CASCADIA SCIENTIFIC INC

# Application of Machine Learning Models to Mine Haulage Sustainability

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# Our Meeting Agenda

- Introductions
- ML & Mine Haulage Sustainability Objectives
- Development of ML Mine Haulage Models
- Evaluating Model Performance
- Model Application - Case Studies & Results
- Conclusions
- Q & A



## Cascadia Scientific Inc

- Est. 2018 Vancouver B.C.
- Founded on High Accuracy Fuel Measurement
- Matured into a leading ML provider for mining
- Customers in 10 Countries on 5 Continents

## Kevin Dagenais, P.Eng, CEO

- Est. 1980 Montreal QC
- M.A.Sc Controls System Engineering (McMaster, 2005)
- Embedded Systems and Vehicle Network Specialist
- Practiced in Data Science since 2018 Co-founding Cascadia Scientific

# Machine Learning

- A study in the field of artificial intelligence focused on the construction of methods that “learn” from training data
- These methods are commonly used to produce models that predict, explain or decide an outcome or a course of action
- Highly applicable in situations where satisfactory algorithmic solutions are unavailable
- Credited with the development of linear regression models, neural networks, random forests and gradient boosting

# Mine Haulage Sustainability Concerns

## Reduce Energy per ton moved

- Reduced fuel usage
- Increased runtime
- Reduced battery/charging requirements

## Reduce Emissions

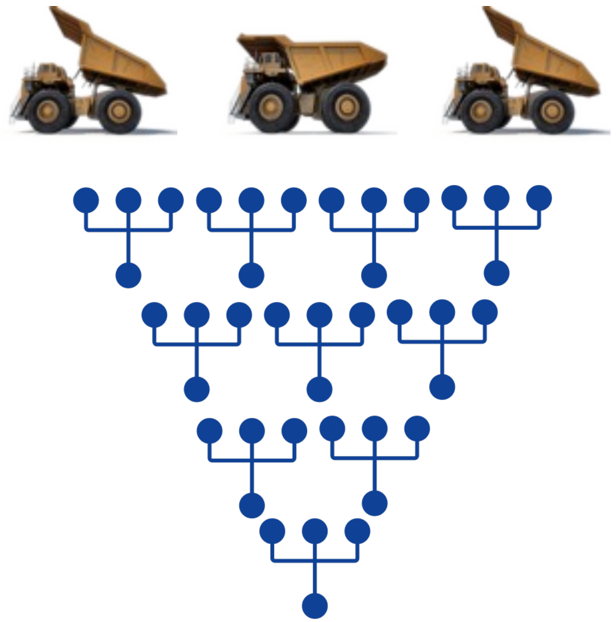
- Renewable fuels
- Pre/Post combustion strategies

