Autopilot of Cement Plants for Reduction of Fuel Consumption and Emissions

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Abstract

The cement manufacturing industry is an essential component of the global economy and infrastructure. However, cement plants inevitably produce hazardous air pollutants, including greenhouse gases, and heavy metal emissions as byproducts of the process. Byproducts from cement manufacturing alone accounts for approximately 5% of global carbon dioxide (CO_2) emissions[1]. We have developed "Autopilot" - a machine learning based Software as a Service (SaaS) to learn manufacturing process dynamics and optimize the operation of cement plants - in order to reduce the overall fuel consumption and emissions of cement production.

Autopilot is able to increase the ratio of alternative fuels (including biowaste and tires) to Petroleum coke, while optimizing operation of pyro, the core process of cement production that includes the preheater, kiln and cooler. Emissions of gases such as NO_x and SO_x, and heavy metals such as mercury and lead which are generated through burning petroleum coke can be reduced through the use of Autopilot. Our system has been proven to work in real world deployments and an analysis of cement plant performance with Autopilot enabled shows energy consumption savings and a decrease of up to 28,000 metric tons of CO_2 produced per year.

1. Introduction

Clinker is the main ingredient in cement, manufactured through a pyro process. In the pyro process, raw material including limestone is fed into a preheater equipped with a pre-calciner which directly discharges into a rotary kiln (See figure 1). The material inside the kiln needs to be heated to around 1450 °C. In order to achieve such temperatures, the flame must be about 2000 °C.

There are two significant sources of CO_2 generated by the manufacturing of clinker. The first source is limestone ($CaCO_3$) that is chemically broken down to CaO and CO_2 at high temperatures. This chemical process alone accounts for 5% of all man-made CO_2 produced (Andrew, 2018). The other source of CO_2 from the pyro process is the burning of fuels in the preheater tower, pre-calciner and kiln, which primarily use Petroleum coke (pet coke) as the source of fuel. For every pound of pet coke burnt as fuel, 3.1 pounds of CO_2 are produced.

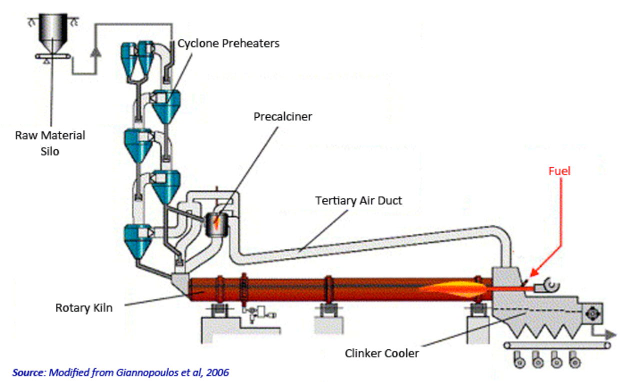

Figure 1. The pyro process that produces clinker

The raw material flows from the preheater to the kiln, and from the kiln to the clinker cooler, where clinker is cooled down and thermal energy is recovered by heating combustion air to be used in the kiln and pre-calciner. The flow of air moves in the opposite direction. Fans force atmospheric air into the cooler, which is then brought into the kiln and preheater by induced draft fans at the start of the preheater. Air that flows from the cooler into the rotary kiln is called Secondary Air, while one that flows to the pre-calciner is called Tertiary Air. Our Autopilot system is able to adjust control parameters of the cooler in order to maximize the Secondary Air Temperature. This helps reduce the amount of fuel required to heat the air and material to their required temperatures.

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Proceedings of the 36^{th} *International Conference on Machine Learning*, Long Beach, California, PMLR 97, 2019. Copyright 2019 by the author(s).

[1]https://blogs.ei.columbia.edu/2012/05/09/emissions-from-the-cement-industry/

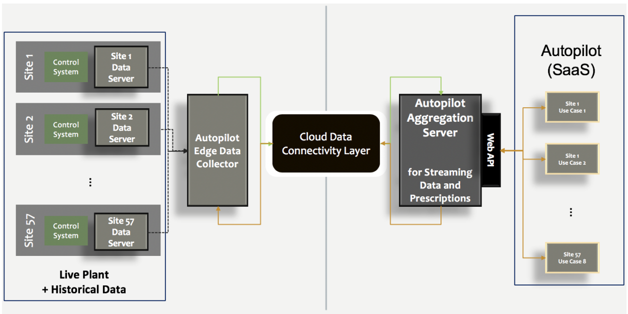

Figure 2. The system architecture of the Autopilot system

2. Autopilot

We have been working closely with several of the largest cement companies in the world to understand cement processes. We worked with plant operators and subject matter experts from these companies to understand their objectives for improving efficiency of operation while reducing fuel consumption and emissions.

