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Artificial Intelligence Models for the Predictive Analysis of Flaring Performance

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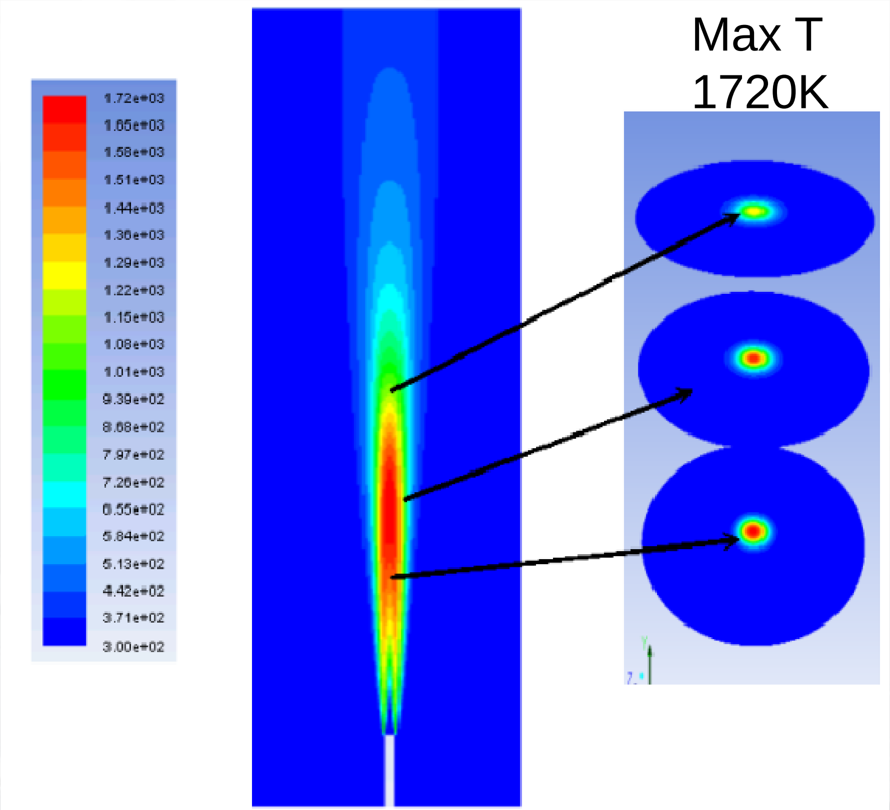
Flares

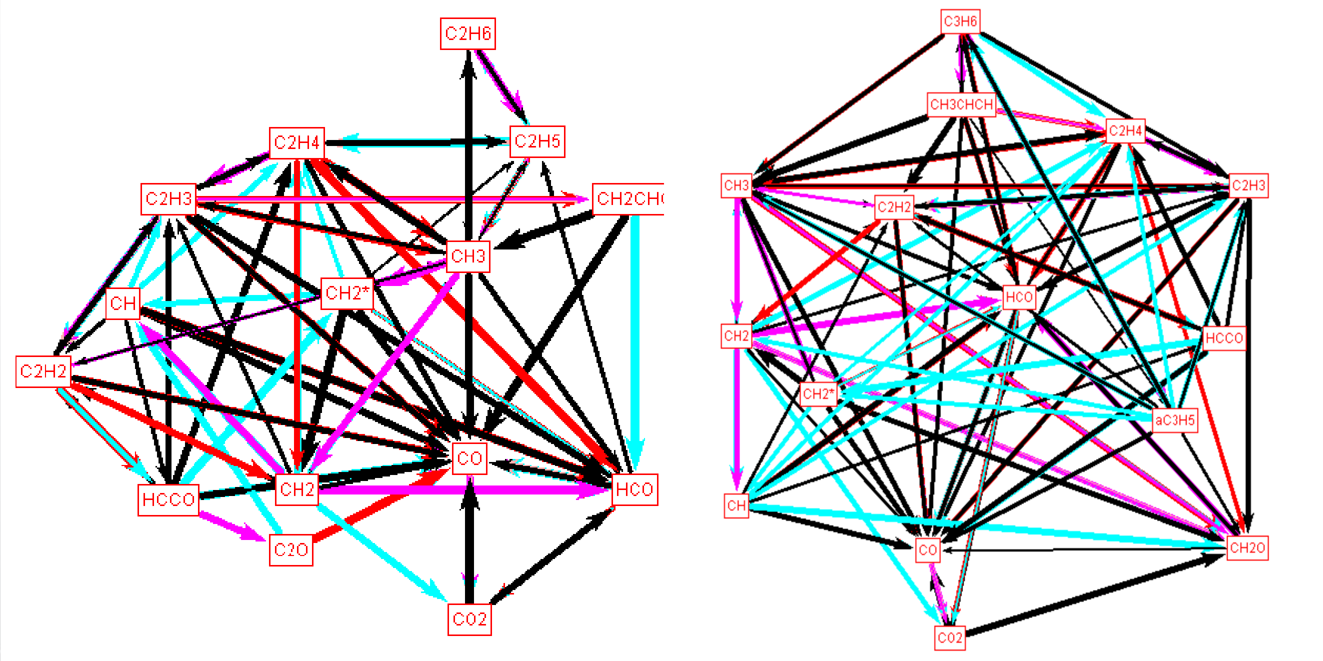
- A safety device to remove potentially explosive vapor clouds from the facility
- Originally not used as environmental control devices
- Flaring
  - Lost raw material
  - Lost product
  - Lost fuel gas
  - Lost $$$
  - Emissions:
    - Unburned hydrocarbons, CO, VOCs
    - Soot
    - Nox, SO_2 …

Refinery Sector Rule (RSR) – MACT CC and UUU

- Compliance Date: January 30, 2019
- Performance Indicators
  - Destruction Efficiency/Combustion Efficiency (DRE/CE): 98%/96.5%
  - No visible emissions
- Enhanced Operational Standards
  - Pilot flame presence
  - Flare tip velocity
  - Combustion zone net heating value NHVcz ≥270 BTU/scf
  - Combustion zone net Dilution parameter NHVdil ≥22 BTU/ft^2