## Extended Component/ Consumable Life

- Wear parts
- Lubricants

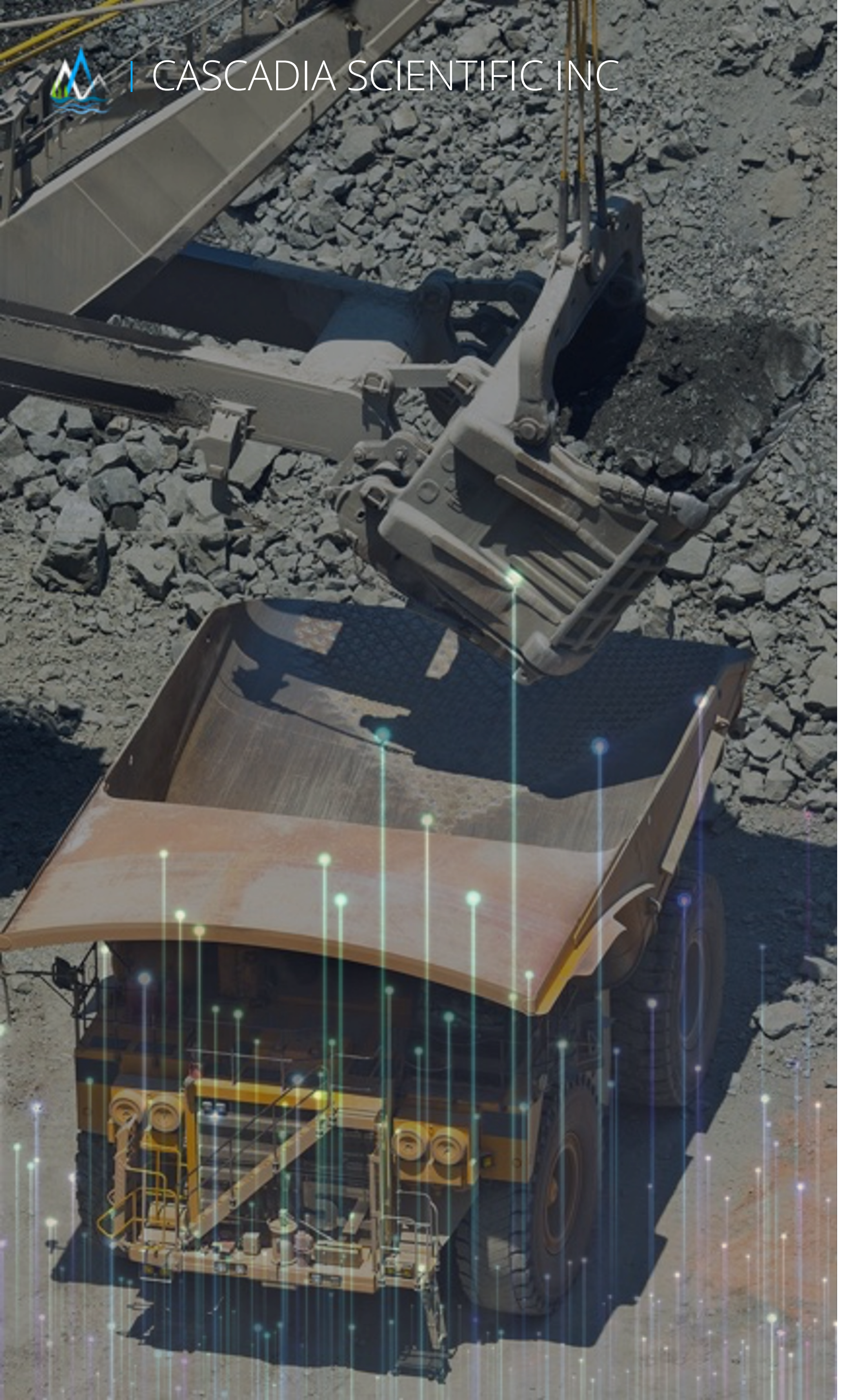

# Applications of ML to Haulage Sustainability

1 Haul Cycle = 1 Model Observation



## Applications:

- Normalized efficiency assessment of haulage assets
- Normalized efficiency assessment of operator practice
- Validation of 3rd party product efficiency claims
- Assessment of Real-time oil condition
- Optimization of mine ops and mine planning strategies




# Developing a Haulage Model

1. **Define the question or hypothesis:**
   "Which trucks in my fleet are over consuming based on the work they perform"