The majority of industrial companies aggregate their real-time sensor and control system data into data historians in order to perform archiving and retrospective analysis of asset and operational data. The Autopilot solution is designed to connect to these plant data servers to efficiently and securely stream the sensor data to a cloud-based service (See figure 2). The system is capable of aggregating this data across many sites, processes and assets in real-time. The data is distributed to the AI and ML models developed to provide predictions and prescriptions for operating various assets to optimize operational objectives while maintaining safe operating conditions. The safety bounds and criteria by which an asset should be operated by are provided by the plant operators and used as additional input to the system. The input data and the suggested prescribed optimizations are also visualized to allow for monitoring and evaluation of the plant operations and Autopilot results.

The Autopilot system also provides an Auto-steer mode, which allows the optimized control prescriptions which have been suggested, to be written to the control system set points and directly operate the asset or process. The system is continuously monitoring and analyzing the input sensor data and control prescriptions for all configured processes. This allows for detection of changes to the data or outlier conditions, as well as cases where a sensor or asset is damaged or malfunctioning.

The Autopilot system has already been operationalized at several cement manufacturing plants and auto-steer has successfully been enabled and resulted in increased efficiency and decrease in fuel consumption in comparison to when the same process is controlled solely by a human operator. Through the use of containerization and cloud technologies, Autopilot is able to efficiently scale and deploy many use cases simultaneously and provide remote auto-steer to optimize the cement manufacturing process at a global scale.

3. Algorithm

3.1. Problem Definition

Given an asset in a cement product line, provide real-time control prescriptions that optimize certain target goals, while at the same time keeping the system in safe operating zone.

As time passes, the sensor status may change and thus cause the sensor measurement distribution to change due to the underlying process or sensor malfunction. The system also exhibits a narrow control space and constraint range, making it harder to satisfy constraints if the system is not consistent and accurate. Any noise in the learned dynamics may lead to more violation in control prescriptions although those controls may be feasible.

Suppose at current time step, we want to find optimal control several steps ahead. Let X be the set of system sensors, O as the objective set, C as the constraint set with C_b the bounds, P as the control or prescription set with P_b the bounds, we want to adjust P to satisfy O, while at the same time satisfy C_b and P_b.

Unlike in common experimental setting where the model assumes presence of every input and output, we allow any sensor in X, O as well as C to be absent due to various reasons such as high environment temperature. Important sensors that act as controls or constraints cannot be averted.

3.2. Method

We have developed a real-time optimal control system with fault tolerance, which is a full dynamic system that accepts change of C_b, P_b, X, C and even O. We model the dynamics of a cement plant using deep learning techniques, and optimize based on the learned dynamics. The control space is multi-dimensional and non-smooth. We developed advanced searching algorithms to search optimal solutions. The algorithms incorporate the feature importance during search process and thus produce the best possible solution by considering the weights among features.

We designed the system so that it can adapt to such dynamic changes in real-time operation. Even when sensors are faulty or not available, our system is still able to make optimal operation suggestions while simultaneously keeping operation in safe zone by leveraging the learned knowledge of the relationships among faulty and healthy sensors.

Through the serving phase when the Autopilot is deployed, the model will receive signal from the Data Historian whenever some sensors fail and react accordingly. We adopt

Table 1. Significant test on model performance.

Data set	Mean	Std	p-value
ON_SAT	1837.7	149.2	7.1×10^{-221}
OFF_SAT	1694.8	269.0	
ON_TAT	1373.8	151.1	8.2×10^{-259}
OFF_TAT	1251.4	182.2	

online-learning in the system so that it can quickly adapt to concept drift and stabilize the automatic operation.

