// 2025

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# AI for **‘Always Optimized’** Industrial Operations

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# About us

Established in 2013 to accelerate AI-powered problem-solving.

Since then we have **delivered $Bns in tangible ROI** for our customers **across 100s of use cases.**

# Mission

Unlock AI-driven **'Always Optimized' KPIs** for any organization

## Global Footprint

Presence across Asia, Europe and US with employees spread across **8 countries**

## Industry Validated

100s of success stories across within **Fortune 500 companies globally**

## Partner first DnA

**Partner-first organisation** with global reach with GSIs

## Enterprise Ecosystem

Azure, aws, Google Cloud, ChatGPT, Claude, Gemini

# Our Technology

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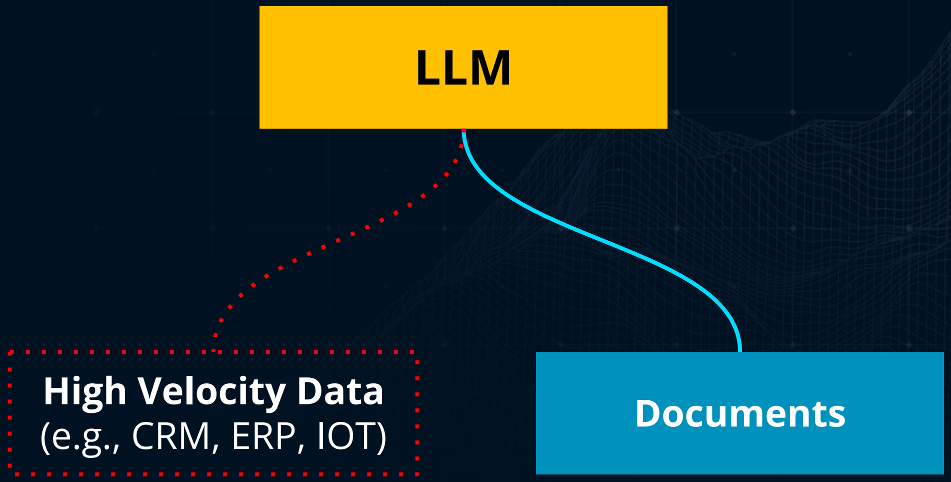
# Generative AI doesn’t understand YOUR business.

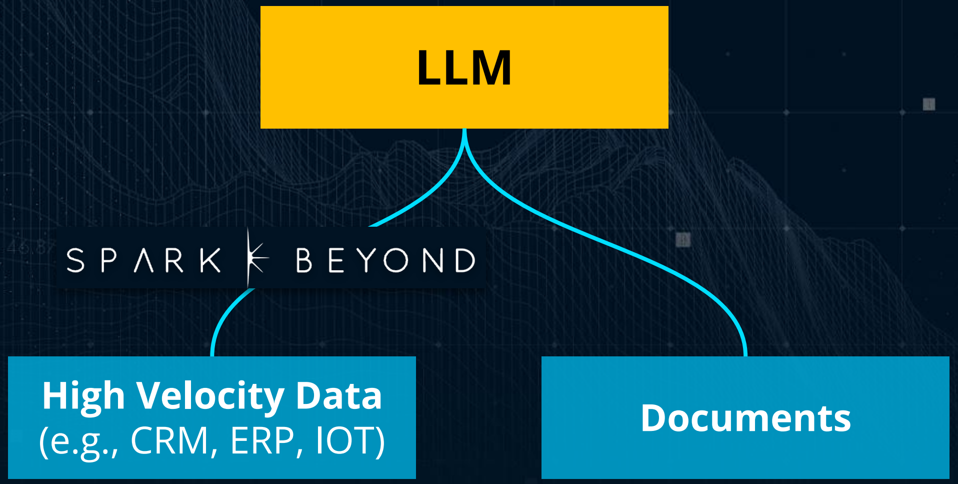
For KPI optimization, AI must leverage knowledge from operational data

## Challenges of LLMs

- Limited in understanding patterns hidden in complex operational data
- Unable to ground business reasoning in data.




