IMPROVING COAL-FIRED PLANT PERFORMANCE THROUGH INTEGRATED PREDICTIVE AND CONDITION BASED MONITORING TOOLS

(Award No. DE-FE00031547)

2019 Annual Project Review Meeting for Crosscutting Research

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4/9/19
Presentation Overview

- **Project Information**
  - Project Team
  - Project Goal and Objectives
- **Background**
  - Microbeam’s Fireside Performance Indices
  - Microbeam’s Combustion System Performance Indices (CSPI) Program
- **Accomplishments**
  - CoalTracker Algorithm Development and Testing
  - Combustion System Performance Indices Algorithm Development and Testing
- **Opportunities for Plant Improvement and Cost Savings**
- **Next Steps**
Project Team

- **Technical Team:**
  - Microbeam Technologies Inc.
  - University of North Dakota
    - Institute of Energy Studies (IES)
  - Rochester Institute of Technology
    - Department of Software Engineering

- **Funding Support:**
  - U.S. Department of Energy, National Energy Technology Laboratory
  - Otter Tail Power’s Coyote Station
  - North American Coal Company
  - Great River Energy

- **Project Support:**
  - Energy Technologies Inc.
Goal
Demonstrate at a full-scale coal-fired power plant the ability to improve boiler performance and reliability through the integrated use of condition based monitoring (CBM) and predictions of the impacts of coal quality on boiler operations.

Project Period
January 1, 2018 – December 31, 2021 (4 Years)
Project Background
Microbeam’s Fireside Performance Indices

- High temperature fouling (silicate) – Plateau and high temperature convective pass
- Deposit Strength – Wall slagging, high temperature fouling (silicate), and slag removal
- Wall slagging – Accumulation potential on the boiler walls
- Wear – Abrasion wear – fuel handling
  Erosion wear – heat transfer surfaces
- Slag flow – slag discharge systems – cyclone-fired boilers and wet bottom systems

Low temperature fouling – Sulfate based

Stack
Wet Scrubber
Precipitator or Baghouse
Air Heater
Project Background
Microbeam’s Combustion System Performance Indices Program User Interface

Coal Quality Outlook Table
Red indicates low forecasted coal quality

Coal Quality Trend Graphs
Plot different coal-quality parameters over time

Plant Diagram
Show plant performance in a given area of the boiler
Testing Sites

**Primary site: Otter Tail Power’s Coyote Station**
- Cyclone Fired Boiler
- MW – 450
- Fuel – ND Lignite
- Daily fuel delivery – 7000 - 12000 tons of coal – 2.5 million tons of lignite annual consumption – Mine mouth plant

**Secondary Site: Great River Energy’s Coal Creek Station**
- Pulverized Tangential Boiler
- MW – 550 (2 Units)
- Fuel – ND Lignite
- Annual fuel delivery – 7.5 - 8 million tons of coal – Mine mouth plant
Project Overview

CoalTracker Algorithms

Coal Mining/Processing

- Coal - stock piles of varying qualities
- Full Stream Coal Analysis - moisture, HV, S, ash composition
- Coal Tracker
- Bunkers/pulverizer/asher
- Properties of coal delivered to each burner-coal flow
- Coal/ash Properties Database (10,000 samples)

Combustion System Performance Indices Algorithms

Boiler Operations

- Soot blowing cycle
  - Temperature, Heat flux
- Transport to Convergent pass surfaces - Temperature, burner tilt
- High temperature fouling - silicate based erosion/oxidation
- Transport to water wall - Temperature, Heat flux
- Low temperature fouling - sulfate based
- Wall Slagging
- Soot blowing cycle
  - Temperature, Heat flux

- Particulate and add gas removal

- Ash Generator - Ash formation and partitioning during combustion
- System design/geometry and boiler operating parameters, air flow, temperature
- Bottom ash or Slag
- Slag flow/cyclone applications

Neural Network - Training and learning for selected predictions - Manage impacts of coal properties and boiler operations

CSM-CT Tools
Inputs/processes
Sensors
Accomplishments

- **CoalTracker Algorithm Development and Testing**
  - Analyzer installation (Coal properties)
  - Database development (Coal properties)
  - Coal Tracking applications

- **Combustion System Performance Indices Algorithm Development and Testing**
  - Access to plant operating/conditions monitoring (Plant operation and performance)
  - Beta version of Combustion System Performance Indices (CSPI) installed at plant
  - Database development (Powerplant Parameters)
  - Neural network training (Plant performance)
# Database Development – Neural network and Machine Learning Applications for Improving Plant Performance

<table>
<thead>
<tr>
<th>Database</th>
<th>Database consists of</th>
<th>Data Points/ No. of Samples</th>
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<tbody>
<tr>
<td>Life of Mine Dataset</td>
<td>Life of Mine coal properties – Ash, BTU, ash composition</td>
<td>16000 Data points</td>
</tr>
<tr>
<td>As-fired Fuel Properties Dataset</td>
<td>As-fired Fuel properties – Ash, BTU, ash composition</td>
<td>500 samples</td>
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<tr>
<td>FSEA Data</td>
<td>FSEA Output - Fuel properties</td>
<td>Minute-by-minute data for 9 months</td>
</tr>
<tr>
<td>Plant Parameter Data</td>
<td>Plant Operating Parameters</td>
<td>Operating data for 25 months - Over 54,000 data points for each month</td>
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CoalTracker Algorithms Development and Testing
Full Stream Elemental Analyzer (FSEA) Installation
July 2018

Before Installation - Coal analysis results from one composite sample representing 7000 – 12000 tons of coal available after 3 days of firing.

