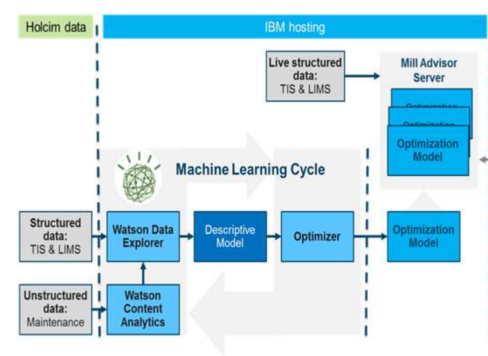
Next steps
“Deploy concept, show look & f

Next three weeks:

- Target user scenario definit
- Optimization solution
- Deployment kick-off

Next three months:

- Data source connection
- User interface workshops
- Defining user interaction
- Evaluation preparation



ult 1: Mathematical models exist that explain and predict mill behavior

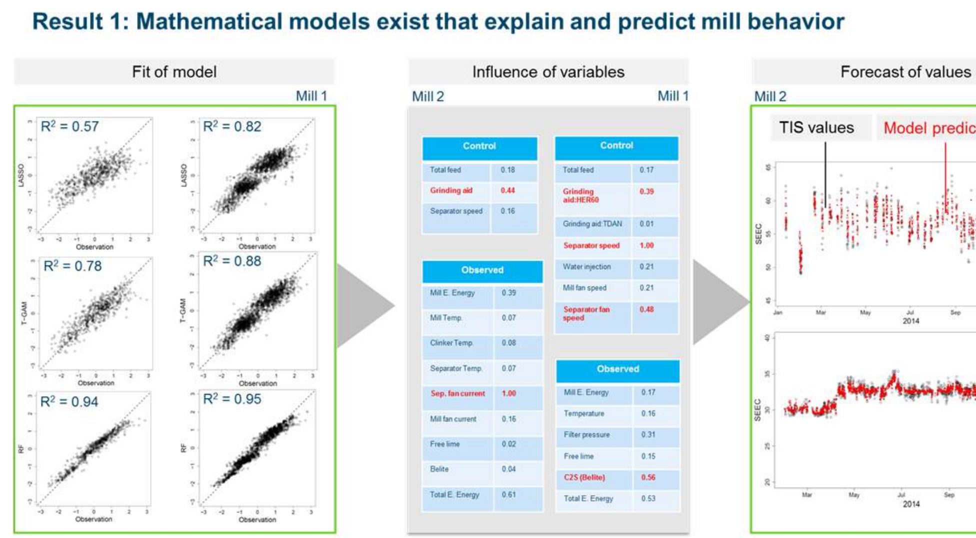
nary: Six different models, linear and non-linear ones, were d to fit the behavior of the historic data from two of Client's nills. (The modeling approach was subsquently verified st two other ball mills)

left to right:

ne best fit was achieved with the non-linear Random Forest odel, that explained the data behavior to >90% fit, shown in the ^2 value.

orrelation tables show the different weight of the variables that fluence the SEEC of both Mill 1 and Mill 2. Tables are given as xamples; full model contains of correlations for all variables.

ne Random Forest model is able to predict the mill behaviour utstandingly well as shown in the graph of the SEEC value (as xamples): The black line shows the measured mill behaviour, e red line shows the mill behaviour that the model simulated ased on the mathematical model.