2. **Define the model target:**
   Normalized Liters per Cycle

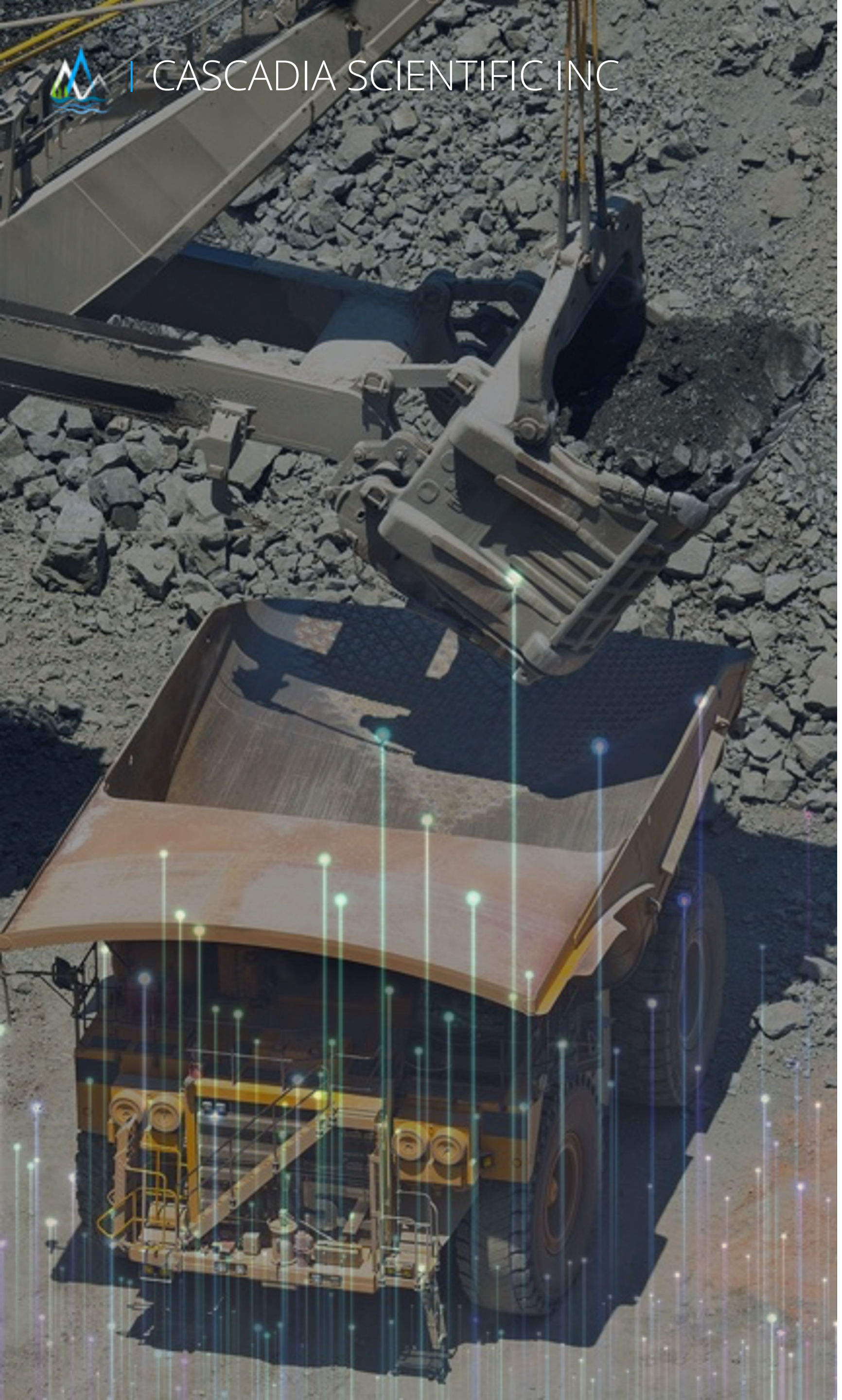
3. **Assess and select correlated model inputs:**
   Truck ID, Tonnage, duration, distance, vertical profile, zone, queuing time, week of year

4. **Select a model type:**
   Gradient Boosted Tree

5. **Establish model sensitivity and reliability aims**
   "1% sensitivity with 95% confidence"

6. **Train the model and evaluate performance**


Consumption 1 0.74 0.22 0.075 0.86 0.84 0.65 0.15 0.19 0.77 0.78 0.48 0.31
Loaded_Vertical_Travel 0.74 1 -0.18 -0.021 0.65 0.75 0.4 0.14 0.044 0.54 0.7 0.22 0.2
Unloaded_Vertical_Travel 0.22 -0.18 1 0.013 0.25 0.1 0.32 0.015 0.2 0.28 0.085 0.32 -0.025
Payload 0.075 -0.021 0.013 1 -0.02 -0.011 -0.022 -0.029 -0.052 0.0073 0.029 -0.011 0.14
Distance 0.86 0.65 0.25 -0.02 1 0.83 0.88 0.11 0.17 0.79 0.71 0.57 -0.14
Loaded_Distance 0.84 0.75 0.1 -0.011 0.83 1 0.47 0.18 0.051 0.66 0.86 0.26 0.082
Unloaded_Distance 0.65 0.4 0.32 -0.022 0.88 0.47 1 0.024 0.23 0.7 0.39 0.67 -0.28
Loaded_Idle 0.15 0.14 0.015 -0.029 0.11 0.18 0.024 1 0.048 0.32 0.54 0.037 0.075
Unloaded_Idle 0.19 0.044 0.2 -0.052 0.17 0.051 0.23 0.048 1 0.63 0.051 0.83 0.076
Engine_Hours 0.77 0.54 0.28 0.0073 0.79 0.66 0.7 0.32 0.63 1 0.7 0.85 0.053
Loaded_Engine_Hours 0.78 0.7 0.085 0.029 0.71 0.86 0.39 0.54 0.051 0.7 1 0.22 0.18
Unloaded_Engine_Hours 0.48 0.22 0.32 -0.011 0.57 0.26 0.67 0.037 0.83 0.85 0.22 1 -0.059
PerKmConsumption 0.31 0.2 -0.025 0.14 -0.14 0.082 -0.28 0.075 0.076 0.053 0.18 -0.059 1
Consumption
Loaded_Vertical_Travel
Unloaded_Vertical_Travel
Payload
Distance
Loaded_Distance
Unloaded_Distance
Loaded_Idle
Unloaded_Idle
Engine_Hours
Loaded_Engine_Hours
Unloaded_Engine_Hours
PerKmConsumption
1.0
0.8
0.6
0.4
0.2
0.0
-0.2