FSEA Impact - Coal properties are reported every minute for every 90-120 tons of as-delivered fuel before firing. Flexibility of coal blending and storage.

Coal Properties from FSEA - Ash, Moisture, Heating Value, S, C, and inorganic constituents based on prompt gamma neutron activation, microwave, and dual gamma attenuation.
Coal from the mine → Belt 1/FSEA → Live Storage → Transfer Tower → Belt 7/10 → Silos → Cyclones/Boiler

- Collect and analyze coal samples
- Continued characterization of FSEA performance
- Obtain detailed data for CoalTracker
- Track power plant performance during the field test
- Use CSPI-CT beta version to predict plant performance
- Validate plant performance with real-time data

Total Number of Coal Samples Collected during the field test → 149
Tracking Coal through the System

Coal from the mine → Belt 1 /FSEA → Live Storage → Transfer Tower → Belt 7/10 → Silos → Cyclones/Boiler

Mine Projected Ash% (As Rec'd)

<table>
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<th>Ash %</th>
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<tr>
<td>12-Nov</td>
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<td>13-Nov</td>
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<td>14-Nov</td>
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All Cyclones Ash Content on 11/15/19

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<th>Time</th>
<th>C4</th>
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Heat Rate

(Assumption – 12 to 24 hour time lag between coal delivery point and burner)

- Peak 1 & 2 – higher heat rate – due to coal compositional changes
- Peak 3 – Drop in load – boiler cleanup

Field Test Conclusion - Coal analysis results are consistent with preliminary CoalTracker algorithm calculations.
Combustion System Performance Indices (CSPI) Program
CSPI-CT program’s beta version was installed at Coyote station on April 25, 2018.
Augmenting CSPI Program

Neural Networks

Why Neural Networks?

- Because they are generic methods which can represent any function.
- They can be trained to be powerful predictors for time series data.
Evolutionary Algorithms Developed under this Project

- **Evolutionary eXploration of Augmenting LSTM Topologies (EXALT)**
  - Progressively evolves larger recurrent neural networks (RNNs) to perform time series data prediction.
  - Can select which input parameters have the best predictive ability and eliminate confuser parameters.
  - Can be executed in parallel over a large number of cores on high performance computing clusters.
  - Evolved RNNs exported to binary files for use within Microbeam’s software.

- **Evolutionary eXploration of Augmenting Memory Models (EXAMM)**
  - Based on EXALT, except with a library of memory cells. Nodes can be LSTM, GRU, MGU, or Delta-RNNs.
  - Can be executed in parallel.
  - Mutations have further refinements from EXALT.
Neural Networks for Cyclone Database

- **Input parameters** –
  - 6 months of operating data
  - 12 operational parameters
  - 12 independent cyclones

- **Predicted parameters** – flame intensity and oil flow

- **K fold cross validation** with 2 files per fold and 10 repeats per fold – **1320 runs** – **14,200 CPU hours**

![Flame Intensity Predictions](chart)

- Create a cyclone parameter database
- Determine the structure of NN model
- Evaluate the fitness and strength of the neural network
- Obtain the best fitness
- Validate the results using k-folds cross validation
- Test with new parameters
- Compute error
- Obtain the best solution
Example of Application
Cyclone Slagging Issues - Jan 2019

- Plant operators changed Over Fired Air setpoint to add more air through cyclones. \((\text{NO}_x - 0.49 \text{ – Very high})\)
- 40000 gallons of oil was added to maintain the slag flow.
FSEA Data
B/A Ratio
Jan-Feb 2019

Ash and B/A Ratio

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Elemental Oxide Daily Analysis January - February

Sharp increase in Si and drop in Ca
Samples collected from Belt 7 were subjected to proximate, ultimate, ash composition and Computer controlled scanning electron microscopy (CCSEM) mineral grain analysis.

Changes in mineral composition were observed which in turn affected the slag flow in cyclones.

Good fuel quality - CQI < 30
Oil Flow in Cyclones

Coyote Station Daily Oil Flow Jan 21 - Feb 10 2019

Total 40,000 gallons of oil was added during this week ~ Cost - $100,000
Neural Network Predictions

Predicted vs Actual flame intensity during the cyclone slagging issues

X axis: Jan. 31 - Feb. 13 2019 (Cyclone Slagging Issues)
Y Axis: normalized flame intensity
%Error: 4.09%
CSPI-CT User Interface
(Feb 1, 2019 – Feb 14, 2019)
Opportunities for Plant Improvement and Cost Savings

- Installation of FSEA
  - Decreased cost of analysis
  - Opportunity to blend coal
  - Opportunity to optimize plant operating conditions to match coal properties
- Improved heat rate – coal property impacts
- Decrease oil firing through optimizing fuel properties
- Decrease fireside ash deposition- reduce number of scheduled and forced outages (maintenance costs)
Next Steps

- **CoalTracker Algorithm Development and Testing**
  - CCSEM mineral analysis on field test samples
  - Improve CoalTracker predictions based on field test and slagging event data

- **Combustion System Performance Indices Algorithm Development and Testing**
  - Conduct neural network analysis on waterwall, superheater and economizer database
  - Improve indices predictions based on field test data
  - Augment indices with neural network derived relationships
  - Installation and testing of a neural network based CSPI-CT

- **Operator and Plant Personnel Training**
Questions?

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