Coal Blend Optimization and Simulation using Machine Learning to Predict Coke Quality

A solution approach that recommends low-cost blend considering final product quality.

WHITEPAPER | MANUFACTURING

Table of Contents

Introduction

Coal is a raw material for metallurgical coke, a variety of coals are available in the market based on qualities and types. One of the salient complications faced at an integrated steel-producing plant is the blending of various coals in order to produce coke, which is used as fuel in a blast furnace. Over time, we have realized that linear blending models were not suitable due to the fact that coal properties are not in a perfect linear relationship, and understanding this concept is still a work in progress. This plays a crucial part in optimum coke making and its application in the blast furnace.

In this whitepaper, we have discussed a solution methodology that utilizes two techniques:

1. **Blending raw coals to produce low-cost effecting coke, using a mixed-integer linear programming model.**
2. **Production of high-quality coke with the help of deep learning neural network model.**

The extracted results are applied as constraints in the model. The results of this model are used in a small-scale oven to study, test, and validate the new improved blend(s) recommended by the model.

Due to the major fluctuations in coal prices and sources, coal blending becomes the need. Using this method, we can not only obtain a low-cost coal blend that is ready for consumption at operational facilities but also reduces costs when it comes to the number of blends being made and tested. Though hypothetical, the data being used to illustrate the performance of the model is still very realistic.

01

What goes behind Coal Blending?

Coal blending refers to the process of mixing or combining different coals that are mined from different locations to achieve the desired quality attributes. The goal is to maximize fuel characteristics and economically reduce emissions. By blending coals, we can improve fuel qualities such as reducing the volatile matter content, Sulphur content, ash percentage, nitrogen concentrations, and increasing the coals' calorific value. A blending of coals allows the use of lower quality, non-compliant coals, thereby increasing coal reserves and ensuring that all coals can be fully utilized.

Firstly, the process of coal blending starts with the selection of coals to be blended. There are various factors that come into play while selecting coals:

- **Cost of coal**
- **Availability of coal**
- **Consistency in supply**
- **Quality of coke required**
- **Transportation costs**
- **Quality of coal**

Apart from the factors mentioned above, during coal selection, we must also take into consideration:

- Rank/Grade of coal
- Physical properties (moisture, volatile content)
- Chemical properties (ash content, fixed oxygen, hydrogen, Sulphur, phosphorous, alkalis)
- Rheology (Study of fluidity & plasticity of coal when it undergoes thermal treatment)
- Petro-graphical properties (microscopic study and description of minerals)

In a typical coal blend, there is a mixture of both domestic as well as international grade

Sl.	Coal blend	Percentage in Mix.
1	HCC (Hard coking coal)	5% - 10%
2	Domestic coal 1	48% - 55%
3	Domestic coal 2	5% - 8%
4	International coal 1	5% - 7%
5	SSCC (Semi-soft coking coal)	22% -30%
6	Spillage (recycled coal)	0% - 5%

02

Process & Parameters

Coal blending optimization is one of the vital segments in the schedule of coal preparation production and is considered as one of the eventual links that signifies product quality control in coal preparation plants.

Coal storage

Coal blending

Coal crushing

Coal stamping

Carbonization in coke ovens

Coke prior to quenching

Quenched coke stored in wharfs

Coke ready for consumption as fuel

The selected coals of different grades/ranks are taken from storage and added in specific ratios based on the requirements, crushed, blended, and stamped into cakes under the application of high-pressure stamps. The caked mixture of coal is converted into coke via an anaerobic (absence of oxygen) heating process in a coke oven. Between 100-600 degrees Celsius, the moisture and other volatile matter get released, the coal reaches its plastic zone, wherein the coal swells up. This is due to the entrapped gas and condensable vapors. Beyond this temperature, there is a release of hydrocarbons and hydrogen. The whole process continues to about 1250 degrees Celsius, at which the coal hardens and shrinks to become coke. The coke upon exposure to air will ignite and burn. To overcome these consequences coke is immediately quenched via a dry/wet method. The cooled coke is then transferred and dumped onto a coal wharf via a coke car, after which it is taken to a facility to be screened and sized prior to being used in the blast furnace as fuel in steel industries.

Testing methods

The coke obtained can be assessed on physical properties, which will help determine the coke's behavior, inside and outside the blast furnace.