## Unlocking LLM-powered KPI-optimization for solution-builders



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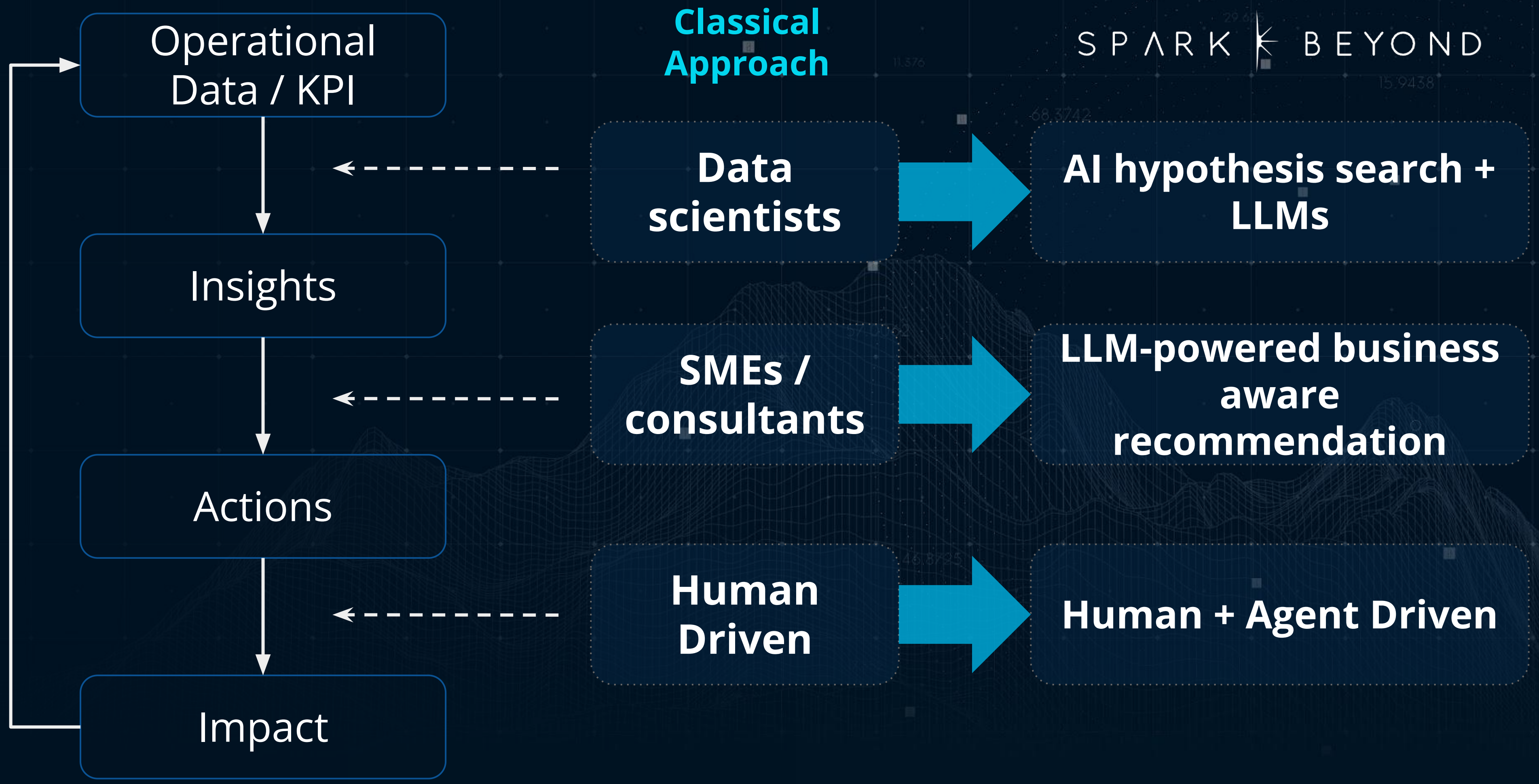
# Making the paradigm shift to 'Always Optimized' KPI Optimization