3.3. Successful Use Case

The cooler is an integral part of a rotary kiln and is responsible for a critical part of the cement manufacturing process, by lowering the temperature of the clinker output material by recycling heat back into the kiln. Our model must comply with several requirements of the operation of this equipment and must meet a group of objectives related to energy efficiency, product quality, and safety. The main objectives are described as follows: 1. *Secondary Air Temperature* (SAT) should be as high as possible in order to have high heat recovery and good conbustion efficiency in the kiln. 2. *Tertiary Air Temperature* (TAT) should be as high as possible in order to have high heat recovery and good combustion efficiency in the pre-calciner. 3. Clinker temperature should be reduced to a minimum value. 4. Kiln pressure must be kept negative. 5. Under-grate pressure should be maintained within a stable range.

We ran a set of statistical tests that show our model has a significant impact on the increase of SAT and TAT, while simultaneously achieving all of the objectives mentioned above. To analyze the model performance, a continuous 26 days of data were collected where Autopilot was turned on and off at random intervals during business hours. Data was split into two groups, ON and OFF, based on whether Autopilot was enabled. Group ON had 243 hours of data while group OFF had 377 hours of data. We then measured ON_SAT, ON_TAT, OFF_SAT and OFF_TAT, based on those groups. To equalize the sample sizes between ON and OFF groups, we further pruned the OFF_SAT and OFF_TAT datasets by removing the data points with the lowest values, to reduce the bias on lower OFF values. As shown in table 1, hypothesis tests were applied to the two pairs of samples (ON_SAT vs OFF_SAT and ON_TAT vs ON_SAT) and the low p-values show that our model had a significant impact on increasing the expected values of SAT and TAT when Autopilot was enabled. Figure 3 visually confirms a higher temperature with Autopilot ON.

The median fuel saved in the pre-calciner burner and main burner is 17.42 mmBTU and 14.09 mmBTU respectively. Given that every 102.41 kg of CO_2 is produced per mmBtu of pet coke[2], running Autopilot has resulted in a relative decrease in CO_2 production by 3,226.9 kgs of CO_2 every hour. Over a year, this theoretically could result in saving up to 28,000 metric tons of CO_2 on a single cooler alone.

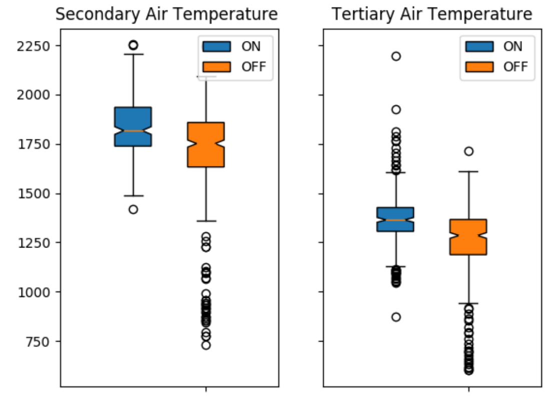

Figure 3. Temperatures (in F) with Autopilot ON vs OFF

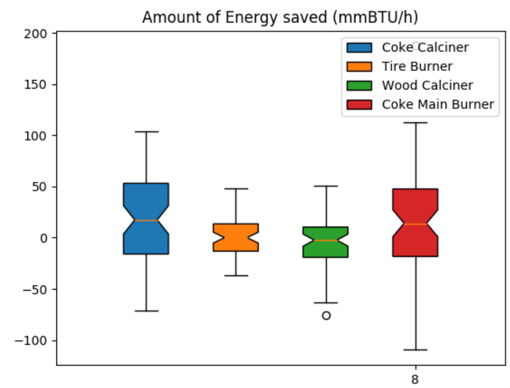

Figure 4. Amount of Energy recuperated in terms of fuel savings

4. Conclusion

We created a fully dynamic Autopilot system, leveraging deep learning to provide real-time optimal operation during cement production that can help reduce fuel consumption and emissions. The system is robust to concept drift and fault-tolerant to unexpected sensor malfunctions encountered during real operations, and was tested and verified in real-world cement plants. Our system is generalized enough to be quickly adapted to other use cases within the cement manufacturing process and deployed to additional cement plants with similar use cases. Running Autopilot has proven to efficiently recuperate temperature from the cooler to the kiln and pre-calciner, thus reducing the need to burn additional fuels. We reached a reduction of CO_2 emissions by over 3000 kgs per hour, or up to 28,000 metric tons saved per year, for each cooler running Autopilot.

[2] EPA Emission Factors for Greenhouse Gas Report 2018

References

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