2.1 Coke Strength after Reaction (CSR):

CSR gives an indication of the strength of coke after being exposed to the reducing atmosphere of the Blast Furnace. After the coke has been exposed to the high temperature and carbon dioxide atmosphere during the coke reactivity test, it is subjected to a tumbler test to determine the CSR, where particles of the desired size are separated. CSR measures the potential of the coke to break into smaller sizes under a high-temperature CO/CO_2 environment (which exists throughout the lower two-thirds of the blast furnace).

2.2 Coke Reactivity Index (CRI):

CRI is measured by a laboratory test which is designed to replicate the loss of coke through reaction in the reducing atmosphere, as the coke makes its way down the blast furnace. Coke is heated up to 950 degrees Celsius in an inert atmosphere and held at that temperature in an atmosphere of CO_2. The coke is then cooled under the inert atmosphere and loses some weight. This loss in weight expressed as a percentage is the CRI value of the coke. CRI measures the ability of coke to withstand breakage at room temperature and gives us information on coke behavior outside and in the upper part of the blast furnace.

2.3 M10-M40 values:

The mean size of coke plays an important role in determining its property. Sizing of coke particles is done via two methods:

- M10 value refers to the percentage of material remaining on the -10mm screen after 100 revolutions in a drum
- M40 value refers to the percentage of material remaining on the +40mm screen after 100 revolutions in a drum

03

Problem statement

As global emission standards are setting boundaries, the number of coals which can meet these set standards are continuously declining. This pushes up the demand for coals that are compliant with environmental standards and results in a price increase. Coking requires large amounts of raw coal to be blended in very specific proportions. Preparing the raw materials alone can account for a majority of the total cost of production. Therefore, reducing the cost of coal blend preparation will directly reduce the cost of the coke. Reducing costs is of utmost importance to a company that seeks to stay profitable and competitive.

In the current scenario, many big players in the industry treat this challenge as a major bottleneck. The traditional methods and approaches to overcome these instances are considerably less effective due to changing business need and market prerequisites. Biggies in the industry are in need of agile and effective solutions to tackle the business problem with the right use of technologies and methodologies.

04

Solution Approach

Effective coal blending solutions can improve the efficiency of workflow and decreasecosts in many ways. Plants blending their boiler feed from a number of coals can maximize the use of the least expensive coal whenever conditions permit; utilities can rationalize the use of coals to avoid over-using premium coals and under-using problem coals; in a way, the utility can deliberately maximize the purchases of better spot-market coals comprehending that they can mitigate the problems by proven methodologies.

We have conducted various tests on the different available models to conduct effective coal blend optimization. Below mentioned techniques are a mere part of our effort.

4.1 Pearson Correlation analysis:

In this method, we obtain the ignition temperature and activation energy of coals and their blends through experiments on a Thermogravimetric tester. The device measures the change in mass of the sample while the temperature is being varied. We obtain the proximate analysis, ultimate analysis, ignition temperature, and activation energy. This method showed that the Pearson correlation coefficient between ignition characteristics and chemical composition of coal (R) were moderate, implying that the correlation between the ignition characteristics and a single factor is neither strong nor weak. Therefore, we have understood that we need to take multiple factors into consideration when predicting the ignition characteristics. It is also noteworthy that the correlation coefficients for ash, hydrogen, nitrogen, and sulphur alone are too low to be considered as inputs for the neural network. The factors that had the highest impact were moisture, volatile matter, fixed carbon, net calorific value, oxygen, and carbon.

4.2 Linear regression model:

To predict the ignition temperature and activation energy, the linear regression model was performed using 4, 5, and 6 input factors. The results of this analysis showed us that the relative mean errors obtained were very large in predicting the activation energy. It was also observed that there was a strong non-linear relationship between ignition characteristics and coal properties.

4.3 Three-layer Backpropagation Neural Network:

The BP neural network was first trained with 90% of the samples and then tested on 10% of the samples. The BP neural network was tested using 4, 5, and 6 input factors (moisture, volatile matter, fixed carbon, net calorific value, oxygen, and carbon), and the results of each were obtained. It was observed that the BP neural network was much more accurate in predicting the ignition temperature and activation energy when compared to an artificial neural network testing only on a single set. The relative mean errors were much lower in the model using 6 input factors, whereas the results from the other models were much larger and proved to be incomplete.