Research I : Combustion Mechanism & CFD Simulation of Flares

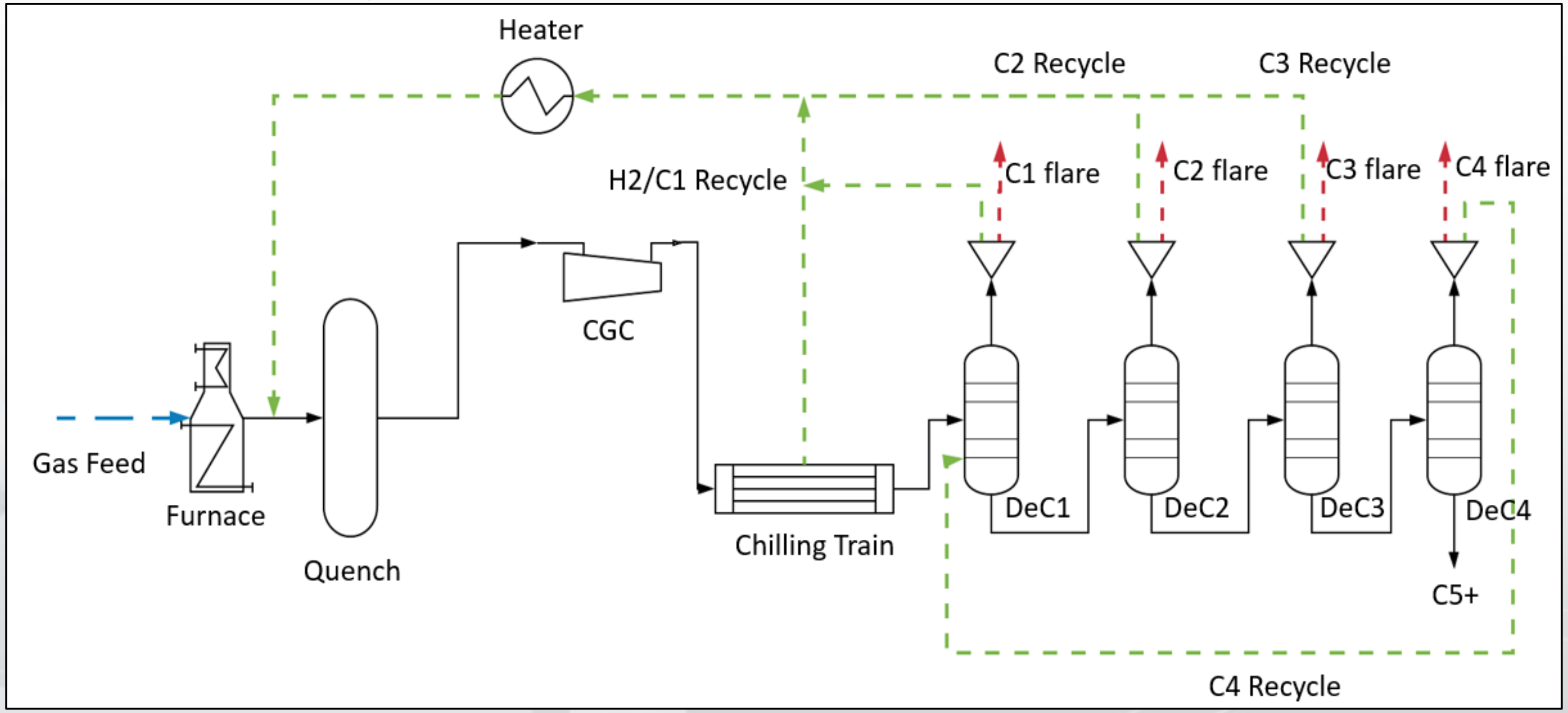




for Hydrocarbons and Sour Gas (H_2S..)

Lou, et al. "Optimal Reduction of the C1−C3 Combustion Mechanism for the Simulation of Flaring," I&EC, 2012

Research II: Dynamic Simulation for Flare Minimization



	startup time (hrs)	amount of flared raw materials (Klbs)				major emissions[a] (Klbs)			
		C1	C2	C3	C4+	CO_2	CO	NO_x	HRVOCs
historical best startup[b] (base case)	25	2163	5569	3017	2782	22 198	106.1	19.5	183.6
design 1	14	905	2242	1068	1088	8995	43.1	7.9	75.1
design 2	14	906	2241	1063	841	8803	41.2	7.6	70.9
emission reduction of design 1 compared with the base case (%)	44.0	58.2	59.7	64.6	60.9	59.5	59.4	59.3	59.1
emission reduction of design 2 compared with the base case (%)	44.0	58.1	59.8	64.8	69.8	60.3	61.2	61.1	61.4

Xu, et al. “Chemical Plant Flare Minimization via Plant-Wide Dynamic Simulation”, I&EC, 2009

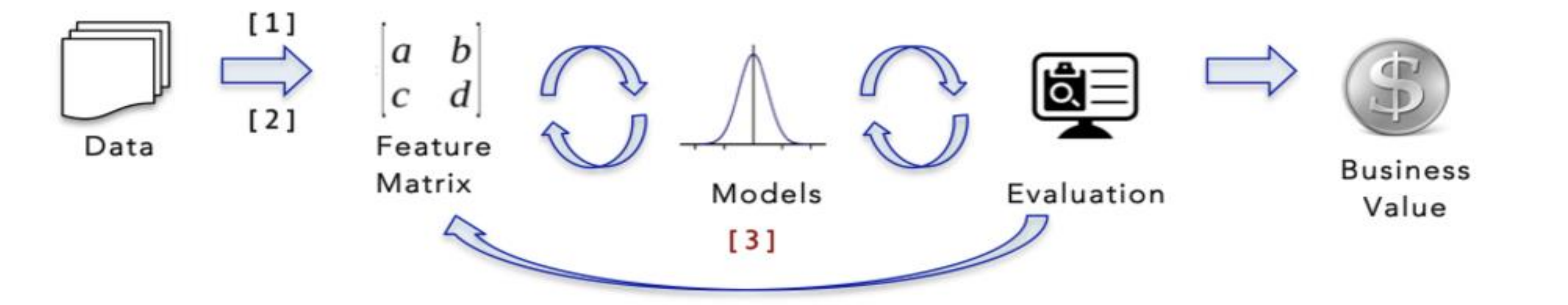
Challenges in Flare Operation

- Vent gas changes rapidly and widely along operation
- Flaring process is non-linear at different operating conditions
- Large and varying time delays (e.g., gas chromatography)