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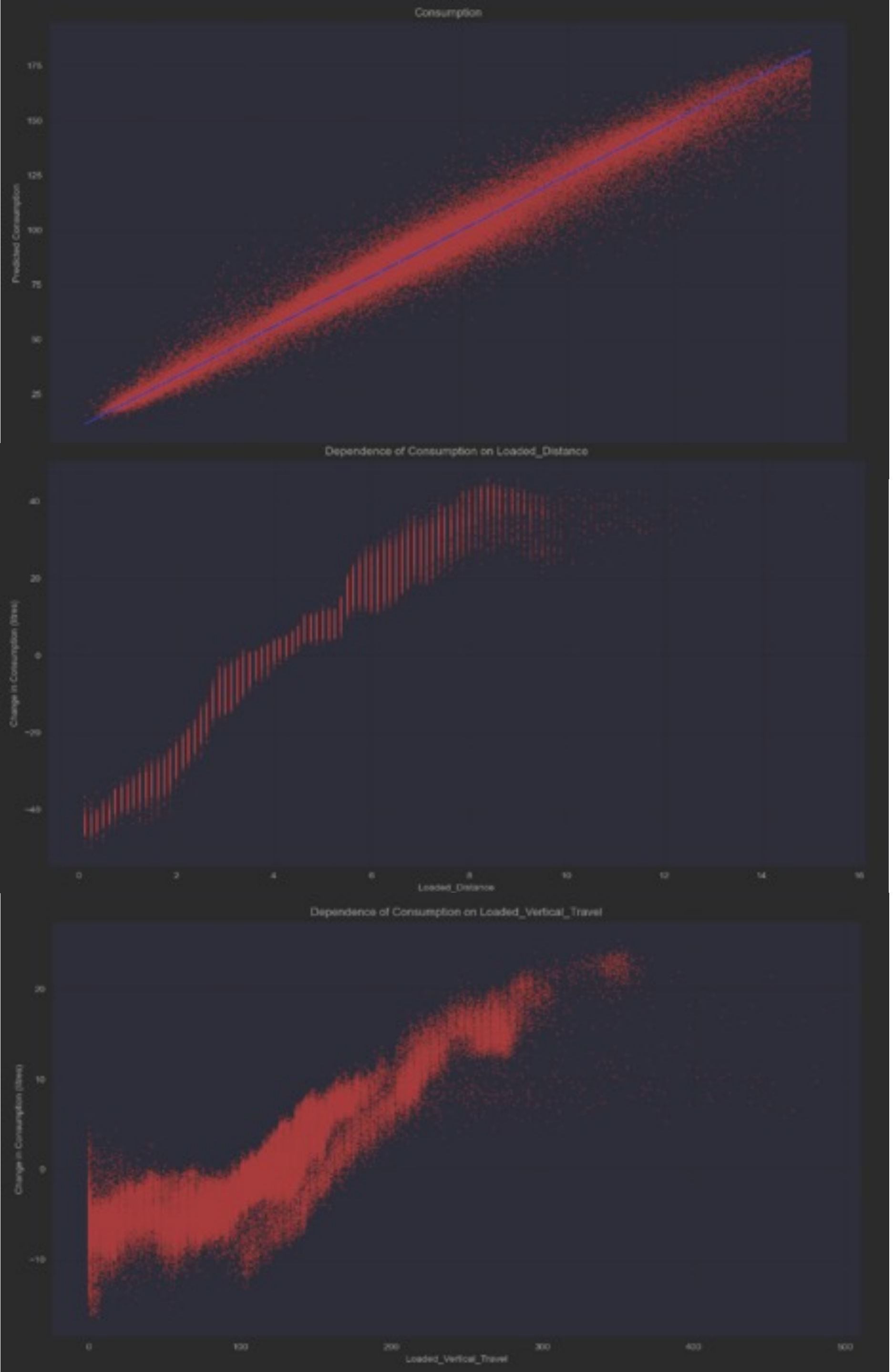