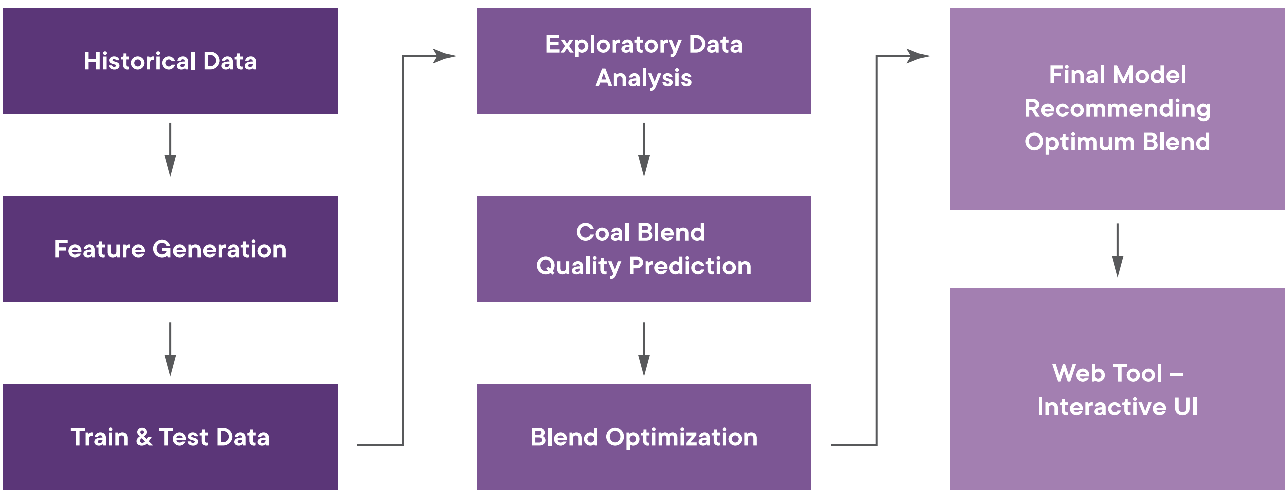
Our aim is to develop an advanced blend optimization framework, consisting of cost & quality as an objective with multiple constraints, which will enable the plant operations team to make the right decisions around optimal coal blend compositions based on inventory stock levels of coals at the coal yard. The analytical approach included comprehensive hypothesis testing to identify relationships in input metrics and decision variables.

Samples of coal are taken after they are mined and before any sorting or blending process. Samples taken are in large volumes as it will give a better indication of the average qualities of the coal rather than smaller samples which may reflect minor variations.

We can implement the use of Programmable Logic Controllers (PLC) at the coal handling facilities to collect data from the gathered samples and the analysis of the samples, which can be used to control the blending ratios on a real-time basis.

There are many parameters that must be considered while selecting coal to achieve the perfect blend. The key parameters are:

- Relative amounts of moisture
- Ash
- Volatile matter
- Fixed carbon content of coal
- Chemical constituents such as oxygen, total Sulphur, hydrogen, nitrogen compounds
- Calorific values of the individual coals
- Hardgrove Grindability Index (HGI)



- Interactive UI to input blend/coal specification data into standardized database
- User options to define coal quality & cost parameters, and simulate the model

Coal blending is proven to be an effective method to lower the ignition temperature of high-ash Indian coals as their quality is not yet at par with that of international coals. This can be achieved by varying the percentage of international & domestic coals in coal blends. The below architecture explains data capturing from different sources like ERP(SAP), Lab System, Vendor data, and processes data. Contextualizing data at coke quality level to create a final dataset for Exploratory Data Analysis (EDA). At the Data preparation stage, data is cleaned, and all features are generated for further model development with quality and process data as input.

Using this method, we can set threshold values for any of the above parameters, so that coals can be segregated and only those fit for use are transferred to the next stage of the coal blending process. For example, if the Ash% for specific coal is above the threshold value “X”, the coal is sent to the preparation plant to be blended so that the new coal has better attributes. The coals which have Ash% below “X” are sent straight to the stockpiles.

Once data on the raw coal quality, desired coke quality, and operational data has been collected, it is uploaded to a dedicated database, in this case, cloud storage. Artificial Intelligence is implemented using a Three-layer Backpropagation neural network model, which has 6 coal quality input factors and process factors to get a final ratio of individual coals to achieve desired coke.