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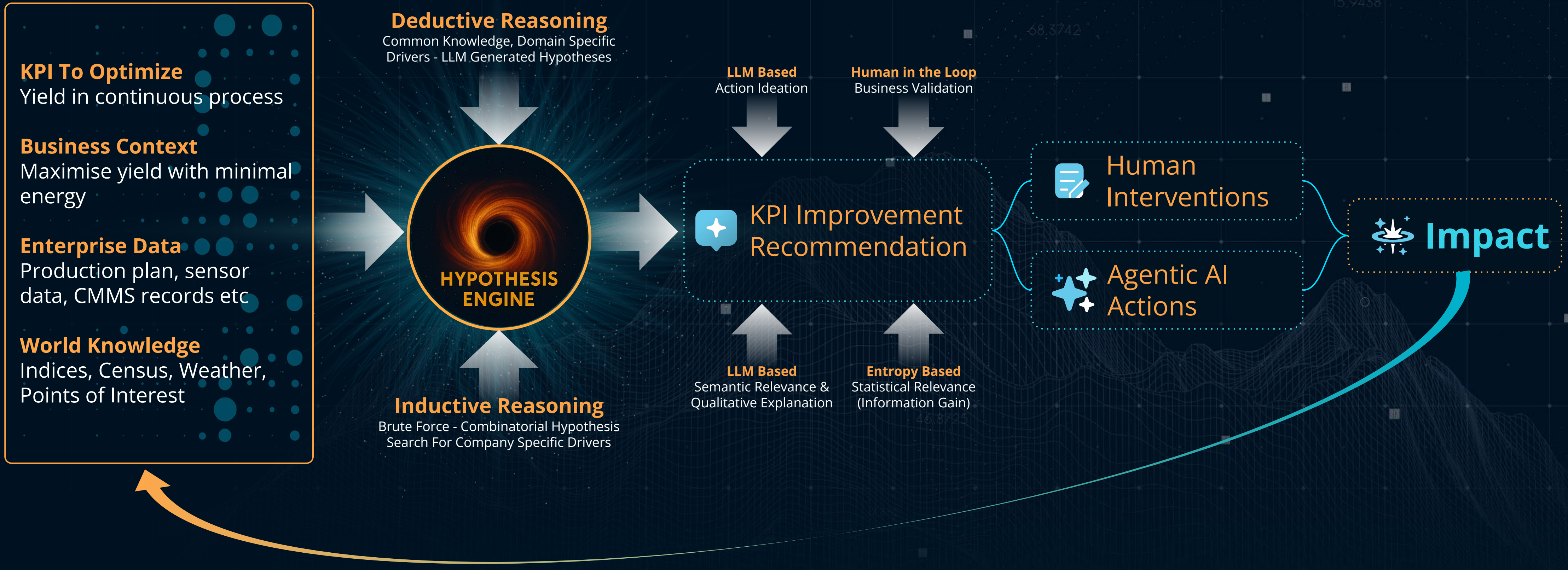
# 'Always Optimized' KPI Architecture

Continuous feedback loop creating impact from enterprise structured data



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# Existing approaches to link LLMs to enterprise data are insufficient to address structured data needs

## Overview of current approaches (not-exhaustive)

### Pre-Training & Fine Tuning

**What is it?**
Pre-training a model on a selected corpus applicable to your enterprise domain
Fine-tuning LLMs to answer domain specific questions

**Limitations**
- Expensive to re-train
- Does not address structured data sources
- Fine-tuning is better suited to teaching specialized tasks or styles and less reliable for factual recall.

### Retrieval Augmented Generation

**What is it?**
Retrieve data from outside a foundation model and augment your prompts by adding the relevant retrieved data in context

**Limitations**
- Structured data requires a query for RAG based solution to retrieve
- Retrieved query needs to be LLM compatible
- RAG is largely limited to searchable documents

### Code Interpretation & Generation

**What is it?**
LLM task to translate a query spoken in natural language into SQL/code automatically

**Limitations**
- User needs to define the intent and insights
- Path to using the insight in an LLM use case is several steps away for a user

### In-Context Learning

**What is it?**
One/few-shot learning example to gain new knowledge (e.g. feeding an existing ppt report about a quantitative analysis)

