

Introduction

Client Background

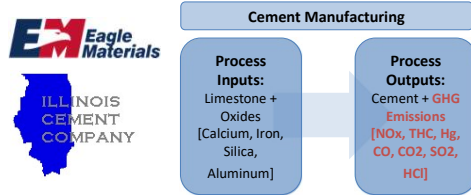


Figure 1: Eagle Materials manufactures construction materials, and Illinois Cement Company (ICC) is a wholly-owned subsidiary based in LaSalle, Illinois. ICC has ~120 employees and was founded in 1897. The process flow on the right shows how cement is manufactured at ICC, with greenhouse gas emissions, which this project focuses on, highlighted in red.

Problem Statement

Illinois Cement Company lacks the necessary resources to identify the optimum amount of aqueous ammonia to be injected into their preheating towers as part of the cement manufacturing process. The ammonia is used to limit NOx emissions to comply with regulations set by the Clean Air Act, but they have not been able to analyze the relationship between the injections, emissions, and confounding variables.

Problem Scope

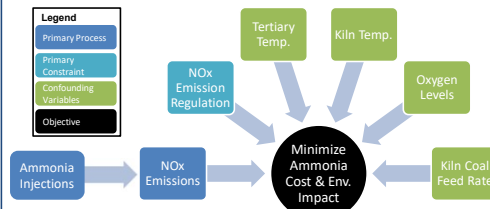


Figure 2: Objective Function with Inputs, constraints, and confounding variables. The ammonia injections directly impact the NOx emissions, which are federally regulated and can't exceed 2.8 lbs NOx/ ton clinker. Tertiary temperature, kiln temperature, oxygen levels, and coal feed rate may all also impact NOx emissions.

Primary project directives: reducing ammonia costs and minimizing environmental impact

Methodology

NH3 → NOx Process Map

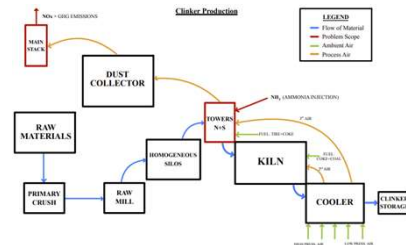


Figure 3: System Model Outlining Ammonia Injection and NOx Emissions

- Aqueous ammonia (NH3) injected into preheating towers (Towers N+5) to limit NOx emissions at main stack
- Primary constraint: NOx Emissions must remain under 2.8 lbs NOx/ ton clinker

Current Control Heuristics

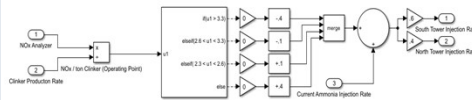


Figure 4: Control System Logic of ICC's Current Process

- ICC's current control is a reactive method that determines adjustments of ammonia injection flow rate based on the current, observed NOx concentration.
- Updates to the injection flow are made every two minutes to allow for the stack analyzer to react to the control changes.

Correlation Analysis

- Correlation testing conducted to identify impactful linear relationships ($R > 0.8$)
- Unable to identify strong linear relationships within the data (Most R values ranged from [0.1] to [0.7])
- Noise and outliers rampant in data causing interference with data quality

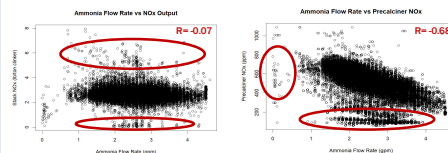


Figure 5: Correlation analysis graphs shown with weak correlation indicated by the R value. The sections in red are the outliers and noise.

MLR Model

- Multiple linear regression (MLR) model created to be used for point predictions of NOx in the precaliner
- Conversion equation needed to produce lb/ton clinker value from ppm, which is beyond the scope of what the data provides

Coefficients:

	Estimate	Std. Error	t-value	Pr(> t)
(Intercept)	5.903e+02	1.377e+03	0.434	< 2e-16 ***
AmmoniaFlowRate	-1.642e+02	6.027e-01	-272.519	< 2e-16 ***
Precal102	-2.368e+01	2.416e-01	-98.032	< 2e-16 ***
KilnFeedrate	5.444e+01	9.943e-01	54.755	< 2e-16 ***
TertiaryTemp	2.195e-02	3.343e-03	6.566	5.27e-11 ***

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Residual standard error: 70.38 on 29996 degrees of freedom
Multiple R-squared: 0.8137, Adjusted R-squared: 0.8137
F-statistic: 3.275e+04 on 4 and 29996 DF, p-value: < 2.2e-16

Figure 6: Multiple linear regression results showing R-squared value of 0.8137, which is a very strong relationship.