05
Business Benefits

Using the least expensive coal with proper quality to meet the product quality demands

Limiting the burn of expensive high-quality coal to only peak generation times by blending different coals at a proper ratio

Managing carbonization through appropriate coal blending at the ovens

Minimizing double handling and better inventory planning

06

Unfolding the Outcome

- **Recommended Raw Material Coal Proportion/Composition based on cost and quality attributes set for Yield Coal Blend**
- **Enable Procurement Decisions of Coal and required stock/lot as per quotations/specs sheet.**

The Three-layered Backpropagation Neural Network model can deliver the smallest relative mean error in prediction of the Coke Quality, ignition temperature and activation energy for the selected blend. When compared to the linear regression model, the relative mean error was close to four times lesser, proving that the Three-layered Backpropagation neural network model as the champion model.

This approach also enables us to identify the best coal mix. Mixing high grade coals with low grade coals doesn't always mean that the characteristics are additive. Sometimes, blending international coals with those domestically available lead to a higher burn rate and higher flue gas (refers to combustion exhaust) flow rate, when compared to other international-domestic coal blends. It is notable that in the past, it would take more than a day to assess the quality of coke being produced. But with the use of Intelligent coal blend optimizing solutions, we can adjust the proportions of raw coal being used during the production process itself!

07

Affine's Success Story in Coal Blend Optimization

Using Affine's extensive set of capabilities across AI, AE & Cloud business can achieve a highly accurate model for predicting the Coke Quality, ignition temperature, and activation energy. Our Decision Science experts can help improve the client's performance & quality metrics by reducing the variation in coke quality parameters like CSR, CRI, M40, M10 values, etc., with optimum blends. It is also possible to determine the best blend using the raw materials at hand. In this manner, we can improve resource utilization, reduce waste, improve quality, and achieve cost-effective coke production.

Devising Blend Optimization Framework to Maximize Value Potential of Coke Production

AI enabled UI tool enhanced performance and quality parameters!

Mini Map

INDUSTRY

Energy Management

FUNCTION

Production & Maintenance

DATA SOURCES

- ERP
- Lab Data (LIMS)
- External data (Vendor)
- Historians

TECH STACK

- TensorFlow
- SQL
- PiML
- Power BI

Who is the Client?

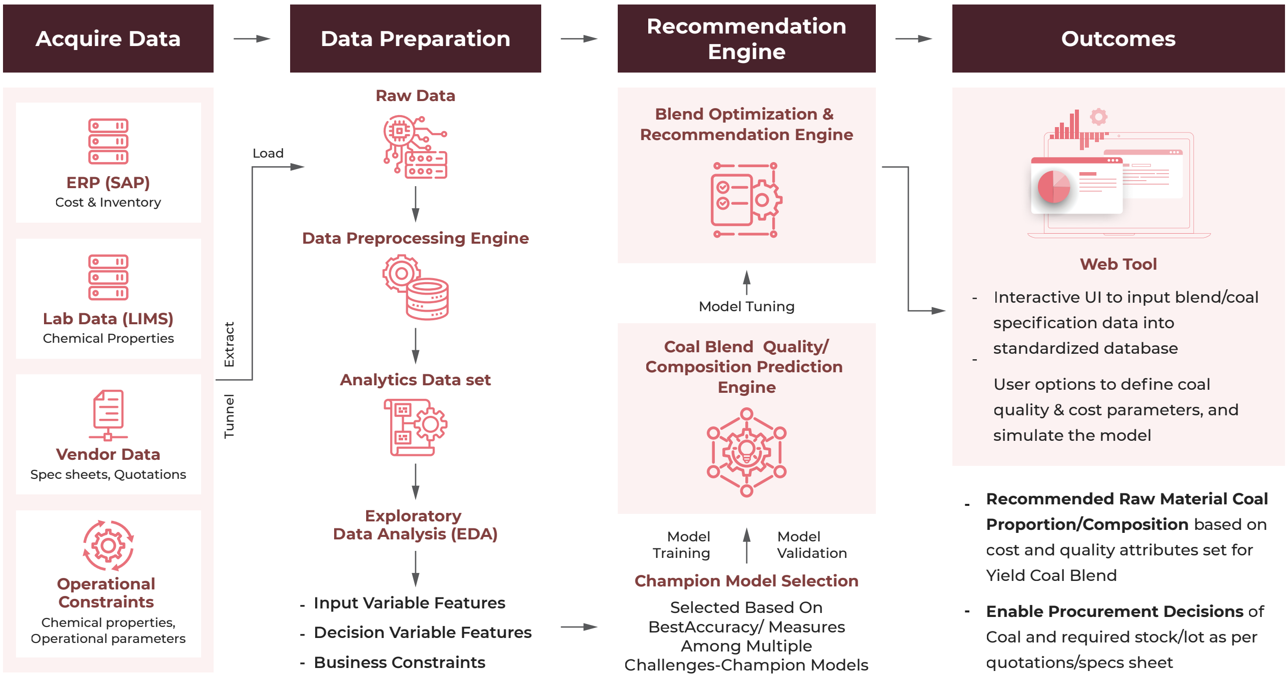
With a formidable impact on the metal manufacturing industry and a globally diversified presence, the client prioritizes self-sufficiency to inject value creation into society through process optimization in manufacturing Iron, Zinc, Steel, and many precious metals, like silver and copper.