Research III: Predictive Flare Control

- **Predict flaring performance under different scenarios**

- **Optimize the operating parameters (steam/air injection and supplement fuel gas)**
  - **Meet compliance of CE/DRE and opacity**
  - **Save money**



Variables in Flare Operation

Measured variables

- Vent gas flow rate (Qvg)
- Exit velocity (V)
- Vent gas net heating value (NHVvg)
- Carbon number (CN)
- Vent gas carbon to hydrogen molar ratio (CHR)
- MW

Controlled variables

- Assisted steam/air flow rate
- Make-up fuel flow rate (F)

Performance variables

- DRE/CE
- Opacity
- Combustion zone net Heating Value (NHV_{CZ})
- Net Heating Value dilution parameter (NHVdil)

Design variables

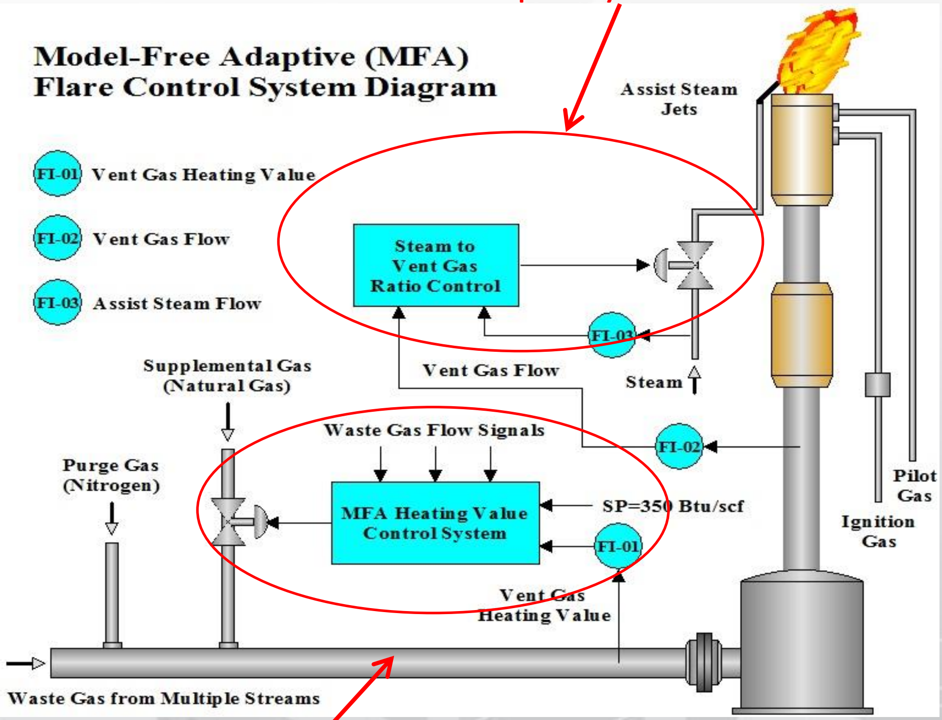
- Flare tip diameter (D)
- Other design specification