**Limitations**
- Context needs to be textual
- Context document can get easily outdated

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# Industrial IoT Use Cases

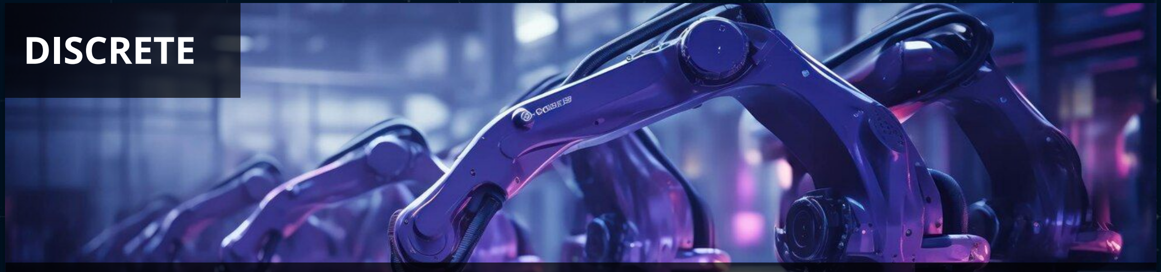
Select top-line and bottom-line impact generating use cases

## MINING

### Fuel/Resource Efficiency
Detect shifts in fuel use and adjusts controls to minimize excess

### Safety Incident Root Cause Analysis
Predict scenarios of safety incidents from historical data

## DISCRETE



### OEE Root Cause Analysis
Track OEE issues continuously to address inefficiencies early

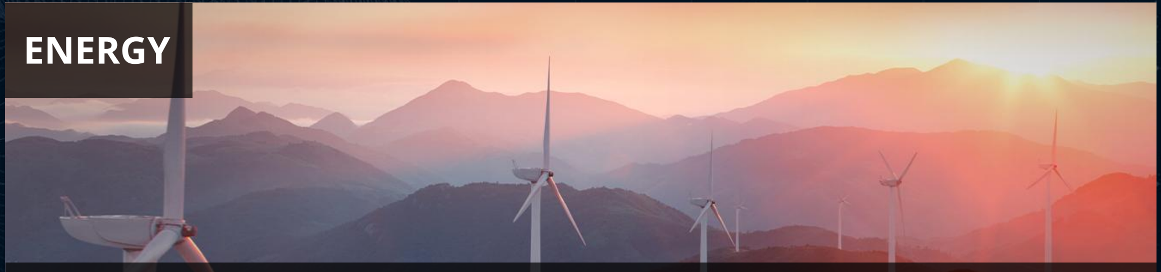
### Operator Copilot
Guide operators to act effectively with automated root causes and SOPs

## CONTINUOUS

### Yield Energy Throughput
Maximize yield continuously while minimizing input material/resource use

### Adaptive QA
Monitor drivers of QA to continuously improve defect rates

## ENERGY



### NPHR Optimization
Optimize plant heat rate by ongoing tuning of parameters to maximise output

### Predictive Maintenance
Detect root causes of potential failures for timely action

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# Cobb EMC Priorities & SparkBeyond IoT Value

Select top-line and bottom-line impact generating use cases

## Cobb EMC's Digital & Grid Modernization Priorities

- **Smart Grid and DER Integration:** Cobb EMC is actively deploying distributed energy resources, microgrids, and advanced metering infrastructure.
- **Data-Driven Operations:** Emphasis on leveraging analytics for operational efficiency, customer engagement, and reliability.
- **Innovation in Customer Experience:** Focus on digital platforms, predictive maintenance, and proactive outage management

## Operational Optimization Offerings

**Predictive Maintenance:**
Reduce equipment downtime and maintenance costs by forecasting failures in grid assets (e.g., transformers, substations, DER systems).

- **Grid Analytics:** Real-time analysis of sensor and IoT data to optimize load balancing, outage detection, and restoration.
- **Asset Lifecycle Management:** Use AI to extend asset life, optimize replacement cycles, and prioritize capital investments.

**Sustainability & DER Integration**

- **Renewable Forecasting:** AI-driven forecasting for solar and battery storage to optimize dispatch and grid stability.
- **DER Value Stacking:** Identify and maximize the value of distributed resources (e.g., solar, batteries, EVs) across grid services.