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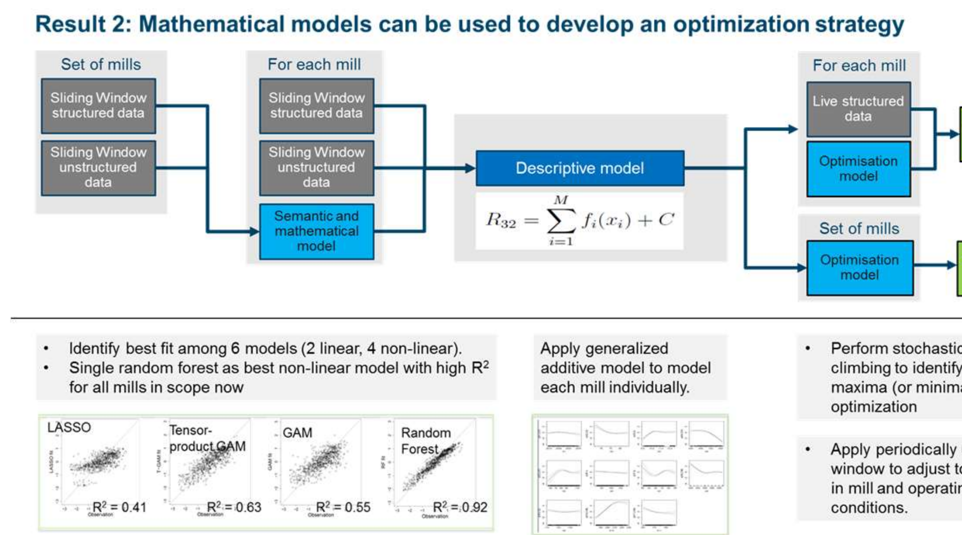
ult 2: Mathematical models can be used to develop an optimization strategy

nary: This slide shows the analytical procedure and essing of data to be applied for the implementation of a e- and cross-mill optimization strategy, based on two rate learning cycles – one that derives a single semantic l from all mills, and one that derives a descriptive model ach mill.

left to right:

a first learning cycle a descriptive mathematical model is rived to mirror the behavior of client's ball mills. This was chieved by analyzing the historic, structured (TIS) and nstructured (maintenance) data of selected mills (ideally all nce the system is operational).

ased on this model, and in a second learning cycle, we derive descriptive model and optimization model for each mill dividually which is then used to drive single mill optimisation nd cross-mill coomparison.



ult 3: An automated machine learning process can be assembled to make predictio dels available to broad range of users at client

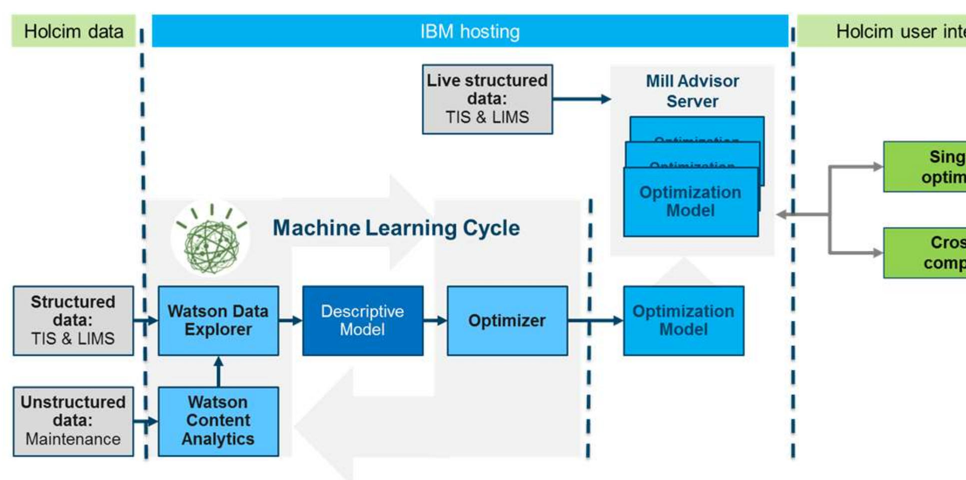
mary: This chart shows how cognitive technology as a ine learning process is implemented in a architectural e for client

left to right:

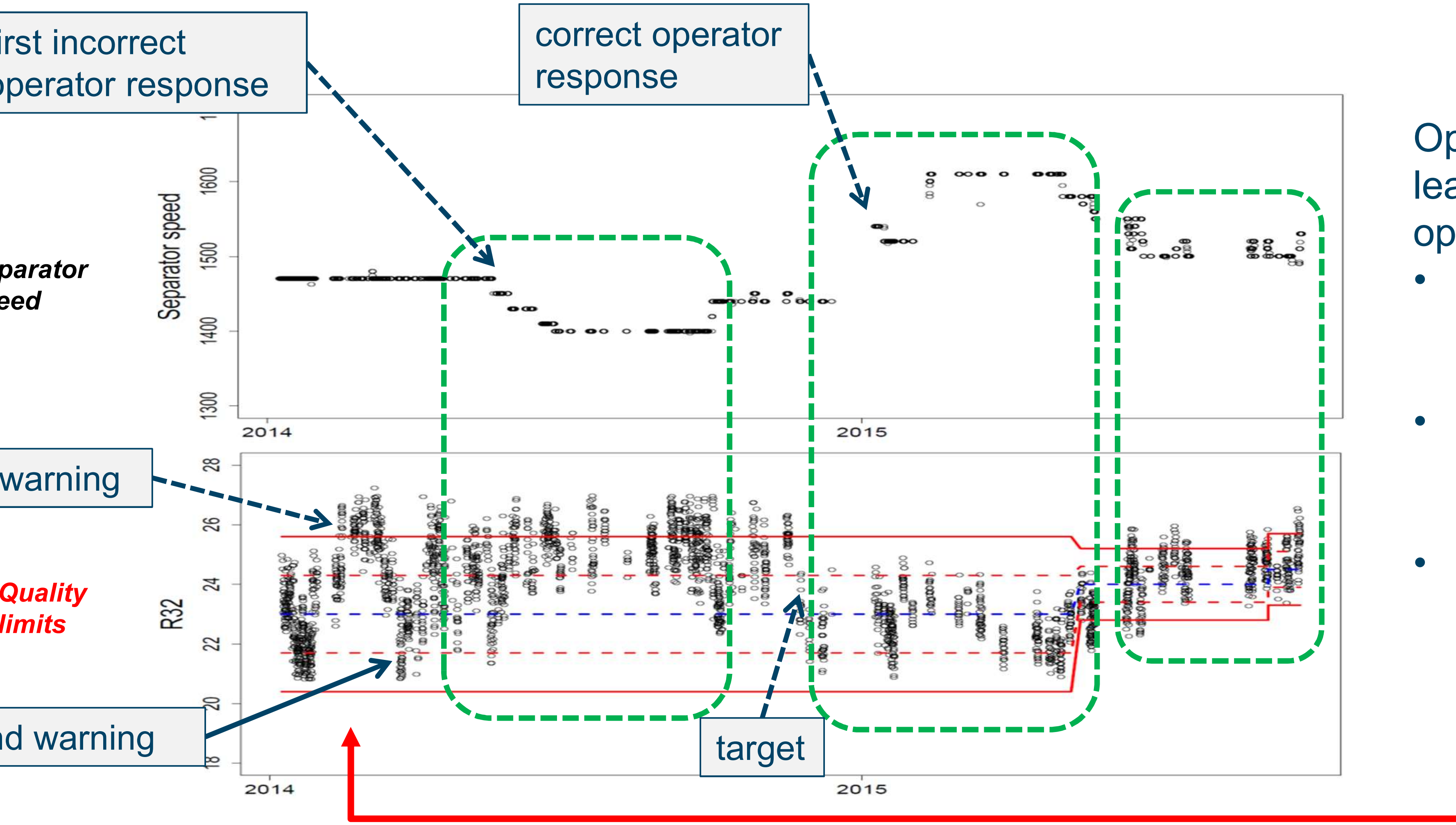
parallel to the integration of structured data through a Data nalytics Engine, key words are analyzed in Watson Content nalytics and fed into the model. Within the machine learning ycle, different «moving windows» are created, each comprising 6 months of data to be digested by the model. As the window regularly shifted, it will be able to adapt and forcast the ehaviour of the mill in the upcoming time span. All the analytics oftware and infrastructure is hosted by IBM during the PoC.

or client's convenience, the mill advisor server itself receives e structured data from their systems to adapt the model in a mely manner.

Result 2: An automated machine learning process can be assembled to make predi models available to broad range of users at LafargeHolcim



sentation of model results to the operator



Operator Behavior
lead to inefficient
operation:

- Inability to recog
long-term trend
to noise
- Desire to maint
stable operating
parameters
- Lack of underst

Attention! The mi
is not running
efficiently.
Recommendation
Set separator spee
to new parameter