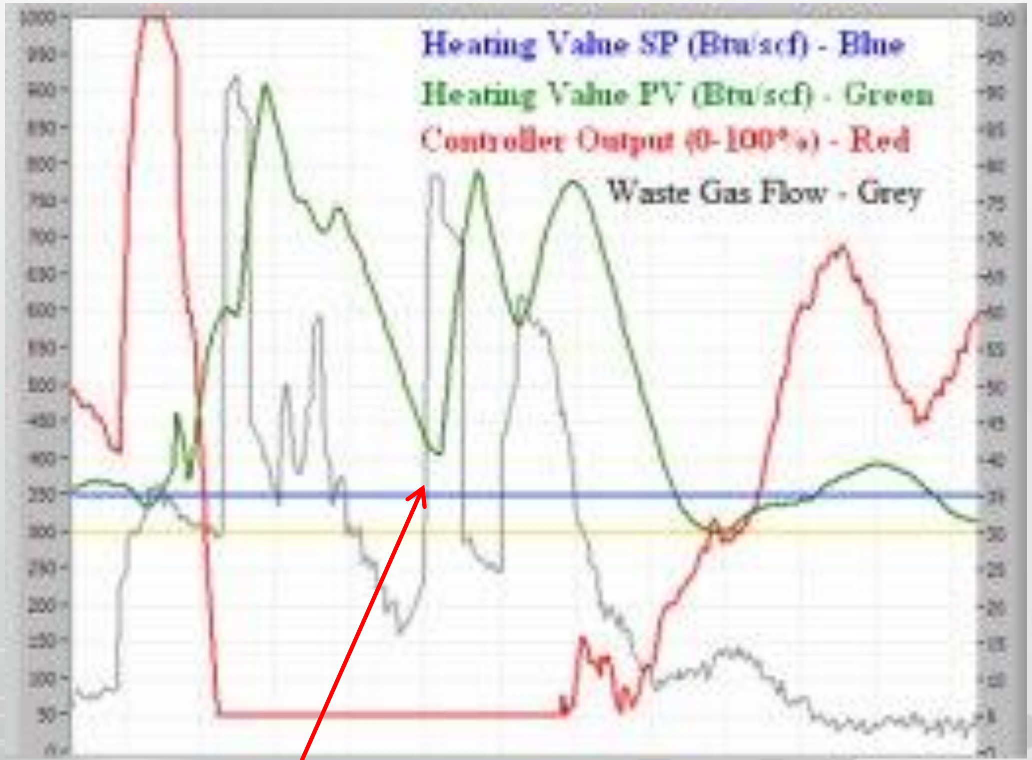
Disturbance variable

- Weather

Current Practice - Opacity and NHVvg Control

Opacity Control





NHVvg Control

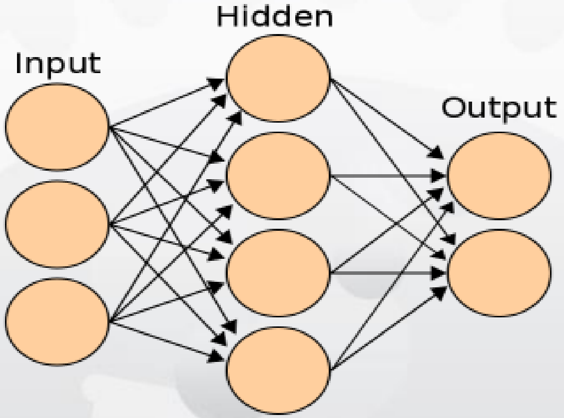
NHVvg SP=300 Btu/scf

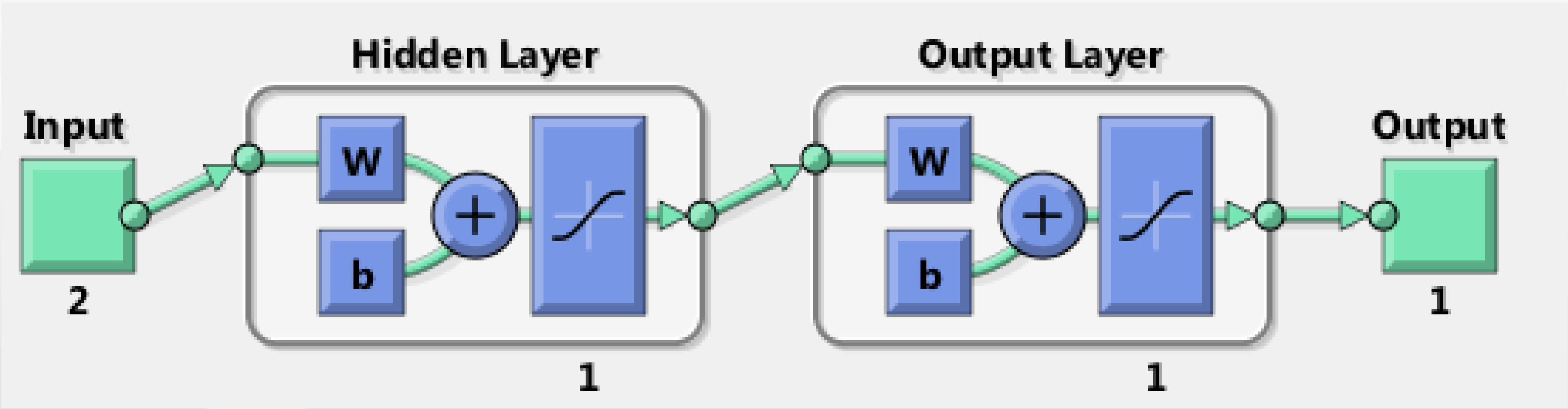
http://www.cybosoft.com/ats/ats_50.htm

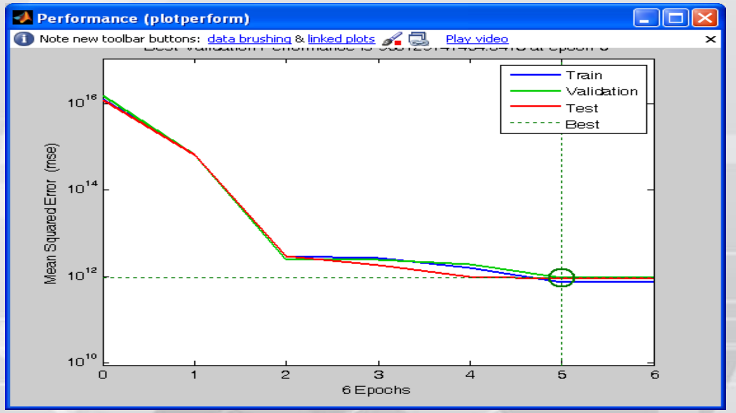
Data Sources

- Totally 262 data sets for steam-assist flares and 90 for air-assist flares.
- 1983/1984 EPA, 2010 TCEQ/John Zink, 2009/2010 Marathon TX City/Detroit, and 2014 Carleton University flare test data.
- Only those flare tests with both soot and DRE/CE data were used in modeling
- CE data were corrected for soot emissions