# Credentials

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# **Boosting beverage production line efficiency** with root cause analysis

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**Identified 13% potential OEE improvement through root cause analysis of production downtimes**

## CHALLENGE

- A leading global beverage manufacturer wanted to improve **Overall Equipment Effectiveness (OEE)** for its filling and packaging lines
- Despite having **Lean, Six Sigma, and excellence programs** in place, they sought to use data to better understand **root causes of downtime** and to **foresee breakdowns** proactively

## RESULTS

- Sparkbeyond autonomously pinpointed key root causes: volume output spikes, older product batches and failures at upstream machines
- Estimated **13% potential OEE improvement** from addressing these causes

## APPROACH

- Collected **performance data** on OEE shifts, outages, process orders, and machine status
- Identified **“built-back” events** as the biggest negative driver of OEE
- Applied predictive analytics to **identify root causes** and recommended targeted actions

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# Achieving fuel efficiency in mining with up to 10% savings

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**Reduced fuel consumption by 10% in 4 months across mining fleet**

## CHALLENGE

- High fuel costs (30% of OPEX) pressured a mining fleet to cut consumption
- Needed to identify controllable drivers across a fleet of 100+ vehicles to reduce operational expenses
- Manual reviews are costly and time consuming prevent fuel used to be optimized

## RESULTS

- Identified **~300 predictors** of fuel efficiency, including payload, tire pressure, and driver behavior
- Rolled out **dashboard monitoring** for key fuel drivers
- Achieved a **10% fuel consumption reduction** in 4 months, with ongoing optimization

## APPROACH

SparkBeyond created a digital twin for each vehicle using:

- IoT Vehicle Management System (30+ onboard sensor data points)
- Fleet Management System (trip data)
- SAP maintenance logs
- External sources (weather, contextual data)

Each digital twin integrated 130+ data points per truck

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# Optimizing the Net Plant Heat Rate by 3.3% based on load conditions

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**Cutting fuel costs and emissions by optimizing plant heat rate with advanced analytics.**

## CHALLENGE

- Low efficiency due to boiler and combustion losses
- Heat rate varies with operational load
- High volume of sensor data from over 3000 sensors from PI system but low actionable insights
- Need to **reduce coal input costs and emissions**

## RESULTS

- Identified 23 high-impact controllable drivers and predicted NPHR impact per driver
- Estimated **3.3% heat rate improvement** corresponding to **~3% reduction in $CO_2$ emissions**

## APPROACH

- Model NPHR by load condition levels (Low, Medium, High)
- Ran learning experiments to rank thousands of features
- Prioritized initiatives and actions via SME workshops
- Built RCA and ideal parameter setting dashboard for engineers

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# $3m impact from optimizing alumina/caustic ratio in alumina refining

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**Reduced variability in the alumina refining process, saving $1.8m per year**

## CHALLENGE

- Controlling the A/C ratio in the digester is critical to the alumina refining process and a major production driver
- However, the client was relying on an outdated predictive model, resulting in high variability throughout the process

## RESULTS

- SparkBeyond identified **several ways to improve consistency** in the A/C ratio, with one improvement alone potentially driving over **$3 million** in added production value
- The client implemented changes valued at **$1.8 million annually**

## APPROACH

The team used SparkBeyond to improve model accuracy through:

- Analyzed internal sensor data from the existing DBO model
- An **iterative process** to identify optimal time windows and interactions between sensor readings
- Built several models, from **linear regression to advanced boosted trees**, to maximize impact

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# Reducing non-conformance rates in shaft annealing process for a bicycle manufacturer

Direct cost improvement from reducing scrap

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**Identified adjustments for annealing process to reduce non conformance rates by 25%**

## CHALLENGE

- Automatically identify the root causes of **non-conformance** amongst a sample of **annealed metal parts,** augmenting engineering intuition of operators

## APPROACH

- Combined **visual inspection data** with **furnace sensor** in historian, **power consumption, nitrogen, oxygen** levels and **environmental factors** (room temp, humidity)
- Generated hypothesis and **identified root causes**

## RESULTS

- Identified **nitrogen pressure and oxygen content levels** during heating and cooling respectively, which when fixed, help reduce non-conformance rates from **29% to 4%**

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# Proactive identification and resolution suggestion for industrial chiller trips at a bicycle manufacturing plant

