Using Neural Network Technology for Virtual Sensing in Crude Refining Units

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Keywords: Digital process automation, neural networks, model predictive control (MPC), virtual sensors, inferential control, property estimation, advanced regulatory control (ARC), regression analysis, oil refinery, crude oil columns (towers).

To optimize the operation of its AVT-1 6 MM TPY crude unit in its refinery in Perm, Russia, Lukoil Company recently upgraded from pneumatic control to advanced digital process automation for the facility's pre-flash, atmospheric, and vacuum columns.

The three towers operate in series with the preheated crude feeding the pre-flash tower, where a heavy naphtha (gasoline) product is recovered overhead along with LPG. The reduced crude is heated in a fired heater and fed to the atmospheric tower where a light naphtha (gasoline) product is taken overhead. Side-draws recover kerosene and atmospheric diesel. The bottom product, Atmospheric Gas Oil (AGO), is heated in a second fired heater and feeds the vacuum tower. The overhead vapors are absorbed with atmospheric diesel and removed as vacuum diesel. In addition, there are side draws for low, medium, and high viscosity vacuum gas oils (VGO) and a slop stream with vacuum residue removed as the bottom product.

The project included upgraded advanced regulatory control (ARC) and model predictive control (MPC) technology that is fully integrated into the new automation platform.

THE CHOICE -- ONLINE ANALYZERS OR INFERENTIAL MODELS?

Lukoil needed to decide whether to deploy online analyzers or to use inferential models for many of the dependent variables configured as inputs to the advanced controls. The choice was made to use artificial neural networks (ANNs) for online, realtime inferential property estimation in what is believed to be one of the world's largest installations (in terms of the number of neural models) on a single crude unit.

The neural networks run as function blocks within the automation system's controllers. Several blocks can execute in the same controller simultaneously, no separate computer platform was required, and the property models are executed and updated as fast as once per second. Since the neural models and MPC functionality resides in the system controllers, the advanced controls enjoy the same level of redundancy and security as traditional control loops.

Neural network pre-processing, design, training, and verification activities were performed automatically using the automation system's standard step-by-step graphical mode. Additionally, an expert graphical mode was called upon from an engineering workstation to work in an off-line mode to change the sensitivity of some inputs by modifying the correlation between input and output. The expert mode also allowed the adjustment of detailed parameters -- outlier limits, maximum/minimum number of hidden neurons, maximum number of training epochs, etc.

Lukoil's neural network undertaking proved to be as much a research effort as an operational upgrade. The company wished to reduce conventional intermittent sampling and lab analyses using a means other than installing costly and maintenance-prone online analyzers. Incorporating neural networks into the new automation seemed an ideal option. Of course, the models require data for training, testing, and verification, so even though the frequency of lab analyses may be reduced in the future, there was a burst effort which had to be managed to collect the data necessary to build the models. Some of the lessons learned on this project were related to planning for and collecting the required data.

The neural models are empirical and require process data from a variety of points in sufficient quantities and of high quality to accurately represent the process. Approximately 100 lab samples of each variable to be modeled were needed to train the models. Data collection and model refinement continues today at the refinery.

10 ANN MODELS MEASURE GASOLINE, KEROSENE, DIESEL, VGO, & RESIDUE

Lukoil initially purchased licenses for and applied 10 neural networks to develop the virtual properties of seven extraction cuts spread over the three columns:

PRE-FLASH TOWER

1st Gasoline (Heavy naphtha)	End Boiling Point

ATMOSPHERIC TOWER

Kerosene	Initial Boiling Point
Kerosene	End Boiling Point
Atmospheric Diesel	50% Boiling Point
Atmospheric Diesel	End Boiling Point

VACUUM TOWER

Medium Viscosity VGO[1]	Flash Point
Medium Viscosity VGO	Viscosity
High Viscosity VGO	Viscosity
Vacuum Diesel	End Boiling Point
Residue	Viscosity

The refinery had considered four other possible models including:

ATMOSPHERIC TOWER

2nd Gasoline (Light naphtha)	End Boiling Point
Kerosene	Crystallization Point

VACUUM TOWER

High Viscosity VGO	Color
Low Viscosity VGO	End Boiling Point

The 2nd Gasoline EBP is essentially the same from a control perspective as the Kerosene flash point, representing the cutpoint between light naphtha and kerosene. The lab test for Kerosene crystallization point was never run to completion, but only run until the sample was determined to be within specification. Modeling the property would have required modifying lab procedures. The other two vacuum tower properties were considered less important as control or constraint variables. Still, it will be possible in the future to consider building neural models for any or all of these properties.

Lukoil had previously relied on feedback from the lab and operator skill to keep products in spec. In other Lukoil refineries, other inferential modeling techniques based upon statistical regression have been tried with some success. This neural project offered the possibility to compare the relative strengths and weaknesses of the two approaches to inferential modeling.

FROM SINGLE LOOP CONTROLLERS TO DIGITAL AUTOMATION

Historically, the refinery's laboratory analyzed samples taken once or twice a day, the results reported to the operator to help him keep the process under control and products within specification. The operator tried to control key temperatures and other variables by manipulating flows including reflux, furnace fuel, pump-arounds, and product draws. Without online analyzers, product qualities had to be controlled open-loop.

For the crude unit column control upgrade project, all panel-based single-loop controls were replaced with DeltaV™ digital process automation. The new system has gained acceptance and has generated a performance improvement. Additionally, the new system's high reliability and diagnostic capabilities increased control system availability and has avoided shutdowns and slowdowns. The most significant benefits, however, are coming from improvements in control design using strategies formerly

[1] Vacuum Gas Oil

impractical with single loop controllers. When the process is stable, it can be operated closer to its economic limits, whether these limits occur at a constraint limit or at an optimum point within the acceptable operating range.

PROPERTY ESTIMATION CALCULATES VIRTUAL DATA POINTS

The columns separate the crude oil into specific cuts by relative volatility, although the cuts are complex mixtures rather than pure components. At times, it's desirable to vary the cutpoints of a product such as kerosene to increase production or to meet requirements for a lighter or heavier grade. The Lukoil laboratory determines product quality and composition using a number of analytical tests including ASTM Distillation (usually initial and end boiling points), flash point, crystallization point, color, and viscosity.

Over time, operators developed the experience to regulate quality and composition -- and to maintain these values between lab analyses -- by monitoring various other measured properties. Every operator had a slightly different way of controlling the process, and some operators did a better job than others. However, even the best operators had other tasks that precluded them from continuously adjusting column controls.

In locations where measurements or laboratory analyses are impossible or too costly, virtual property estimation technologies give Lukoil the opportunity to supplement measurements and lab work. Property estimators are not new, but the use of neural networks for such calculations are not common. The goal of a property estimator is to provide an accurate gauge of product quality, especially after lab results have become stale -- which is most of the time. Property estimators are not intended to eliminate lab analyses, although the frequency of analyses may be reduced once estimators have been proven. Even though estimators may not be as accurate as lab analyses, they can be very worthwhile calculated variables to help Engineering and Operations monitor, troubleshoot, or understand the process in addition to controlling it.

Property estimator models can be derived from first principles or developed empirically. First principles models are more robust but also more difficult to develop and may require measurements not physically obtainable. Empirical models, such as neural networks, take advantage of existing measurements to calculate new ones, and they can incorporate process knowledge to some extent. These models are not limited to variables that have a causal relationship and can discover variables that are highly correlated simply as a “reflection” of the process. Empirical models should not be considered as robust as first principles designs, however, and they do not extrapolate reliably outside the range of data that was collected to model and train them. The latter caution is particularly true of non-linear neural models. For this reason, care must be taken when using these property estimators as inputs to a control strategy.