Artificial Neural Network Models



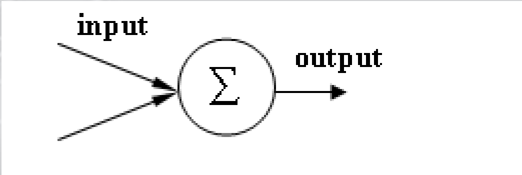




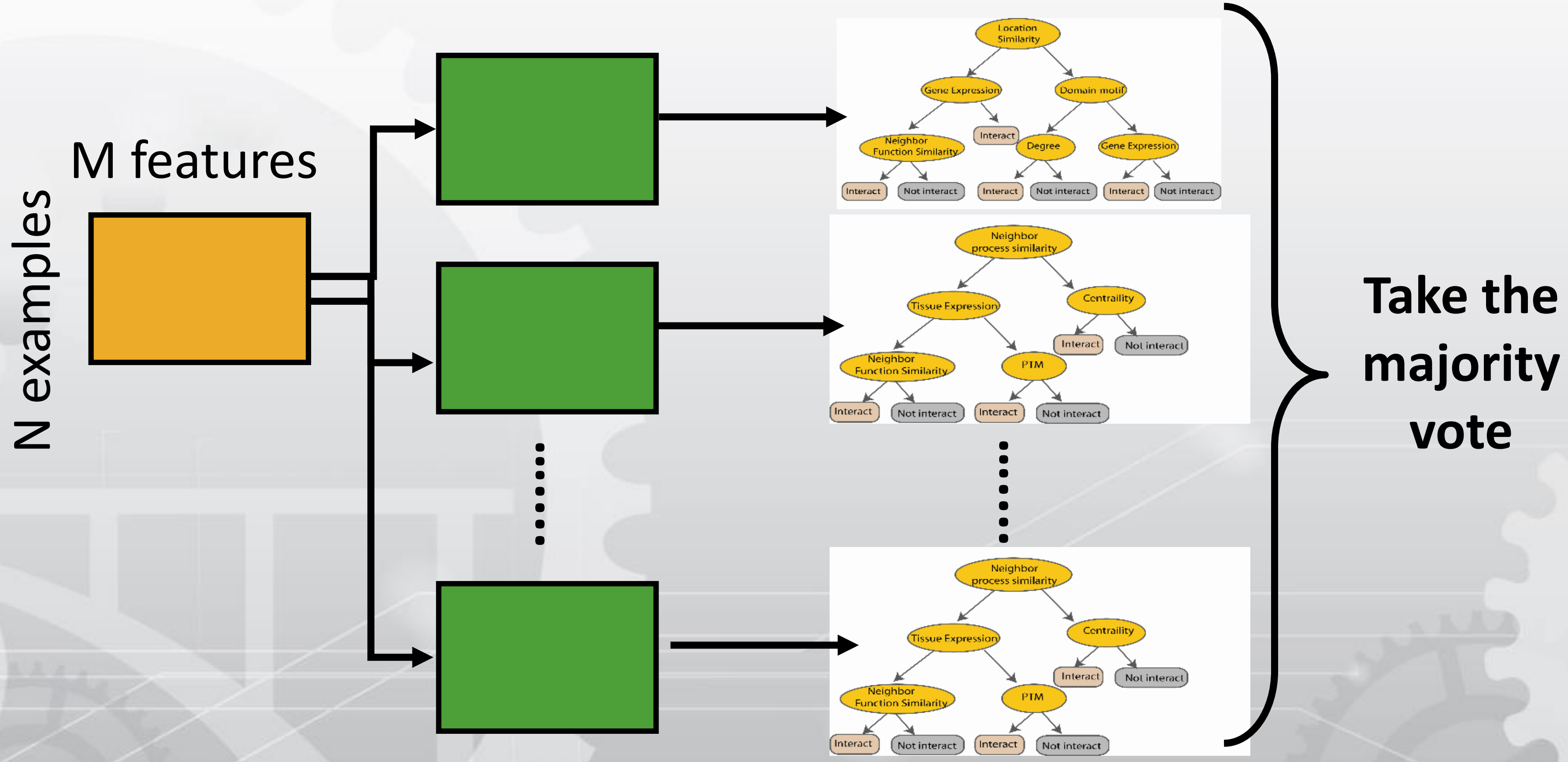
Algorithms

Tansig function

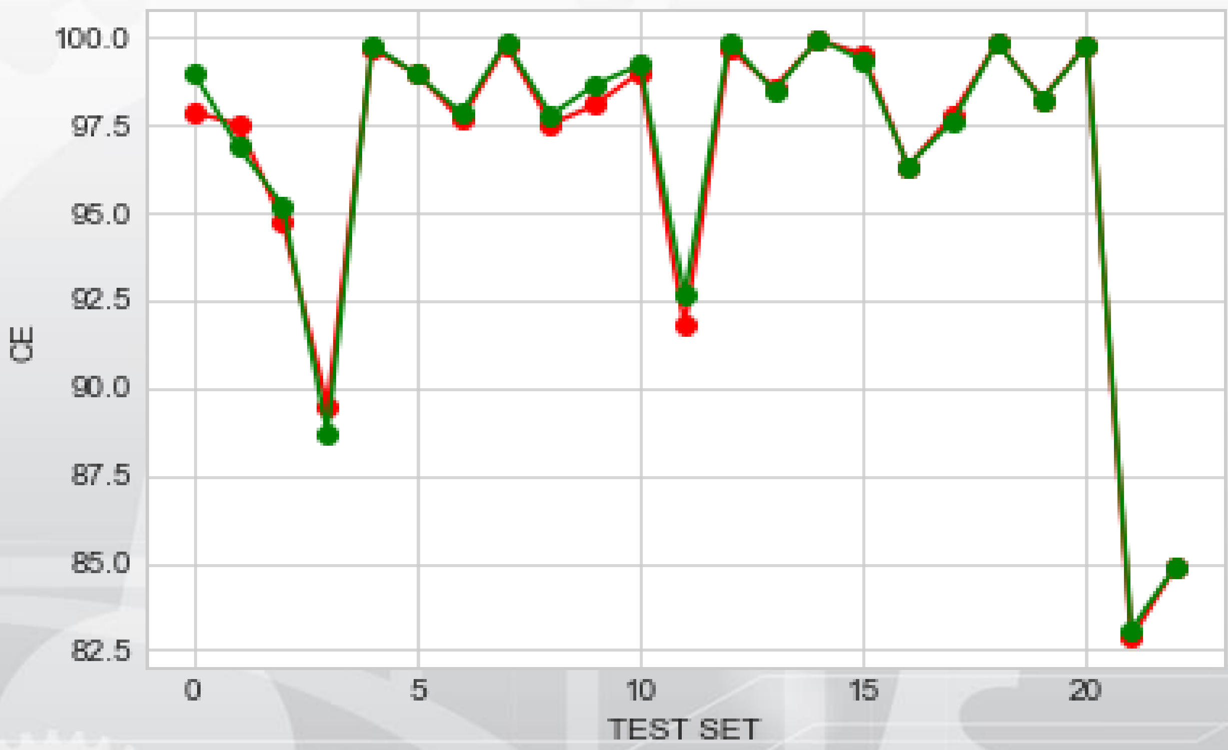
a = tansig(n) = 2/(1+exp(-2*n))-1



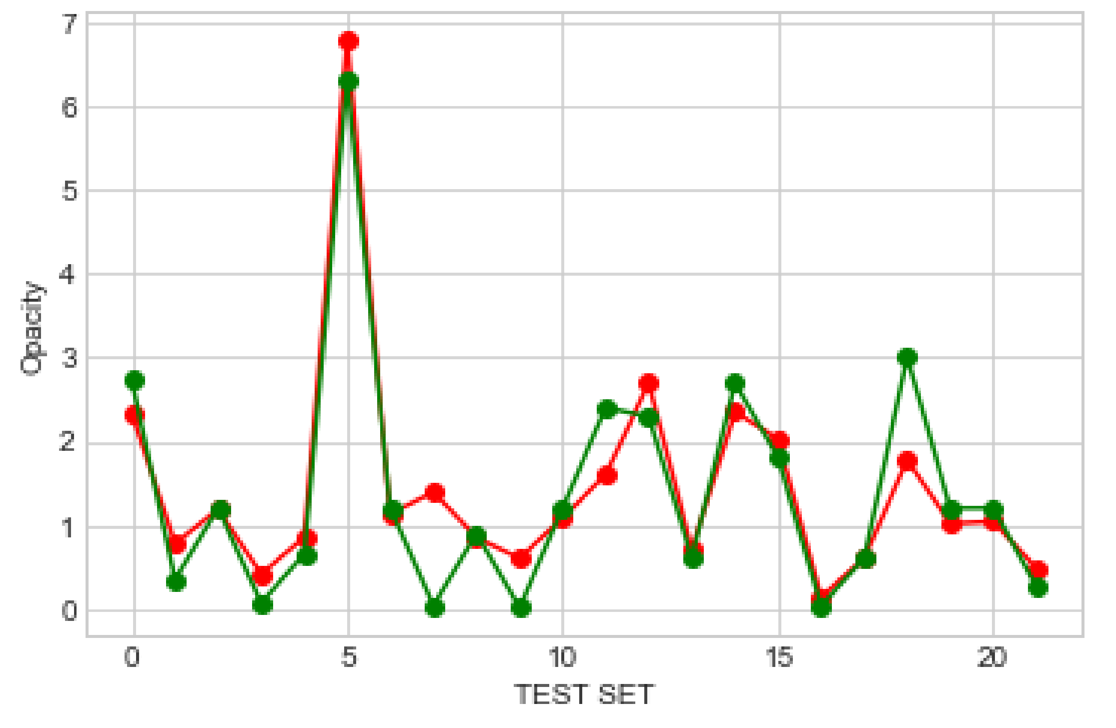