Avoid throughput losses

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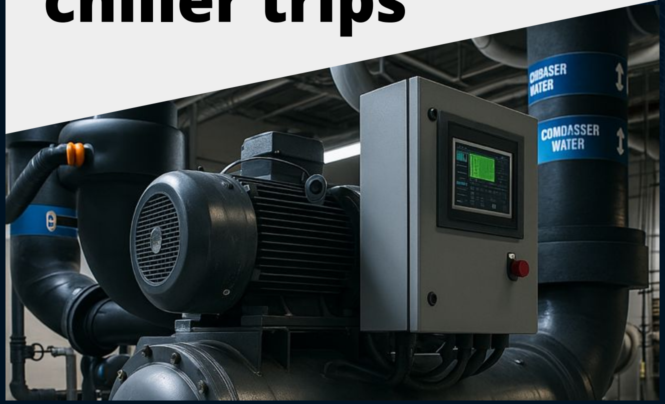
## Prevent temporary loss of plant capacity by proactively preventing chiller trips



## CHALLENGE

- Greenfield site with new **industrial chiller system for cooling** tripped frequently and abruptly with no consistent explanation - each trip while lasts a short duration leads to **plant downtime**

## APPROACH

- Generate hypothesis from sensor and other data from **SCADA** and **operational systems**.
- Use LLMs to bring **engineering and physics knowledge** to boost insights.
- Use **LLMs + OEM manuals** to validate actions and recommendations.

## RESULTS

- Developed a highly accurate predictive model with **85% recall and 80% precision** for identifying trips - $ value for preventing temporary plant shutdown not known to SparkBeyond

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# Predictive Maintenance of ESPs (Electrical Submersible Pumps)

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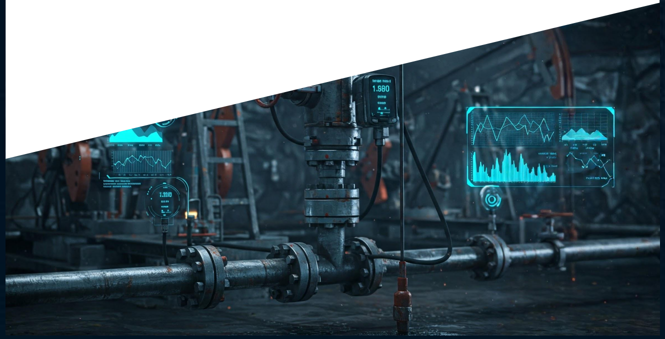
**$2M Impact per Early Warning for Key ESP Failures**



## CHALLENGE

- Client needed to anticipate and manage ESP failures to minimize production loss
- Built a model to predict the probability of ESP failure within the next 100 days
- **Data Sets Used:** Past ESP failures, sensor readings, well trajectories, coordinates, completions

## RESULTS

- **$2M impact per early failure alert**
- Enabled proactive maintenance, minimizing downtime and production loss

## APPROACH

- Reframed task as remaining uptime prediction due to dataset imbalance
- Identified if an ESP is likely to fail within the next 100 days
- Used Discovery Platform with 8 datasets to uncover failure drivers
- Delivered insights as both code and natural language
- Provided daily SHAP-based predictions and explanations
- Outputs shared with maintenance teams to support preventive action

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# Proactive Predictive Maintenance for PCP Pump Failures

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**30+ Days Predictive Horizon | >50% Failure Detection Accuracy | 0–15% False Positives**

## CHALLENGE

- **Improve the life of wells** to increase production and reduce CapEx
- Build a predictive model despite incomplete data
- Integrate analytics with the client's **IT infrastructure**

## RESULTS

- Identified **>50% of system failures** with a 0–15% false positive rate
- Defined 9 predictive parameters contributing to model power
- Achieved a **30+ day predictive horizon** with additional system data

## APPROACH

- Focused on **Analytics & Insight and IT Integration**
- Built a live model to predict failures in PCP sub-systems from incomplete data
- Delivered an **integrated view of the IT infrastructure** and provided software improvement recommendations

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# Predictive Maintenance for Bearing Failure in CMP wafer process

