Triggering a PLC Change using a Cloud-based Machine Learning Model

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Abstract

Dense medium cyclones (DMCs) are a class of process separation equipment used in coal preparation, iron ore, the pre-concentration of diamonds and in metalliferous and industrial minerals. Under unstable process conditions a symptom called “surging” occurs disrupting the efficient separation in the DMC causing production losses. This can account for millions of dollars of lost revenue per annum per site. There are different reasons that cause this “surging” condition, and it is difficult to detect with limited direct sensory feedback from the DMC. Commonly, if surging is suspected it needs to be visually confirmed in the field and a decision needs to be made on what process control set points need to be changed to rectify this behaviour. These changes typically need to be made manually by an operator in the control room.

Although in most cases there is no direct indication from the DMC, symptoms of the surging are evident in downstream equipment trends with distinct patterns across multiple tags. By applying a cloud-based multivariate Machine Learning (ML) model on these trends, it is possible to automatically detect this condition. Furthermore, the output from this model can be used to trigger a response at the control system layer, without the model residing there, like with Advanced Process Control (APC) or Model Predictive Control (MPC).

This method provides a means to validate ML model performance and quantify the actual production value before deploying the model at the site PLC level. The successful hybrid integration of cloud-based machine learning with edge-based control systems offers new possibilities for older equipment, avoiding costly hardware upgrades while still achieving a similar outcome. The knowledge gained from undertaking hybrid PLC testing could prove pivotal in the decision to upgrade a plant control system, reducing risk for the plant owner and operator.

Introduction

Machine Learning is a class of Artificial Intelligence where algorithms are trained using specific data sets to develop models that can then identify similar patterns in new data. It is a method of data analysis that automates analytical model building. Machine learning provides systems the ability to automatically learn and improve from experience without being explicitly programmed. There are mature products provided by control system manufacturers that perform these functions on edge computers and PLC hardware, but they are typically expensive to implement and maintain. By using Platform as a Service (PaaS) and other Internet of Things (IoT) software services it is possible to train and test machine learning models in the cloud, using data streamed from operating facilities and remote mine sites. Training and testing of models in the cloud can be done without making changes to the control system logic, which reduces the risk of process interruption and impact to productivity. If a high level of certainty can be achieved with a particular model, it can be decided to deploy the model on the edge as part of MPC, or as a trigger to enact a modified control philosophy. The later was done in this circumstance, to test the ability to automatically correct DMC density stability issues on a control system without any advanced control capabilities.

Methodology

Communications

The challenge was to design a communication loop that would enable the control system to funnel data to the cloud, but also receive feedback on what actions to take. In the interest of cyber security, the decision was made for any action to be preconfigured on the PLC level and just a binary trigger value from the cloud used to activate the change. This was done via an industrial gateway device (Red Lion) that could receive internet messages and communicate to the PLC over industrial protocols, meaning even if the connection was hacked the trigger variable could only be changed from 0 to 1, switching the logic on or off. Additional rules would also be put in place to control the frequency of logic activation. Furthermore, the Red Lion was deployed in an Industrial Demilitarised Zone (IDMZ), preventing other means of a jump to the PLC or other devices via the Red Lion connection.

The continuous communication cycle and flow of data between the PLC and Cloud services is shown in Figure 1.

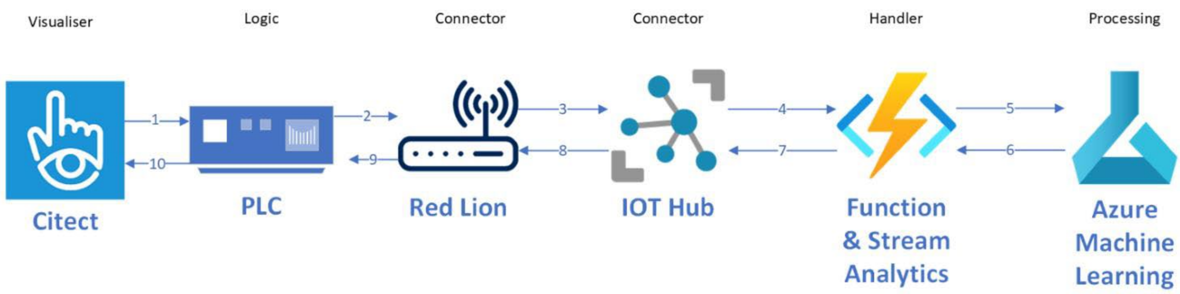

FIG 1 – PLC to Cloud data communication cycle

1. Control Room can select activation status of secondary density control loop (active/ not active) in Citect
2. Data from PLC is written into tags collected by the Red Lion
3. Red Lion sends the tags to Azure IoT Hub cloud services via the site internet connection
4. Stream Analytics selects relevant tags for model and groups data into processable chunks
5. Processed data sent to ML Model which calculates certainty of the data matching surging behaviour
6. Model output is sent back to a Function that averages to 0 or 1 over a time window
7. Binary Trigger value is packaged and formatted sent to IoT Hub
8. IoT Hub Cloud to Device message is sent from the cloud back to Red Lion
9. PLC watches for trigger value to activate surging density control logic
10. "Surging controller Active" shown on Citect

Controls

The existing control philosophy was a simple closed-loop controller for a slurry density, whereby a control output is used to regulate a measured density process variable at the designated set point density. The plan was to implement a secondary "surging" control loop in parallel that would take over from the primary density controller should the machine learning model reach the trigger value for density instability. The logic for the two independent controllers are described below.

