Use Machine Learning to Optimize Oil Refining

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Industrial machine learning for factories

Current data analytics software struggles to solve the process improvement challenges facing modern industrial companies. Fero Labs was founded by a group of machine learning and industry experts to bridge this gap.

Oil refineries are particularly well-situated to benefit from Fero. In one of Europe's largest refineries, Fero succeeded in **doubling the forecast window accuracy** of a critical metric. This allowed the refinery to **reduce maintenance downtime** and **maximize production throughput**.

Significant improvement over existing data analysis techniques is only the beginning. Fero machine learning (ML) software automatically handles **complex and messy data** and **continually improves in accuracy** as more data flows into the software.

With Fero's easy-to-use ML software, factory personnel gain access to an adaptive data analytics toolbox to predict **production quality** issues, minimize **machine downtime**, identify **production bottlenecks**, and intelligently **schedule maintenance**.

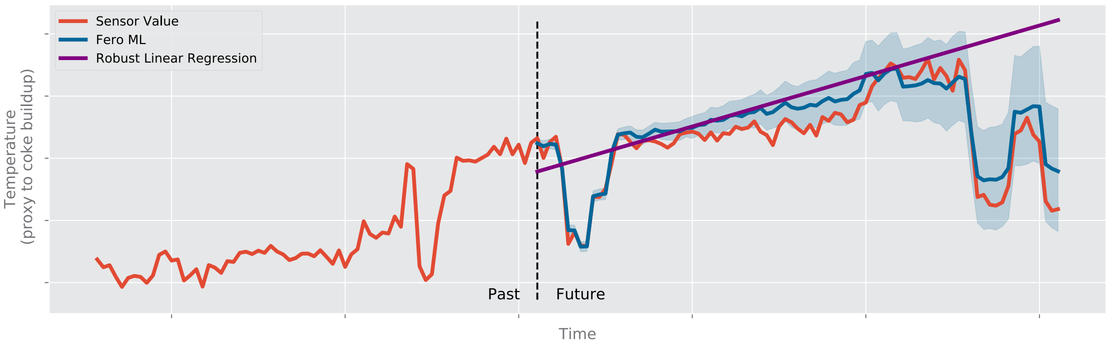
Fero delivers an expected revenue increase of $4.1M per year

OPPORTUNITY:
Coker units apply heat to turn crude oil into lighter hydrocarbons and coke. Over time, coke accumulation within pipes leads to clogging and a host of other problems. The non-linear rate at which this buildup occurs is crucial for scheduling maintenance (online spalling). The surface temperature of the pipes is a proxy to coke buildup. **The rate at which this temperature increases is challenging to predict**, as it depends on many factors. Improving forecast accuracy can decrease spalling frequency, increase output, and generate **an additional $4.1M in revenue** per year depending on production rates.

FERO DIFFERENCE:

- Fero's state-of-the-art ML engine exhaustively explores **all possible combinations** of how factors affect the non-linear rate of coke buildup. It can **identify the primary factors** that are challenging to discover and model by hand.
- Fero's ML model predicts pipe temperatures **19 out of 21 days** (at 5% tolerance). This means that **91% of the time**, Fero's predictions are within **5% of the true temperature levels**. Traditional SixSigma methods, such as robust linear regression, only attain this level of accuracy 9 out of 21 days (43% of the time). See Figure 1 below.

Figure 1: Fero ML prediction (blue) vs. robust linear regression (purple), as compared to actual sensor values (red). Fero's predictions also come with a confidence interval; this help users decide when to trust Fero's predictions.



Fero benefits for oil and gas

Decreasing the frequency of maintenance (online spalling) directly reduces manufacturing costs. In addition to this, there are additional benefits to gain from Fero's ML software.

- Users can **identify how different oil grades lead to different rates of coke buildup.** By simulating different production schedules, users may extend the periods between spalling procedures while optimizing oil flow.
- Users can **decrease wear and tear of equipment** and pipes due to fewer number of spallings. They can reduce common deteriorations around fittings caused by the erosive nature of spalling.
- Coke buildup acts as an insulator within the pipes. This is directly reflected in the increase of temperature at which the coker unit heats the pipes. Users can **minimize energy consumption** by predicting how much overheating is being caused by coke buildup.

One of Europe's largest refineries implements Fero

Our customer, a large **200,000+ bbl/d** refinery, has successfully applied Fero ML to one of their coker units. Fero was able to accurately identify the direct factors that contribute to coke buildup and predict pipe temperature levels **19 out of 21 days.** This gave our customer confidence in leveraging their data in a novel and effective way. Our customer now base their maintenance scheduling on **accurate forecasts**, and executes **fewer spalling operations per year**.

Success at the coker unit has raised the question: What else can be achieved with data from the rest of the refinery? Fero is now exploring **over 40 additional use cases with this customer.**

How is Fero different?

Since its inception, Fero has focused on creating value for heavy industries. Our **statistical machine learning (ML) models are different from classical ML and neural networks** in several ways.

	Fero Labs	Classical ML & Neural Networks
Interpretable	Our interpretable models **explain their predictions**, so you can identify the root cause of problems.	Classical models are typically black-box: they do not provide useful insights for process improvement.
Confident	Our probabilistic models always **output confidence intervals** with each prediction so you know when to trust them.	Classical models only output raw predictions, so engineers cannot reliably decide whether to trust predictions.

	Fero Labs	Traditional SixSigma
Exhaustive	Our models **process all your data at once**, including unstructured text fields, so that you can extract the most value.	SixSigma methods only use small subset of available data and are typically limited to numerical or categorical measurements.
Adaptive	Our models **continuously adapt to changes in the factory** by learning from recent data, thus providing up-to-date predictions.	SixSigma projects are done offline and have to be regularly repeated, which is time-consuming and expensive.

Fero delivers bottom-line returns

There is much hyperbole around ML, so we want to guarantee value for our customers before we deploy our models. To that end, we start every engagement with a **Fero Pilot**.

During the pilot, we apply our ML models to your historical data, **without interfering with your day-to-day operations**. We grant unlimited access to our models and guide you to derive insights firsthand. We move on to a full deployment of our models only after their accuracy is verified. As Fero is a product rather than a consulting service, we encourage you to build new ML models for other use cases within your operations. You only pay for the models that attain good predictive accuracy for your use cases.