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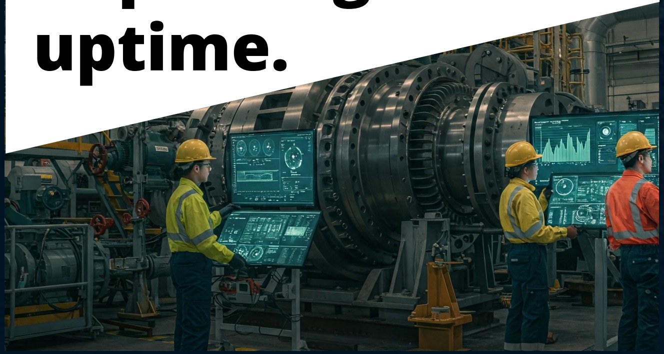
**Advanced analytics predicted failures weeks ahead, improving uptime.**



## CHALLENGE

- **Short lead time** limited predictive capacity
- **Manual process** unable to anticipate failures in advance
- **8-hour downtime** affects all 4 chambers

## RESULTS

- **Earlier failure prediction** than manual process
- **Weeks of advance warning** enabled
- Improved **maintenance scheduling**
- Reduced **unplanned downtime**

## APPROACH

- **Connected data** from vibration and maintenance sources
- Used **APC system** to track sensor signals up to 0.5Hz
- Leveraged **Maintenance records** with free-text.
- **Analyzed observations** before bearing failures

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# **Optimizing wind farm production** by continuous temperature adjustment

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**Improved wind farm throughput by 2% in just two weeks by managing temperature impact**

## CHALLENGE

- A large European energy company faced **unexpected asset downtime** across multiple wind farms, impacting production and IRRs
- Traditional methods were **missing key drivers** behind the downtime

## RESULTS

- SparkBeyond uncovered that **moving from cold to hot weather impacted turbine lubricant viscosity**, and reduced performance over time - so “temperature rate of change” was the most valuable metric
- Initiatives to control the rate of change led to a **2% improvement in throughput** in a two-weeks

## APPROACH

- Automated **time series analysis of sensor data** across various periods (12h, 3 days, 1 week, 1 month)
- Identified **temperature sensors** as critical to performance
- **Augmented internal data with weather datasets** to uncover new drivers

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# Maximizing mean annual increment for a plantation

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**Built a predictive model explaining ~40% of variability in forest growth rates**

## CHALLENGE

- A forestry company in Asia wanted to better identify **predictors of tree growth**
- They struggled with **inconsistent data** from two different MAI measurement methods and sought to **develop a consistent methodology** while **discovering new opportunities** to boost growth rates

## RESULTS

- Identified human-controllable drivers of forest growth, validating expert knowledge
- Built an **elaborate model explaining ~40% of MAI variability**, even after excluding biological factors like tree diameter and height

## APPROACH

- Reduced data preprocessing time and generated **100+ predictive models** across two datasets, including time series models
- Identified **critical features** (e.g., text list variables) improving MAI predictions
- Detected gaps in maintenance and planting methods
- Paved the way for **adaptive and autonomous AI systems** to ensure quality results

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# Industrial agents combine knowledge from operational systems and documents to improve operator performance at keeping KPIs optimized

## 1 KPI Definition

Get engine to optimize the KPI - quality control specification in manufacturing process

## 2 Hypothesis Generation

Generate hypothesis from sensor and other data from operational systems. Use LLMs to bring engineering and physics knowledge to boost insights.

Validate against historical data.

## 3 Natural language translation

Translate mathematical functions and statistical calculations into natural language text document compatible with LLMs for downstream applications

## 4 Live State Inferencing

Predict quality issues during live operations, infer root causes, cross validate with historical data and OEM manuals

## 5 Action Recommendation

Generate appropriate actions based on process SOPs, OEM manuals, domain knowledge and physical constraints

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# Industrial agents = sensor knowledge + SOPs/OEM manual knowledge

**what causes industrial chiller trips?**

By analysing your data we found:

1. **Chilled water return flow rate in the last 2 hours was below the threshold of 40.254 l/s:**
   - **Lift**: 8.57
   - Source
   - **Potential Impact**: This indicates a significant reduction in the flow rate, which can lead to inadequate cooling and potential chiller trip.
2. **The minimum chilled water return flow rate for Chiller 2 in the last 1 hour was below 19.08 l/s:**
   - **Lift**: 5.23
   - Source
   - **Potential Impact**: A low flow rate can cause insufficient cooling and trigger a trip.
3. **High differential pressure in the main chiller header bypass valve in the last 30 minutes:**
   - **Lift**: 13.68
   - Source
   - **Potential Impact**: High differential pressure can indicate a blockage or restriction, leading to a trip.