Primary Density Controller Functional Description (Existing):

Operator sets density set point (PP424_D_SPY) and water addition (PP424_D_OPY) is used to keep actual density (PP424_D_PVI) close to set point relative density (RD).

Surging Density Controller Functional Description (New):

This alternative control loop changes the set point density over a set period of time and then reverts back to the original set point.

Set point change: Increase PP424_D_SPY density set point 0.01 RD every 2 minute for 10 minutes until a maximum total offset of 0.05 RD reached (offset to be configurable on Citect details page), then return density set point to original value.

The following activation criteria must be satisfied for the controller to enable:

- Floating trigger value is 1.
- Watchdog tag is increasing meaning communication is flowing successfully.
- Feed has been on for greater than 15 minutes.
- Citect page indicator next to density control input showing "Surging controller Active" when active.

If any of the following criteria occur during activation, the controller will disable and revert back to the Primary controller:

- The five set point changes have been completed.
- The trigger value changes to 0 for 1 minute during the step changes.
- Override button selected or density SP moved during Surging controller activation.

The additional conditions were set to prevent excessive activation of the surging controller:

- Maximum of 2 activations in any given hour.
- 15-minute cool down on surging controller to prevent immediate re-trigger.

The surging controller in action is demonstrated in Figure 4 in the results section.

Modelling

A supervised machine learning technique was chosen to classify time series blocks of data into either a surging or non-surging group. The model was trained on labelled surging data to correctly identify the adverse condition. To successfully classify live data, firstly, it is passed through a Principal Component Analysis (PCA) function to reduce the dimensionality of the data into two dimensions which explains most of the data variance. Then, the Mahalanobis distance (Johnson and Wichern, 2007) is calculated, which is a measure of similarity between the simplified points and a distribution of confirmed surging events, providing a measure which indicates a level of confidence between the normal or adverse operating state.

Figure 2 shows a DMC cyclone surging event with a distinct cyclic pattern across multiple weigher, centrifuge and screen tags. Such events in historical data were used to train a multivariate model to detect future events. In this plant, there are centrifuges and desliming screens that are situated at both the underflow and overflow ends of the cyclone. By contrasting the power being drawn by the machines at either side and the weighers, a distinct mirroring of the cyclic pattern is evident during surging.

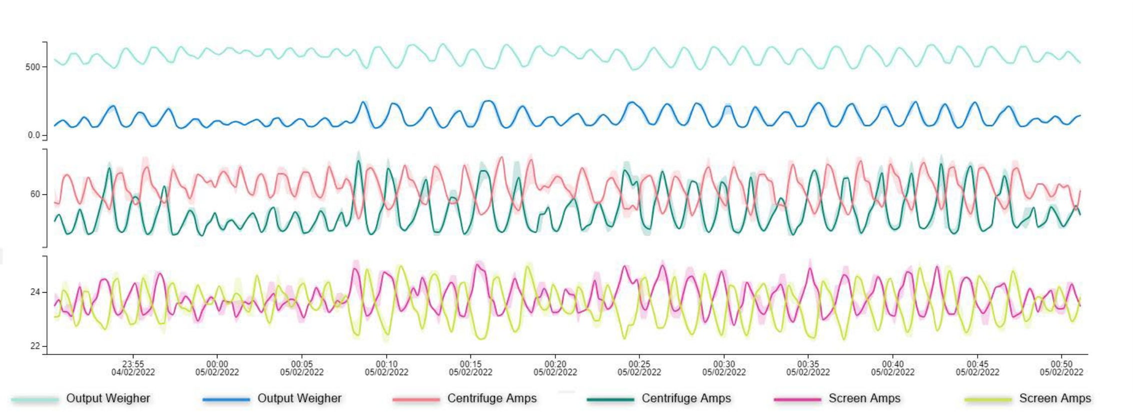

FIG 2 – Plant weigher, centrifuge amp and screen amp trends showing DMC surging event

In combination, the live tag data is analysed by the ML model and a binary classification variable is created to indicate if a data point is an anomaly (1) or not (0), as shown by the red line in Figure 3. This is used to flag if the DMC is surging or not.

Results

The machine learning model was first deployed virtually, to see how the model would perform before using it to trigger the surging controller. It was applied to a two-product coal plant (Coke and Thermal), whereby the primary DMC reject feeds the secondary DMC. If not monitored closely, the primary coking product can be displaced to secondary thermal product. The secondary product price is much lower that the primary product price, which can result in a net financial loss.

Figure 3 demonstrates a DMC surging event that triggered following a decrease in plant feed rate, or solids loading, to the DMC.