Random Forrest Algorithm



CE and Opacity Prediction

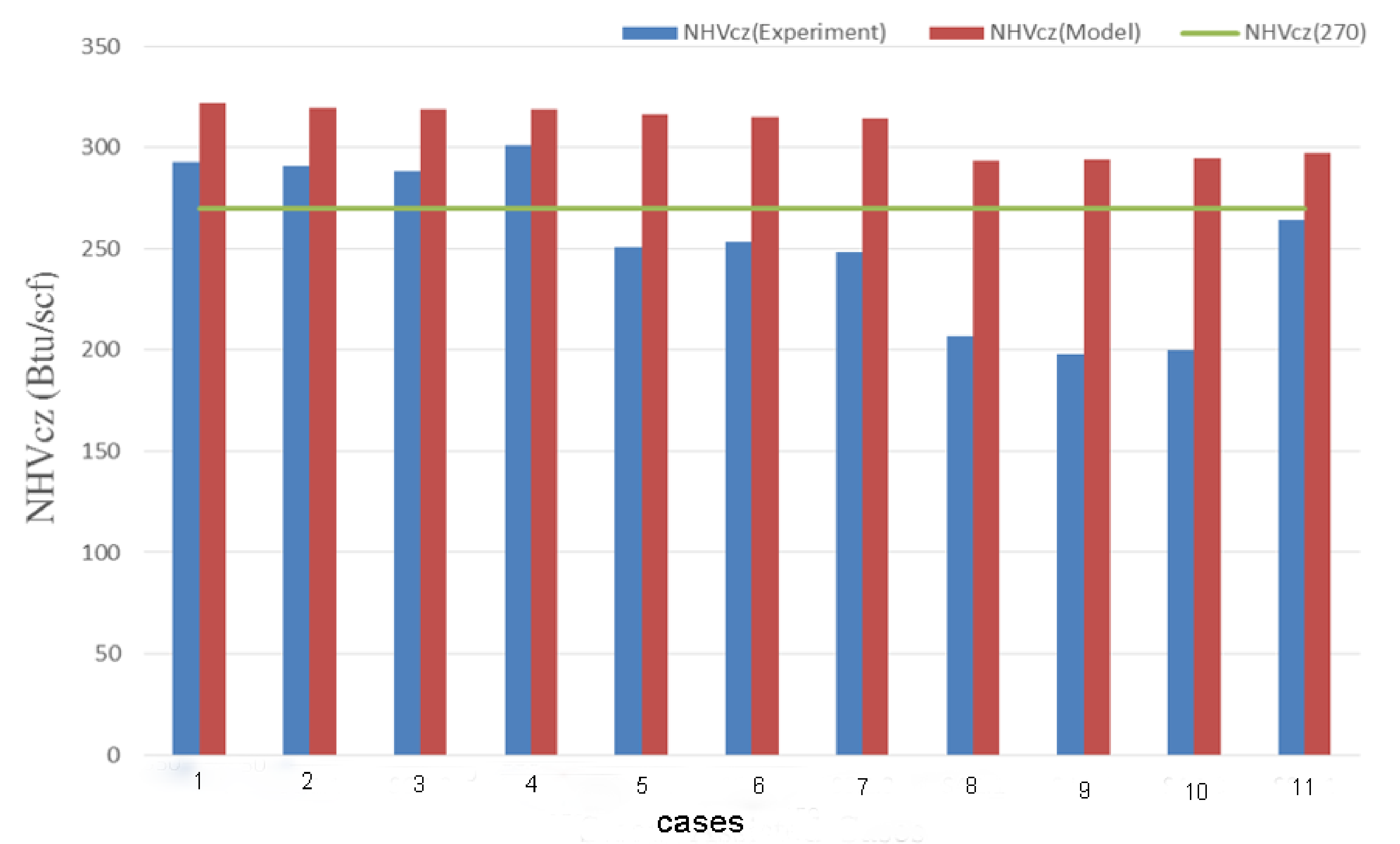


CE

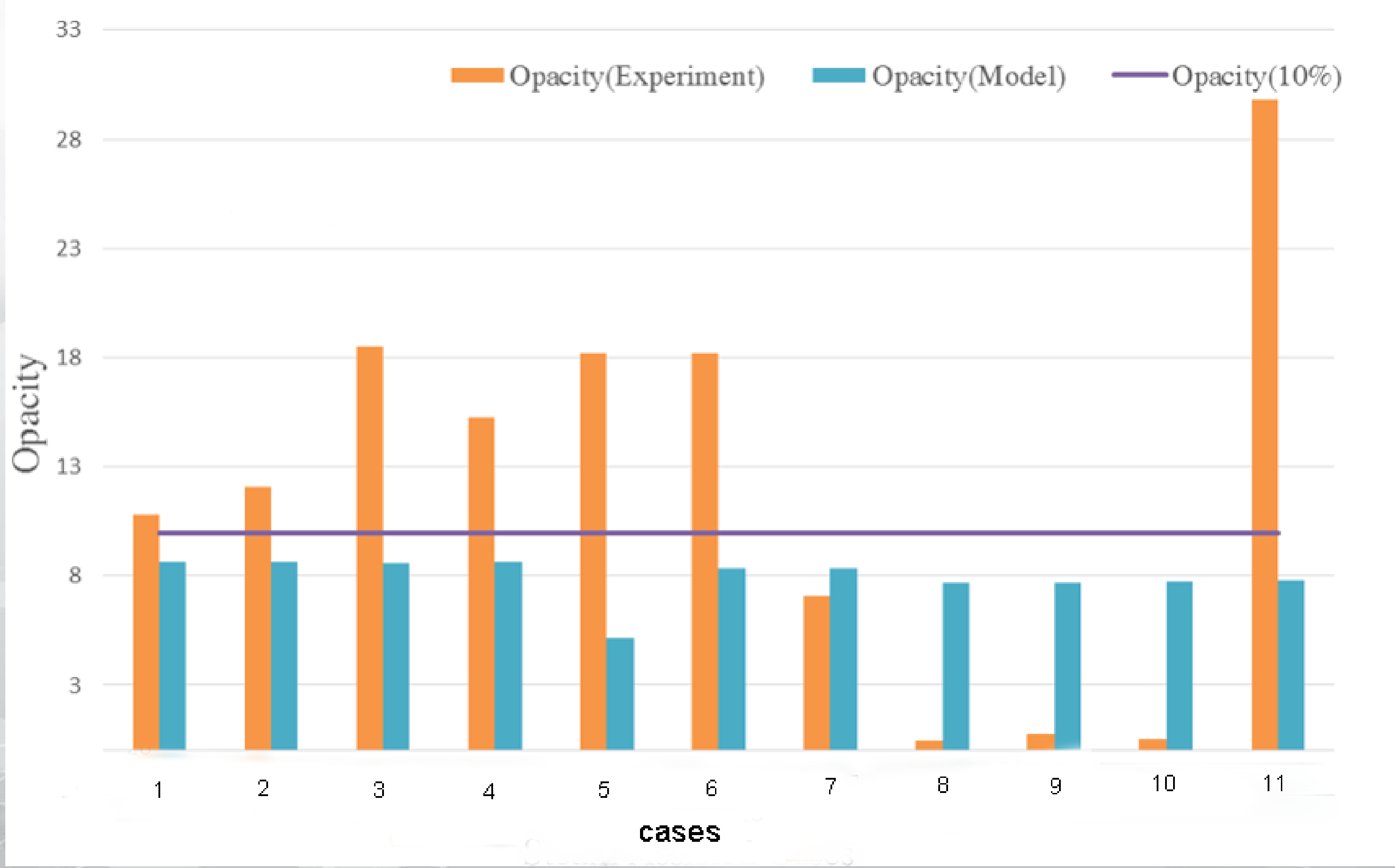


Opacity

Optimized NHVcz vs. Historical Operational Data



Optimized Opacity vs. Historical Data