Chilled water return flow rate in the last 2 hours was below the threshold of 40.254 ls
lastValue(CHILLED WATER RETURN FLOW RATE (ls) in the last 2 hours before datetime) < 40.254

The maximum value of CHSYSCTRFPMXCT_1SYS_1_ST_TO_PMX_A in the last hour was at least 0.5
maxValue(CHSYSCTRFPMXCT_1SYS_1_ST_TO_PMX_A (nan) in the last 1 hour before datetime) ≥ 0.5

The minimum chilled water return flow rate for Chiller 2 in the last 1 hour was below 19.08 L/s
minValue(CHILLER 2 CHILLED WATER RETURN FLOW RATE (Ls) in the last 1 hour before datetime) < 19.08

High differential pressure in the main chiller header bypass valve in the last 30 minutes
lastValue(MAIN CHILLER HEADER - BY PASS VALVE DIFFERENTIAL PRESSURE (kPA) in the last 30 minutes before datetime) ≥ 198.25

**What's the industry standard for the chilled water return flow rate?**

By analysing your data we found:

The industry standard for the chilled water return flow rate can vary depending on the specific application and system design. However, based on the provided technical data, some key points t consider include:

1. **Chilled Water Return Flow Rate Thresholds**:
   - **Below 40.254 l/s** in the last 2 hours is a critical factor leading to chiller trips.
   - **Below 19.08 l/s** for Chiller 2 in the last 1 hour is also significant.
2. **Flow Rate and Pressure Drop**:
   - The flow rate and pressure drop for various chiller models are provided in the technical data example, a chiller with a cooling capacity of 351.7 tons has an evaporator flow rate of 54.26 l and a pressure drop of 15.5 kPa.
   - Source
3. **Chilled Water Plant Control**:
   - The chilled water system control aims to maintain supply water temperature and provide stabilized pressure for the load side.
   - Source
4. **Green Mark Computation**:
   - Chiller plant efficiency and heat balance are computed based on all chiller plant equipment power consumption versus building load.
   - Source

NSP-DT-ACMV-03-001.pdf

DAIKIN

## Technical Data

| Model | Cooling capacity | | Power Consumption | Efficiency | | Evap. Flow Rate | Evap. Pressure Drop | Cond. Flow Rate | Cond. Pressure Drop | Rated Load Amps | Chiller Weight | Operation Weight |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $ton_R$ | kW | kW | $kW/ton_R$ | COP | L/s | kPa | L/s | kPa | A | kg | kg |
| HXEV350SSTTF/E2209-RH/C2009-MK | 100.0 | 351.7 | 54.26 | 0.5426 | 6.481 | 15.09 | 15.5 | 18.90 | 13.3 | 97.27 | 2927 | 3358 |
| HXEV400SSTTF/E2209-QH/C2009-KK | 150.0 | 527.5 | 90.77 | 0.6052 | 5.811 | 22.66 | 21.1 | 28.76 | 22.5 | 151.3 | 2990 | 3463 |

BMS_Chiller.pdf

**2. Chilled Water Plant Control**

**2.1 Overview**

The purpose of chilled water system control is to maintain supply water temperature and provide stabilized pressure for load side.

To achieve supply water temperature as set point, Chiller plant controller will monitor building load and determine necessary chillers to operate with comparing design capacity of chillers.

**The Chilled Water Control System consists of :-**

| No | Equipments | Qty |
|---|---|---|

**2.7 Green Mark computation**

To comply with Green Mark 2015 requirement, Chiller plant efficiency and heat balance is computed in BMS.

Chiller Plant System Efficiency is calculated based on all chiller plant equipment power consumption versus building load. It is the criteria for BCA green mark assessment.

$$\text{Chilled Plant Efficiency [KW/RT]} = \frac{\text{Chiller [KW]} + \text{CHWP [KW]} + \text{CWP[KW]} + \text{CT[KW]}}{\text{Building Load [RT]}}$$


Thank You
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