Around 13:20, the cyclic behaviour began following a drop in plant feed rate. Following the rolling 10-minute average buffer period, the machine learning model output reached a value rounding to “1” (red line) indicating surging of the primary DMC was occurring. The density was then manually raised from 1.27 RD to 1.30 RD around 14:15 alleviating the surging conditions with the model output returning to “0”. A yield uplift in the Primary product was observed by correcting this instability.

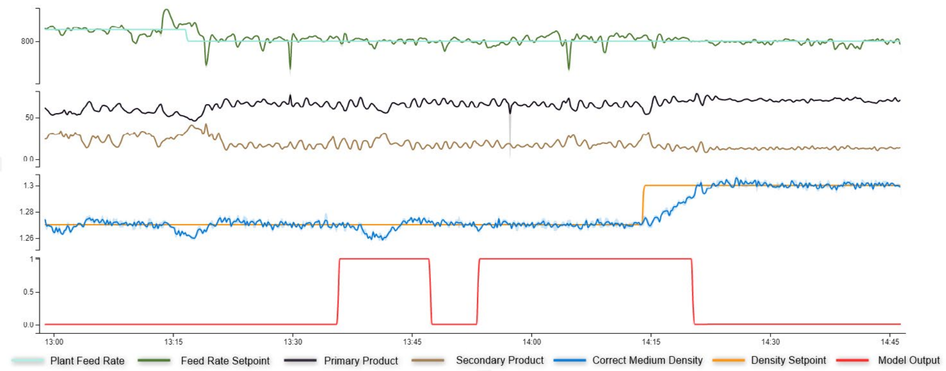

FIG 3 – DMC surging detected by ML Model (red line) corrected with a manual density increase

After two weeks’ validation of the Machine Learning surging model in the cloud, the model output was used to trigger the edge-based PLC surging density control loop automatically. This meant when surging was detected, the surging controller would be triggered to step up the density set point by 0.01 RD every 2 minutes for a maximum of 5 step changes until the surging model deactivated or the sequence had finished. Figure 4 shows a surging event that was rectified automatically, and without human intervention, using this logic. Surging was detected from 12:43 with the model activating at 12:49 sending a “1” to the control system triggering the logic. It can be seen that after the third step change at 12:55 the amps in the Secondary and Primary Product centrifuges inverted indicating the shift of load back into the Primary product. After the fifth step change the surging model deactivated “0” and the density set point returned from 1.29 RD to 1.24 RD.

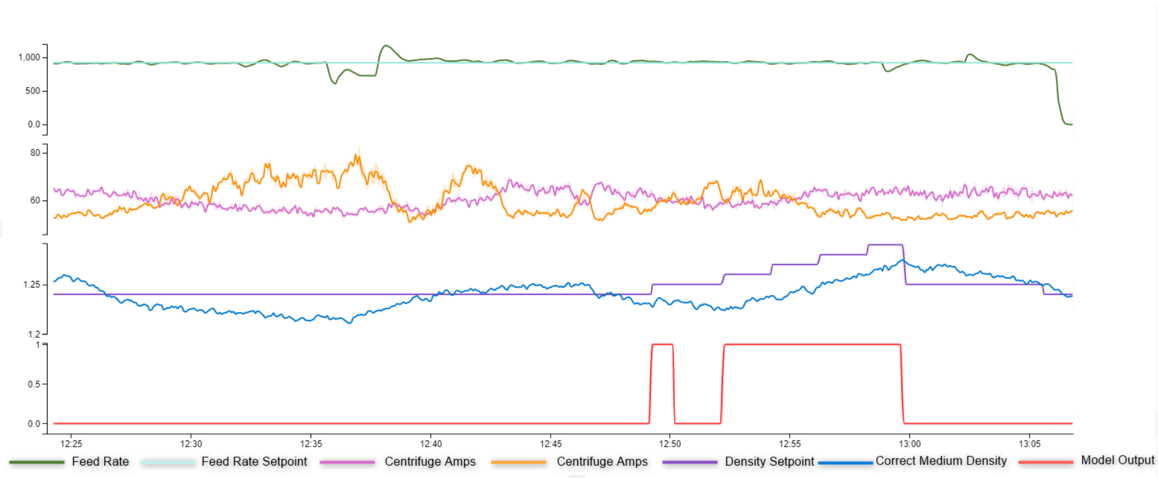

FIG 4 – DMC surging detected by ML Model (red line) corrected with automatic surging controller

The stabilisation of the DMC trends indicated the surging control logic was successful in correcting the abnormal behaviour.

Conclusion

The results above demonstrate how a machine learning model in the cloud can be used to trigger a change in the edge-based control system and validate its effectiveness. Longer term this model would be deployed on the control system, with retraining required should the model accuracy decline due to process changes or equipment maintenance. This method also provides a mechanism for older or less advanced control systems to achieve machine learning control functionality. Most importantly, it shows that complex issues such as DMC surging can be detected and rectified without human intervention, which could be expanded to all manual set points in the plant.

References

1. Johnson, R.A. and Wichern, D.W. (2007) “Applied multivariate statistical analysis (6th ed.)”, Pearson, Chapter 2, London.