It's important that Lukoil Operations continue to monitor the accuracy of its neural models with laboratory sample data. It's also important that the operators who collect samples, and the lab technicians who analyze them, follow procedures that assure data integrity. When an unexpectedly large discrepancy occurs between values from the lab and the model, Lukoil determines the reason as quickly as possible. However, having a “continuous” input from the property estimator, gives the operator a new and improved gauge for monitoring the process between lab samples. Abnormal conditions produce an off-spec value and are “flagged” immediately. The operator can be alerted to take the appropriate control action, even if the property estimator is not part of a closed-loop control algorithm.

NEURAL MODELS BUILT AND TRAINED AUTOMATICALLY

Several steps are followed when building any empirical model, including neural models. They include:

- Data collection
- Pre-processing
- Design
- Training/Testing
- Verification

One of the challenges of building neural models is the many inherent pseudo-correlations evident in process data. Auto-correlation, cross-correlation, and other statistical concerns will often fool a modeler into believing a true correlation exists when actually it's only a temporary or coincidental one.

Training a neural model with as much laboratory data and process data from multiple sources as possible is the best way to assure true correlations are correctly identified. Ideally, no step-testing or manual disturbance of the process is necessary during network development and training. A highly stable process can make it easier to correlate process data with lab analyses, but that's a double-edged sword. Some process variability is required to observe a correlation. And as noted before, empirical models do not reliably extrapolate. If the process doesn’t vary very much, the model won't be reliable if the process wanders into a range where no training data has been collected. Slow changes or steps that are held for relatively long periods are the best inputs for training the neural model.

The DeltaV Neural™ configuration software can automatically perform the data collection and model training needed to build and prove the neural networks -- and to even stop over-training when detected. Configuring data collection, model building, and model training involved familiar Windows graphical conventions.

Up to 20 process variables were automatically collected by the digital automation system's historian for use as inputs in configuring each neural network. The configuration allowed input sensitivities to be viewed, abnormal operating conditions excluded, and variables shown to have little or no effect on model outputs eliminated. Although not the case at Lukoil, input data could have been collected by other PC software as well, such as Microsoft® Excel®, and downloaded to the configuration.

During model building, the configuration software identified the time delay between when a process measurement was observed and a corresponding lab sample was extracted. It also quantified the relative sensitivity of the various prospective inputs at different time delays. The software further allowed if-then analyses of process changes based on future predictions of critical parameters. All of these capabilities presented a wealth of information to Lukoil process automation engineers. There have been many cases in various fields where neural network technology led investigators to discover unexpected correlations and therefore new ways of looking at a process.

Building the models at Lukoil was a learning experience for everyone involved. For instance, the company followed Emerson's recommendation to put switches at sample points to trigger accurate time stamps within the automation. But instead of pushbuttons, technicians went one step further and installed proximity switches on the sample valves. It seemed like a good idea until it was discovered that the valves were being opened frequently to grab samples for visual checks without subsequent lab analyses. So while the sample timestamps were accurately recorded in the system, there were additional sample events that had to be reconciled.

COLLECTING DATA A MAJOR TASK

Like in many similar projects, lab data collection was the biggest concern and challenge. The lab data must be accurate. Any error introduced during sample collection, analysis, or reporting will affect the quality of the neural model. One well known concern is accurate time-stamping of the lab data. The time stamp should reflect when the sample was extracted from the process -- not when it was scheduled to be sampled, or when the lab technician performed the analysis, or when the lab results were reported. This was the reason for the switch noted above. The sample time is recorded in the system historian as a discrete event with a time-stamp that is coordinated with the other system measurements.

Since there was no previous system history that could be used for modeling, the data had to be collected from scratch. The original goal of collecting samples during process step-testing for 10 models soon proved to be overwhelming. So data for model development was eventually collected over several months and used to build preliminary models. While these models were promising, they were still not good enough. So normal lab sampling was continued and over time the models showed much improvement.