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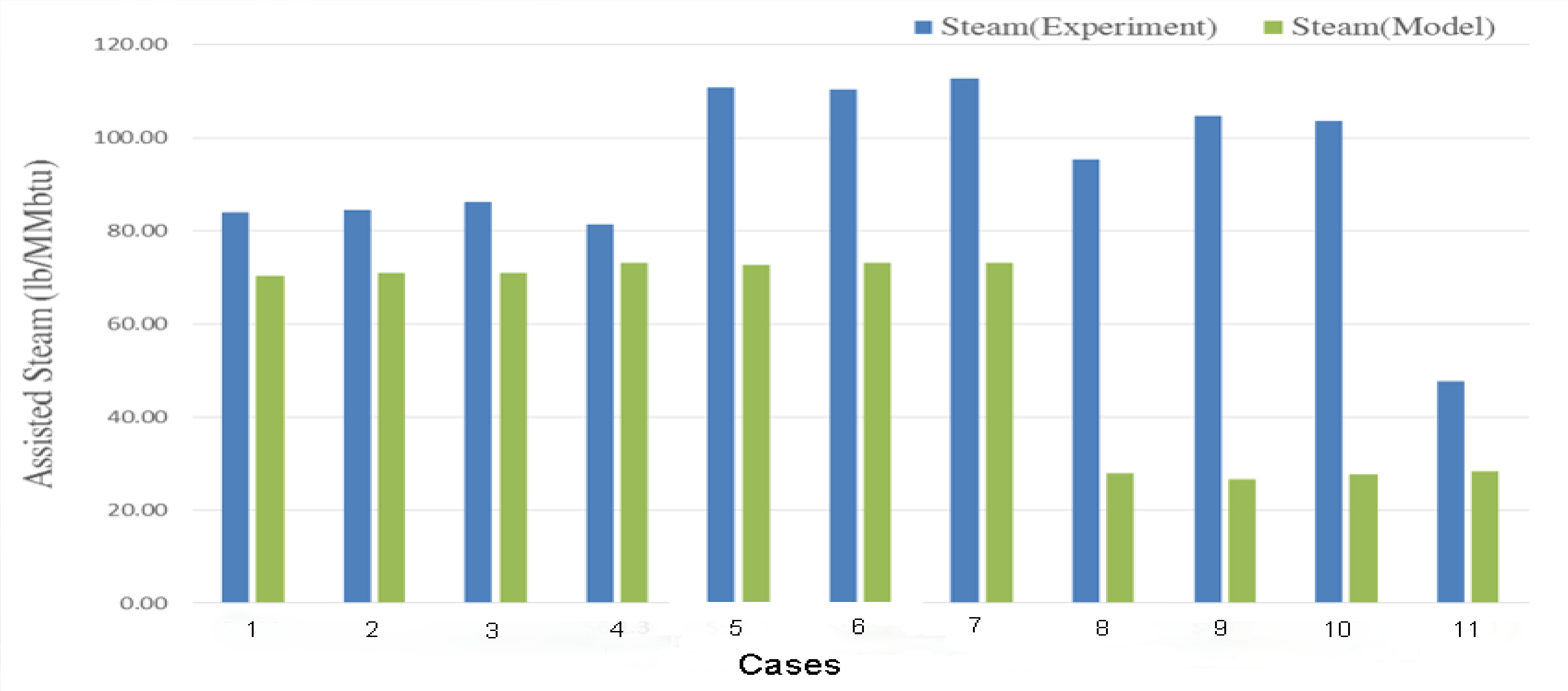
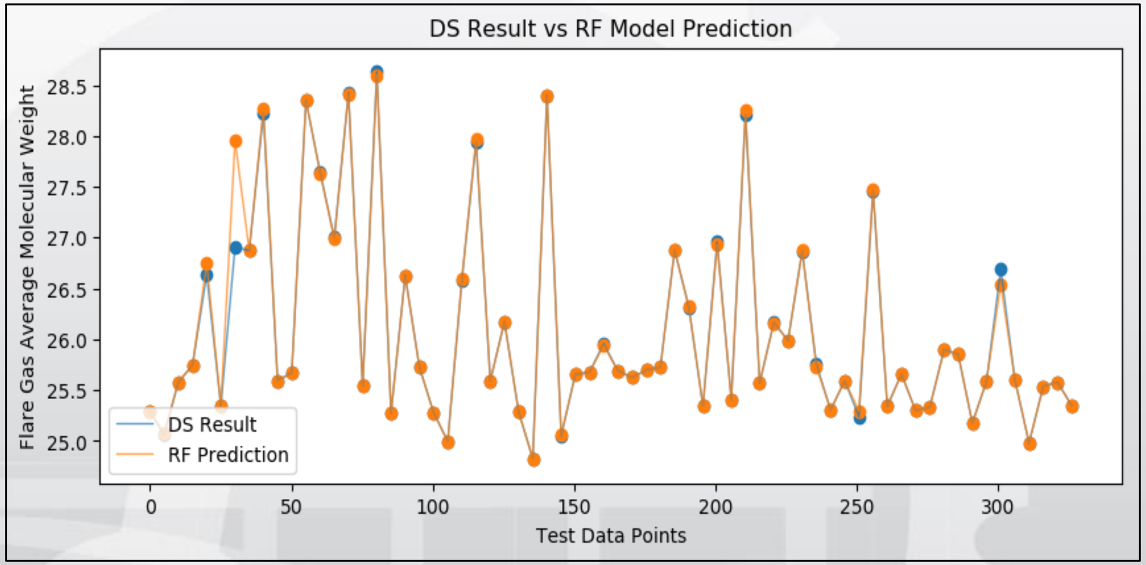
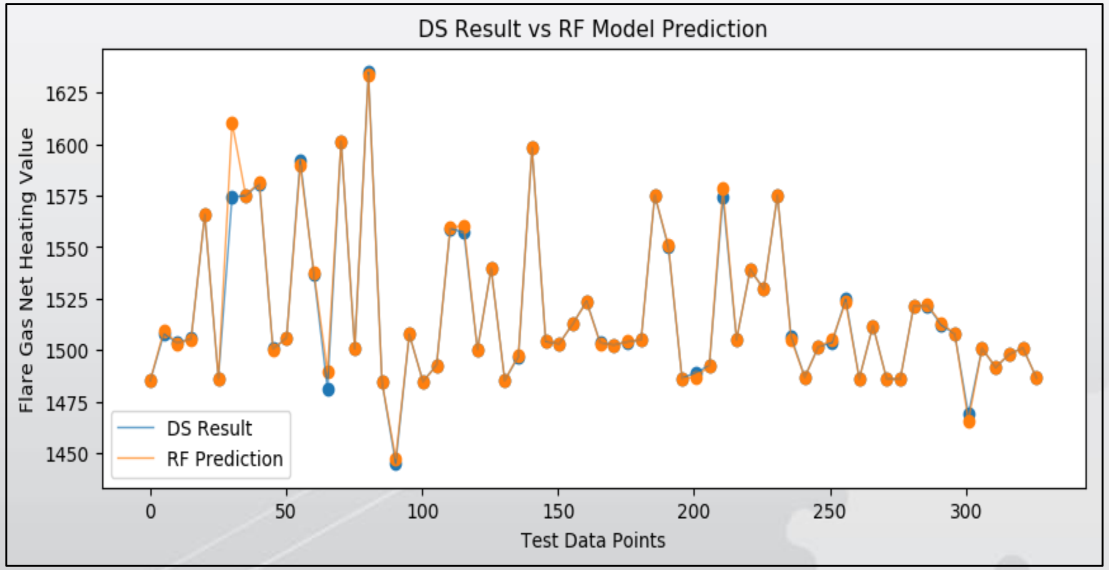
Optimized Assisted Steam Flow Rate vs. Historical Data



Net cost saving:
Avg – 38.5%
Min – 16.0%
Max – 74.6%

Data-Drive Models for Flare Gas Prediction





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Conclusion

Big data analysis and artificial intelligence

- **Bring new insights to the process**
- **Enhance the profit and reduce emissions**

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