# Evaluate Model Performance

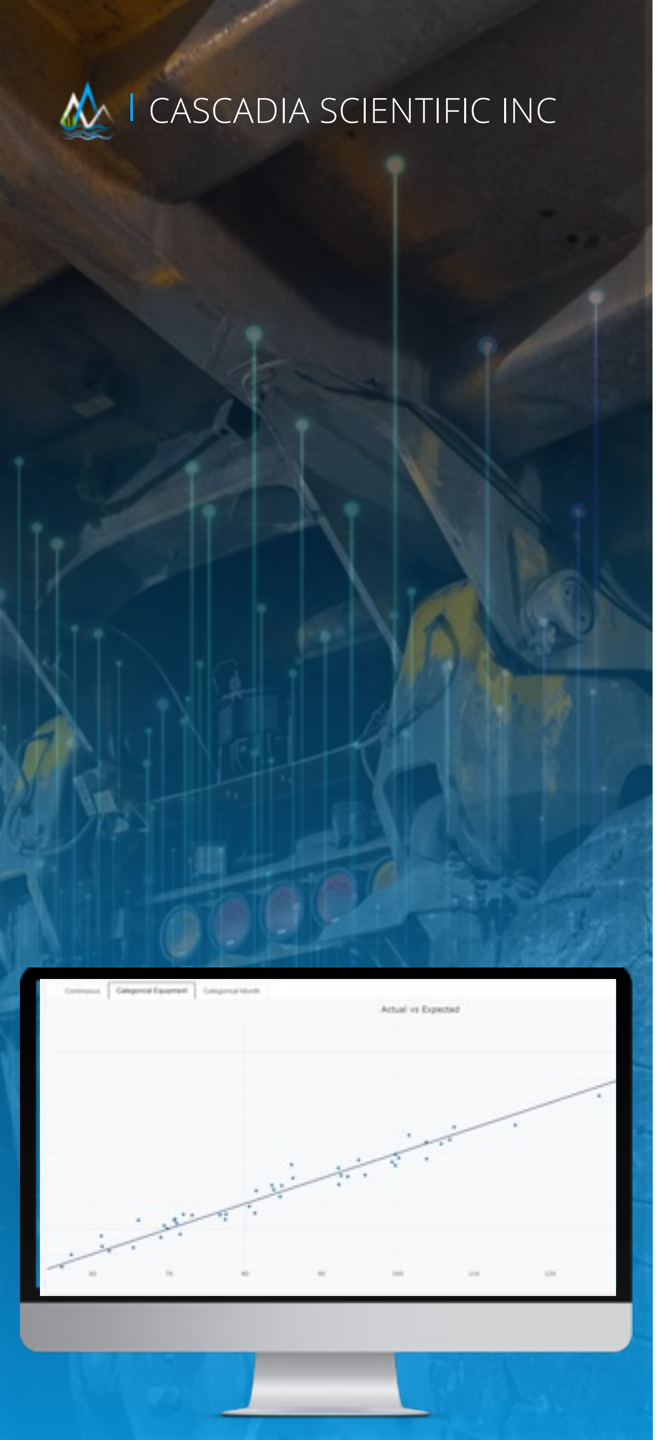
1. **Withhold training data and quantify error:**
   Randomize and Repeat

2. **Visualize and evaluate model error:**
   Limited scatter, centered on y = x.

3. **Assess correlation between well understood variables and targets**
   Does the model make sense

# Applying Models to Practice
# Case Studies

- Targeted Truck Restorative Maintenance
- Fleet replacement/upgrade decision support
- Operator Performance Management System