Business Quandary:

Coke constitutes 50% of the cost of molten metal extraction. Choosing the right blend of two or more coal types is challenging but critical to producing the desired coke quality at a low cost. The client needed Affine to build an automated system to simplify this decision-making process of choosing the right blend without compromising on calorific performance and quality composition.

How Did We Solve the Problem?

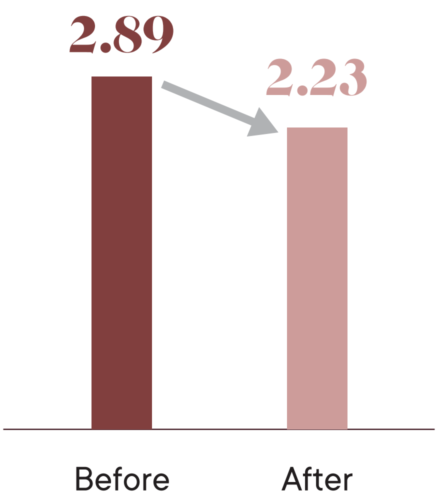
Our team of Decision Science experts pre-processed different data sources (lab data, vendor spec sheets, and cost/inventory information) that play a role in blend composition. This was done through Linear Programming and MILP. Later, we trained a model through Machine Learning to develop an advanced blend optimization framework using this analytical dataset. The model analysed cost and quality relationships to help the client choose cost-efficient and high-quality coal blend compositions.



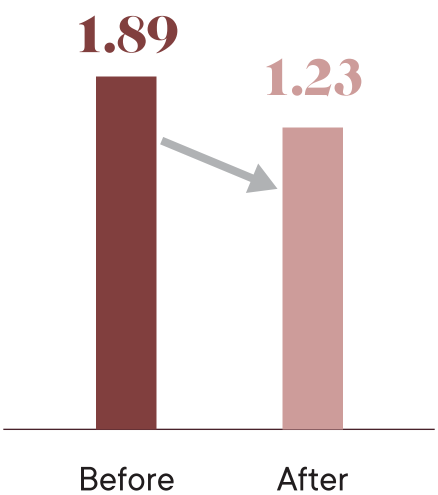
The Pay Off:

We designed and customized an autonomous web user interface tool for the client. This tool identified profitable linkages between input metrics and decision variables using neural networks and genetic algorithms. It reduced the variation in coke quality parameters, including CSR, CRI, M40 and M10 with thin blends. The client obtained recommendations based on cost and quality attributes to choose optimal coal blends that were superior but inexpensive. They were also able to innovate their procurement approach for restocking and inventory.

Coke CSR Variability



Coke CRI Variability



Augmented Outcomes:

The client accomplished the following milestones:

Reduction in Variability

4%-6%
Coal consumption

Increase in procurement savings

08

References

- A machine learning approach to improve ignition properties of high-ash Indian coals by solvent extraction and coal blending - ScienceDirect

- (PDF) Determination of Coal Quality using Artificial Intelligence Algorithms (researchgate.net)

- Metallurgical Coke Testing & Analysis – MSK (mitrask.com)

- 072014_Blending of coals to meet power station requirements_ccc238.pdf (usea.org)

About Affine

Affine is a leading professional services & solutions firm, enabling global enterprises to affect their transformation & innovation, leveraging the unique Trifecta of AI, Data-Engineering & Cloud. With a globally distributed team of 500 + analytics professionals, Affine covers end-to-end capabilities spanning modern data engineering to core AI and scalable cloud deployment across North America, Europe, and Asia.

Affine combines the hyper-convergence of AI, Data-Engineering & Cloud, with its deep industry knowledge, particularly in Manufacturing, Gaming, CPG, and Technology segments. Affine demonstrates thought leadership in all relevant knowledge vectors by investing heavily in research through its highly acknowledged Centres-of-Excellence and strong academia relationships with reputed institutions like UC Berkeley and premier IITs in India.

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