Optimizing Furnace Performance Utilizing Big Data Analytic Techniques

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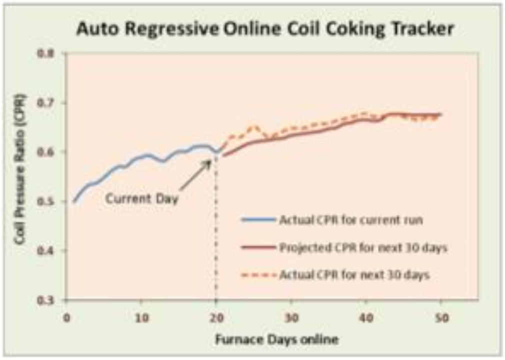
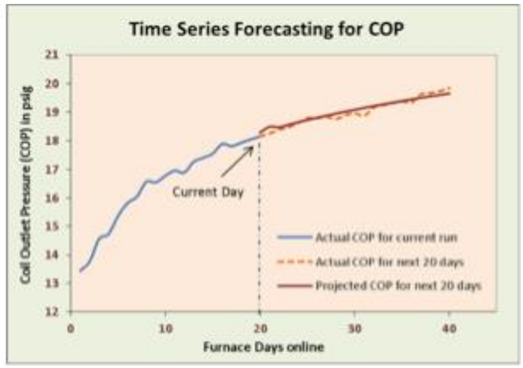
Objective and Scope:
Furnace run length and operational performance depend on many factors including feed stock, cracking severity, burner balance, and steam to hydrocarbon ratio. Utilizing Big Data techniques allows a detailed understanding of the handles to be monitored and adjusted to optimize the runs per the needs of the facility. Typically within 2 to 3 days of decoke, sufficient input is available to put into a developed analytical engine to be able to accurately predict operating conditions to the end of run. Furnace predictive modelling has not been used in the GCC to date. It is however being actively and successfully applied at two US facilities. While several Ethylene plants have used subsets of these big data analytical techniques quite successfully to enhance run length, the full application of the big data techniques allows development of a model that is both predictive and prescriptive. This paper discusses the principles being utilized, successes being achieved, and an approach to making this successful for all Ethylene furnaces.

Methods, Procedures, Process:
Machine Learning does the primary heavy lifting in parsing and doing primary analysis of the data. While a combination of big data analytical techniques can be applied including multivariate prediction, neural network analysis, time series modeling, and degradation analysis; Pattern recognition, PCA and PLS are the most utilized in these successful ethylene plant applications. Data is clustered, there is a primary identification of outliers and a model is developed based on the data, which is able to predict plant behavior, however only in the range in which the data inputs that were used. This model is effectively used to detect deviations in key process parameters from expected values and hence serving as an early alert for possible anomalies with the process, equipment and instrumentation.

Fundamental models must be used as “Surrogate” models to provide physically interpretable proxy models, to explain the results from Machine Learning models, which are often complex and opaque with respect to the “why” of an observation. Coking models, which are based on a combination of iterative runs between data driven models and commercially available yield / kinetic modelling software, can then actively predict coking and its indicators (i.e. COP and CPR).

Results, Observations, Conclusions:
The ability of this to match actual operation is uncanny.





The plants utilizing this have typically extended run lengths by upwards of 50% and enabled maintenance / decoke scheduling at a heretofore accuracy never achieved.

Benefits of the Paper:
This paper provides a high level overview of the tools and applications applied to be able to deliver these results. While these techniques are being used on Ethylene furnaces, the applicability to other process units is clear. The paper is to logically explain the tools and enable unit managers and engineers to consider their options to apply these techniques at their unit.