While data collection could be done in the online mode, it was preferable to collect the data and use the offline sensitivity analysis for model development. While the system supports this, the tools do not have as rich a functionality with respect to data and file manipulation. The local engineer developed some useful tools for preparing the data for model building. These tools were intended to help search and sort the historical data, merge data from different files (e.g. process history and lab data), and reformat the data in the required correct form. These homemade tools did not perform any data conditioning or pre-processing, which is done by the model development system, itself.

Another consideration of data collection is that the process data should not be filtered or manipulated. Raw snapshot data usually makes for the best models. However, the long time to steady-state and the large amounts of data needed meant that some kind of data compression would be considered. This was an artificial requirement imposed by using Microsoft Excel with its limited number of rows than of the actual tool or technology. While the approach was not recommended, the models were eventually built from five-minute averages and yielded good results. This approach can hide important information, especially transients, but the risk was accepted since the columns normally operate fairly calmly. Transients are rare and not likely to occur; if they do, they might be discounted as outliers anyway. Whenever the online model sees input data (or intermediate values) that are outside of the training range, the model status will be changed to "Uncertain" and the operator can be alerted. This is a limiting characteristic inherent in any empirical model. When online models built with the compressed data were deployed, the inputs were filtered to provide a similar averaging affect. Further testing could be performed to better understand the true affect of input filtering in this application, but for now, the refinery is happy with the results.

The tool is able to identify the variables having the greatest significance. It uses statistical techniques like Partial Least Squares (PLS) and Principle Component Analysis (PCA) to identify not only the sensitivity of each input, but sensitivity over the time to steady-state. This enables the identification of time delays between when a process measurement is observed and when the corresponding change in lab property is observed. Each input is considered with its own time delay. And the preprocessing analysis helps identify and eliminate inputs that don't contribute to the model.

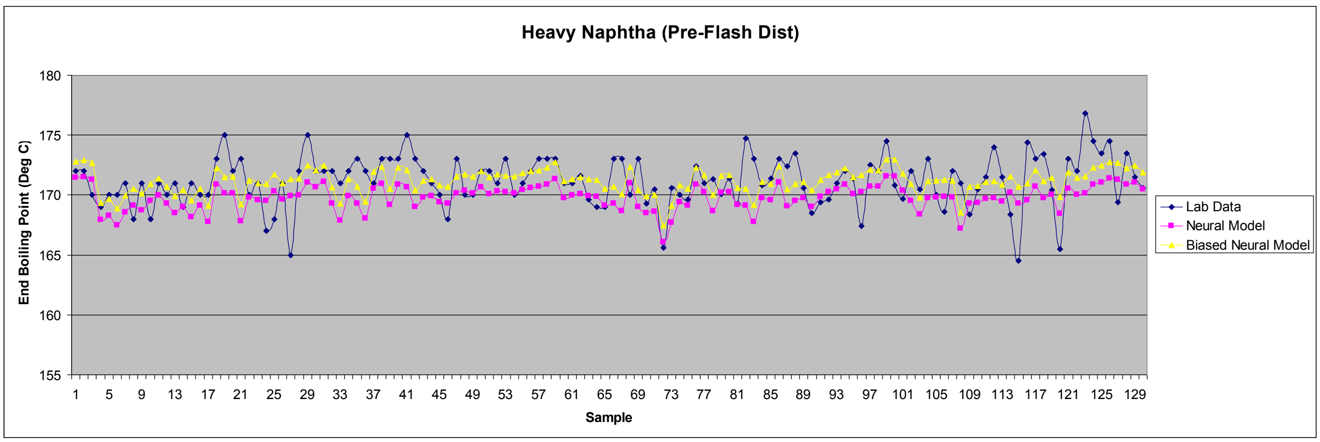
Sometimes inputs that seem to be important are ignored. There are several possible reasons, including that the input may not have had any variability, or that another input or combination of inputs (causal or reflective) may have provided the same information. Including the additional input can be useful by increasing robustness in the event that a process measurement fails, but the overall model is degraded because the new information is redundant and noise inherent in any measurement is additive. One of the problems experienced early on was a lack of lab data. This was overcome by using part of the data twice. While it isn't typically a good practice and may not be mathematically sound, it overcame the constraints when the tool didn't have enough data to build a model and allowed for initial models to be built and tested. Later, when enough data had been collected, this practice was discontinued.