# Targeted Restorative Maintenance

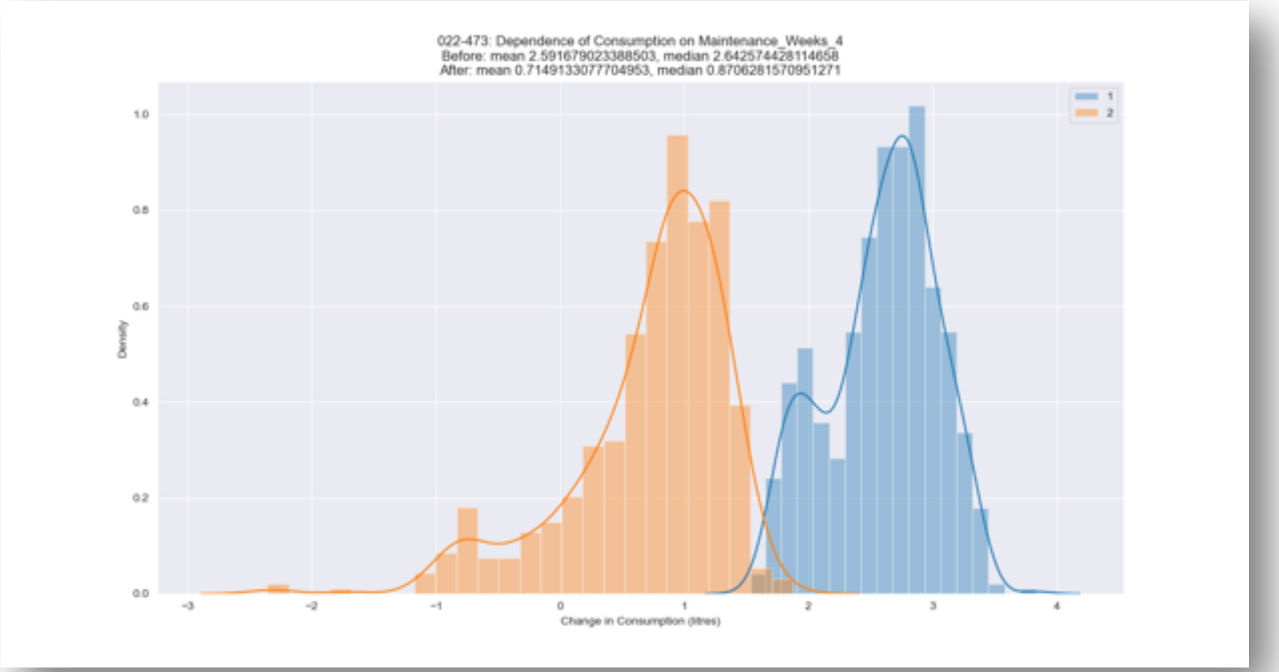
- Models produced weekly & examined for equipment penalty
- Equipment penalties > 1 gal/cycle trigger maintenance referral
- Standardized level-1 efficiency service performed
- Service dates and details captured for post intervention assessment

Ranking

| Rank | Name | Haul Cycles | Impact (L/Cycle) | Actual | Expected |
|---|---|---|---|---|---|
| 50 | 022-475 | 130 | 8.2693 | 151.4030 | 139.2472 |
| 49 | 022-478 | 291 | 7.7113 | 95.4056 | 86.0809 |
| 48 | 022-430 | 175 | 5.8706 | 73.4195 | 65.9895 |
| 47 | 022-448 | 335 | 4.9476 | 67.1279 | 61.1245 |
| 46 | 022-489 | 169 | 3.8042 | 107.1263 | 101.4804 |
| 45 | 022-484 | 271 | 3.2359 | 75.6949 | 71.8818 |
| 44 | 022-488 | 129 | 3.1801 | 87.2443 | 83.5018 |
| 43 | 022-426 | 256 | 2.8729 | 90.0907 | 86.2620 |
| 42 | 022-447 | 240 | 2.1940 | 85.0601 | 81.4446 |

# Targeted Restorative Maintenance

- Typical findings related to leaks, filters, injectors, cooling issues
- Inconclusive findings trigger level-2 intervention
- Impact assessed with second model trained with intervention flag
- Average annualized benefit per intervention 4,862 gal (CAT 793D)