MPC Performance Evaluation

- Model predictive control (MPC) system
- Employ a neural network (NN) to map process inputs to outputs
- Input Layer:** Precaliner NOx, ammonia feed rate, coal kiln feed rate, tertiary temperature, precaliner 02%
- Output Layer:** NOx output (lbs/ton clinker)
- Constraints:** High-noise data (inputs map to multiple outputs), neural network chases outliers.

Normalization Method	Hidden Layer Architecture	Activation Function	Best MSE (Convergence < 0.017)	Approx. Training Hours (Epochs)
[0 1]	12, 6, 2	Logistic / Sigmoid	0.01501 (No)	0.50 (200k)
		Tanh	0.03057 (No)	0.65 (200k)
	16, 8, 4	Logistic / Sigmoid	0.02490 (No)	0.60 (200k)
		Tanh	0.09344 (No)	0.75 (200k)
[-1 1]	12, 6, 2	Logistic / Sigmoid	0.03955 (No)	1.15 (200k)
		Tanh	0.07376 (No)	1.30 (200k)
	16, 8, 4	Logistic / Sigmoid	0.07554 (No)	1.50 (200k)
		Tanh	0.08108 (No)	2.00 (200k)

Table 1: Results of Neural Network Architecture Performance Analysis

Future State MPC

- Time-series NN to better analyze noisy, time-dynamic data:
- Time-Series Deep Belief Network (Xu, Q., et al., 2022)
- Long Short-Term Memory: used for speech pattern recognition

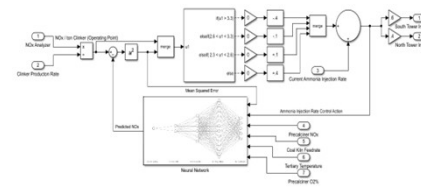


Figure 7: Future MPC Method Using Time-Series Neural Network

Discussion

Results

MLR Results: Using the MLR model, point predictions can be made of the precaliner gas NOx percentage using real time data. The value can be used in a conversion that takes the NOx value measure in PPM and turns it into a value measured by lb/ton clinker, which is the same value measure for the output of NOx from the stack. If converted, point predictions, combined with heuristics in a feed-forward system can reduce NOx emissions proactively. Conversion is currently unknown and out of the scope of the data provided.

MPC/ NN Results: To best utilize a neural network to solve this data analysis problem, we need to implement a time series deep neural network in order to capture the time related dynamics associated with the process control action and stack analyzer delay. Such models include the Time-Series Deep Belief Network and/or Long Short-Term Memory.

Project ROI

$$ROI = \frac{67,000 - 5,000}{5,000} * 100 = 1240\%$$

Saved personnel costs: \$181,590 for 5 full-time engineers for 3 months, instead project was \$5K.

Final Recommendation

The expected value of our current information is \$67k. We believe that by implementing a future state model predictive control system to improve their current heuristic control system, Illinois Cement Company can eventually reduce ammonia usage by 10%. This would lead to potential cost savings of \$90k per year with our results.

Next Steps

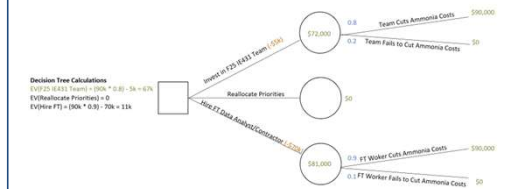


Figure 8: Decision tree showing what the expected payoff of different pathways forward might look like, including a new IE431 team or a dedicated full-time hire.

References

Xu, Q., Hao, X., Shi, X., Zhang, Z., Sun, Q., & Di, Y. (2022). Control of denitration system in cement calcination process: A Novel method of Deep Neural Network Model Predictive Control. Journal of Cleaner Production, 332, 129970. <https://doi.org/10.1016/j.jclepro.2021.129970>