Later, the inputs for each model will be presented. Some may be surprising, but the results have been good so they are presented. However, by the time the process data and lab data have been collected and prepared and the best inputs and time delays have been selected, most of the work is done. The tool splits the data into two sets, one for training, and one for testing. The training and testing is done in such a way that the ideal number of hidden layer neurons and best weighting factors are identified. This is all done on the system processor in a matter of seconds, or at most minutes. The resulting model can be verified against the training and testing data or another set of data. Initially, when there was limited data, verification could only be performed against the training and testing data, but later, it could be verified against data it hadn't seen during training and testing. This ensured that the model was truly able to perform as a general model. Continued monitoring of the predicted value with lab data identifies an outlier condition or when the model performance begins to deteriorate.

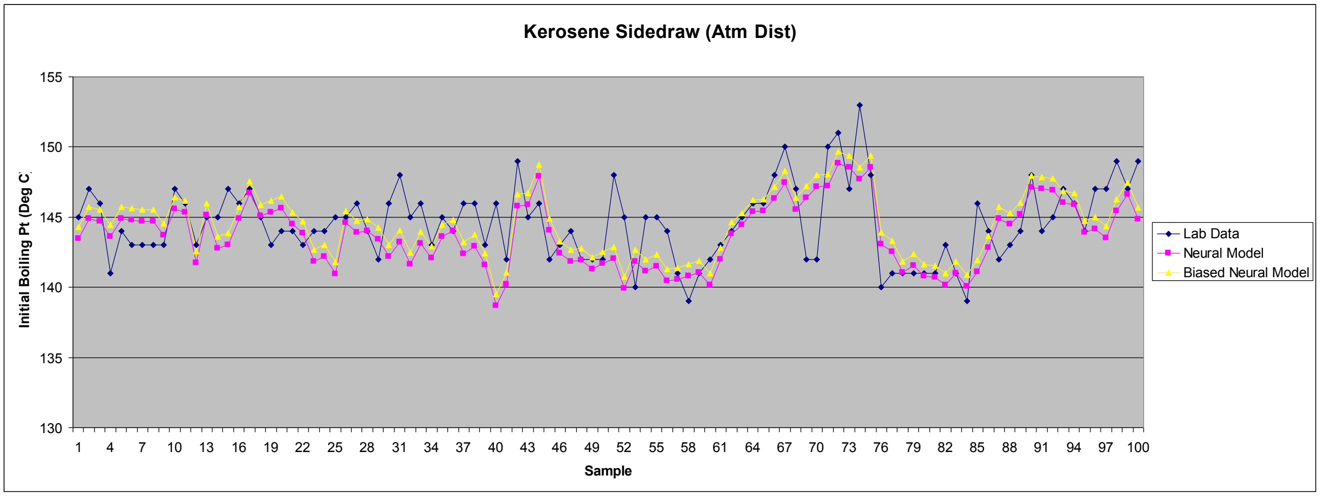
RESULTS

The following data was collected during May and June 2006. It used the existing neural models, which were trained and deployed earlier. The neural models can be biased, although during the period of data collection, no bias was applied. A trend has been added with a bias applied to the model in order to make the average error approach zero. It has been estimated that the lab data has an average error with a standard deviation of approximately 2 ^{o}C. This is inherent in the sample extraction and analytical processes.