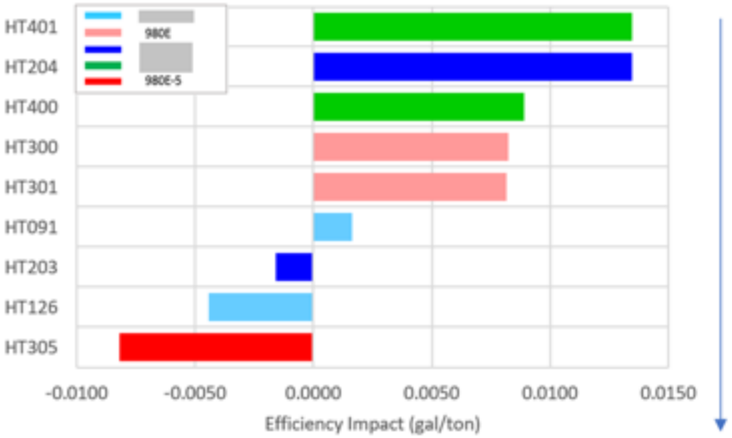



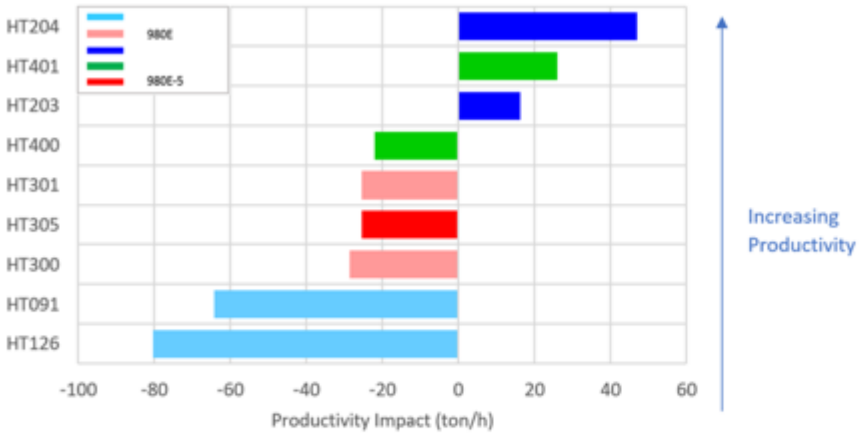
# Fleet Upgrade Decision Support


Large operator of mixed manufactured fleet considering repowering or replacing aging units.  Evaluated performance of various configurations:

- Electric Drive vs. Mechanical Drive
- Engine Upgrades vs. Equipment Replacement
- Various payload sizes
- Multiple OEMs
- Truck Revision upgrades

# Fleet Upgrade Purchasing Insights




- Model trained on fuel per ton, rather than normalized cycle consumption
- Most efficient asset showed 6.2 gal/cycle reduction compared to previous generation (based on 400-ton payload)
- Most efficiency asset delivered above average productivity (t/h)

# Fleet Upgrade Purchasing Insights

Minero DIGITAL

## Komatsu-Mitsui y Antamina concretan importante acuerdo para renovar flota de camiones


This is the acquisition of a fleet of 20 Komatsu haulage trucks, model 980E-5SE, which have a load capacity of 400 MT.

These units are equipped with Cummins QSK95 engines, 4400 Hp, recognized for having the highest power on the market. A vehicle and an engine that, together, make this mining haul truck the fastest and most productive in the industry.

This commercial agreement has a potential of great relevance, since it contemplates the possibility of buying up to 100 trucks of the same characteristics. A fact that, if materialized, would become a historic purchase agreement for mining in Peru.

"This is certainly a milestone within the mining industry and therefore also for Komatsu-Mitsui. Never had a company made an agreement to purchase equipment of this size and magnitude in Peru. We are proud of the trust that has placed #Antamina in us and in our technology offering, through our Komatsu and Cummins brands," said Tomas Eloy Martínez, executive president of Komatsu – Mitsui Maquinarias Peru.

Allies in the future of mining

The relationship between both actors in the mining

# Operator Performance Management

## Retrospective Analysis (SmartRView)

- Models trained on rolling 3-week periods
- Model derived operator penalties extracted
- Struggling operators are contacted
- Simulator based training is made available

## Short Interval Control (ML Coach)

- Model trained without operator ID’s
- Active shift cycles compared to predictions
- Average deviation calculated across fleet
- Consistent model underperformance through shift triggers radio callout

# Operator Performance Management

## SmartRView

Retrospective Analysis

- Average savings/intervention 0.39 gal/h
- Annualized benefit of 175,000 gallons saved

## MLCOACH

Short Interval Control

- On-site “Base” is being constructed
- 24/7 “dispatch” style monitoring
- System augmented with “Bad practice” alerts
- Work on-going to train models to identify ideal situation operator behaviors

# CASCADIA SCIENTIFIC INC

- ML Haulage models can accurately explain nuanced details of mine haulage
- These insights can be used to effectively improve mine haulage sustainability today
- These techniques will have continued, if not increased, relevance as we pursue decarbonization as an industry

# Thank you