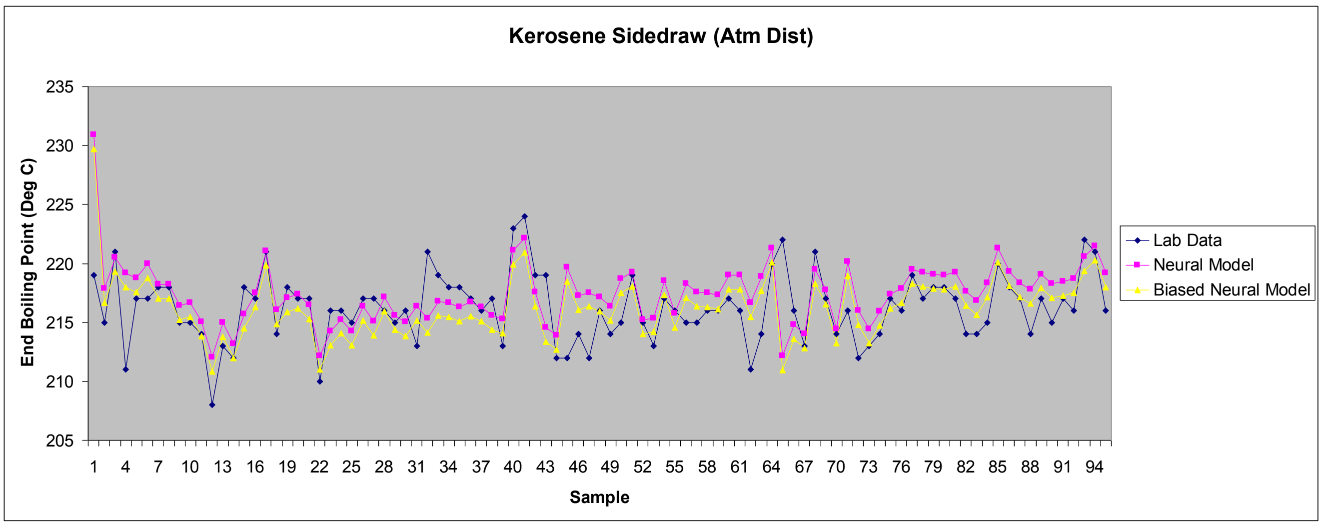
Most of the data presented here are analyses of initial boiling points or end boiling points. It is well known that the presence of trace amounts of low boilers or high boilers can significantly affect the end point and initial point detection. Furthermore, human observation of the initial and end points are the most difficult of all of the boiling point curve. Nevertheless, Lukoil prefers to use the end point and initial point determination instead of near end and initial points (e.g. 5% and 95%). Experience suggests that the models would be even better if near initial and end points were reported and modeled.



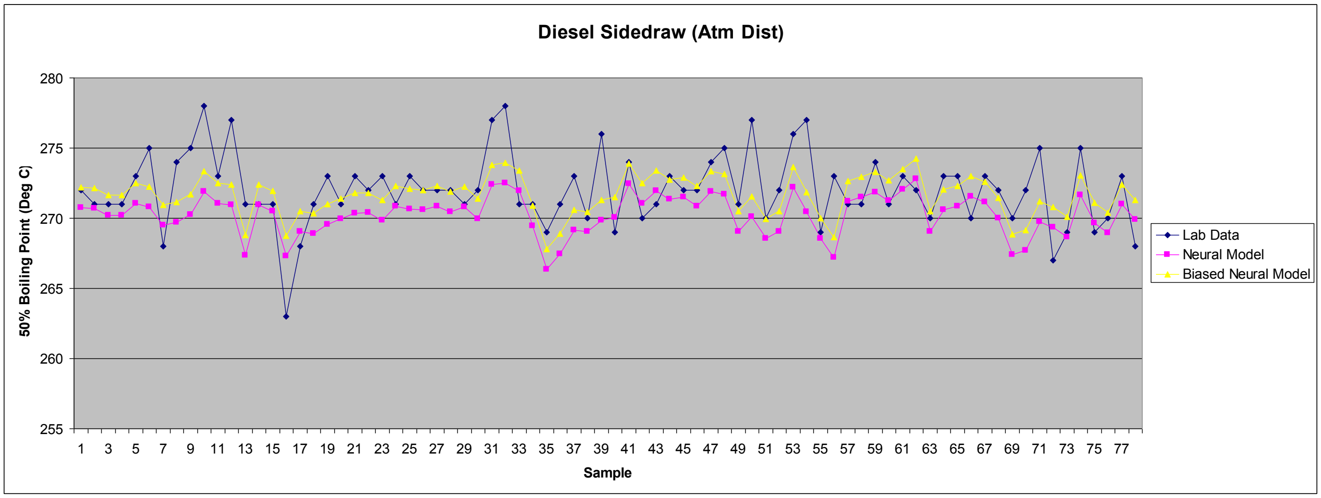
The first plot presented is the End Boiling Point of heavy naphtha (aka, 1st Gasoline) taken as the overhead draw from the pre-flash distillation tower (K1). There was a difference of more than 12 ^{o}C between the lowest and highest lab values. When the lab data was compared with the predicted values, the average offset was almost 1.5 degrees. The standard deviation of the prediction error was less than 2 degrees.



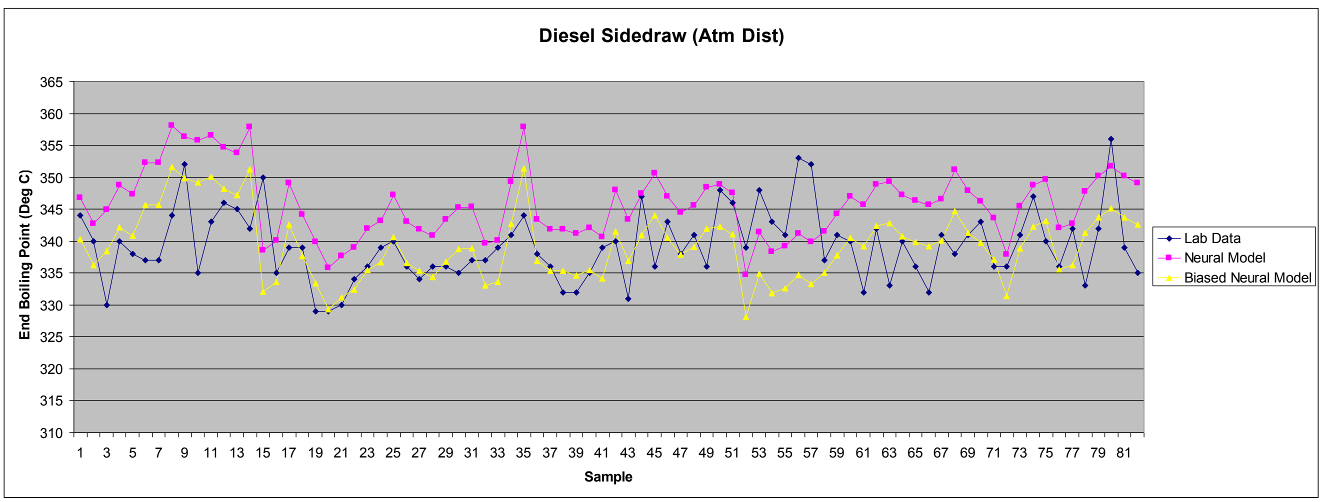
The next plot presented is the Initial Boiling Point of Kerosene, the first sidedraw of the atmospheric distillation tower (K2). There was a difference of over 14 ^{o}C between the lowest and highest lab values. When the lab data was compared with the predicted values, the average offset was almost 0.8 degree. The standard deviation of the prediction error was less than 2.3 degrees.



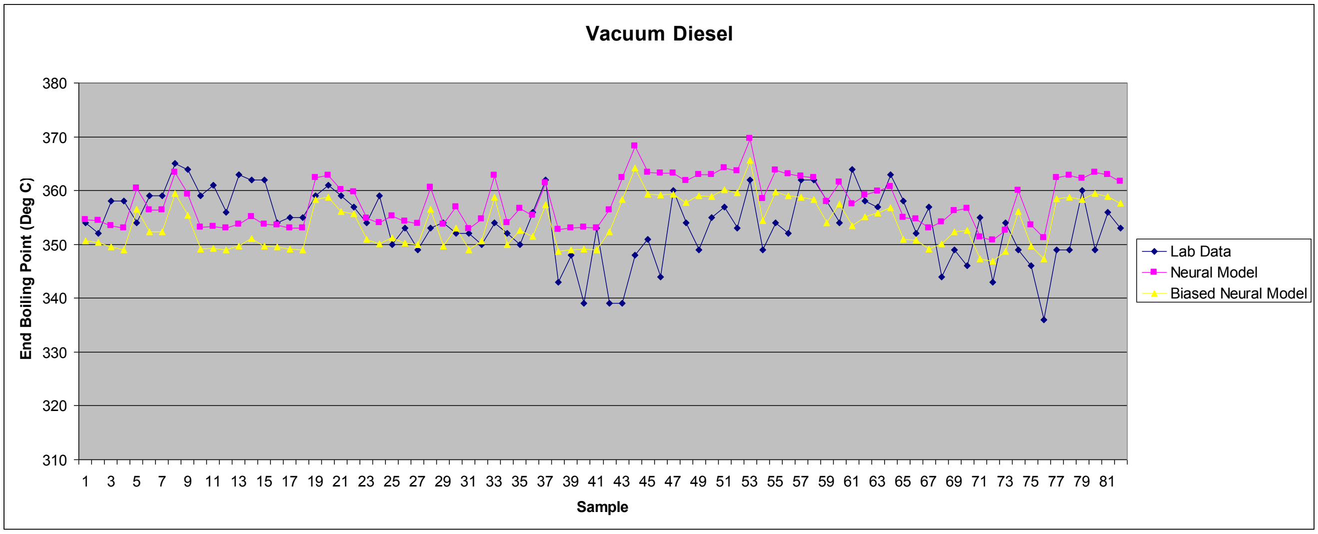
The next plot presented is the End Boiling Point of Kerosene, the first sidedraw of the atmospheric distillation tower (K2). There was a difference of over 16 ^{o}C between the lowest and highest lab values. When the lab data was compared with the predicted values, the average offset was almost 1.2 degrees. The standard deviation of the prediction error was less than 2.75 degrees.



The next plot presented is the 50% Boiling Point of Diesel, the second sidedraw of the atmospheric distillation tower (K2). There was a difference of over 15 ^{o}C between the lowest and highest lab values. When the lab data was compared with the predicted values, the average offset was almost 1.4 degrees. The standard deviation of the prediction error was less than 3 degrees.



The next plot presented is the End Boiling Point of Diesel, the second sidedraw of the atmospheric distillation tower (K2). There was a difference of more than 27 ^{o}C between the lowest and highest lab values. When the lab data was compared with the predicted values, the average offset was almost 16.5 degrees. The standard deviation of the prediction error was less than 6.4 degrees.



The final plot presented is the End Boiling Point of Vacuum Diesel, which is collected by absorbing the Vacuum Distillation Tower (K5) vapors in atmospheric diesel. There was a difference of over 29 ^{o}C between the lowest and highest lab values. When the lab data was compared with the predicted values, the average offset was almost 4 degrees. The standard deviation of the prediction error was approximately 7 degrees.

CONCLUSIONS

Clearly some of the estimators were better than others. The ones estimating lighter products tended to be better. In virtually all cases, the results exceeded expectations, but still require some refinement before they will be accepted as reliable controller inputs.

The neural estimating tool has the ability to apply an online bias that can update when a new lab result is obtained. The ability to bias online should improve short term performance of the estimator, but has not been deployed at Lukoil to date.

Lukoil has been pleased with the performance of the Neural modeling tool. They have not closed the loop with the neural property estimators as control inputs for reasons having more to do with factors other than the neural models, themselves. However, the property estimators are used by the operators and have been well accepted as beneficial automation improvements.