SLUDGE DEWATERING OPERATIONS OPTIMISATION, UTILITZING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

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KEYWORDS

Artificial Intelligence, Predictive Control, Analytics, Energy Optimisation, Chemical Optimisation, Sludge Dewatering, Centrifuge, Sludge Quality

EXECUTIVE SUMMARY

Artificial Intelligence (AI) and Machine Learning (ML) can be applied with digital twin concepts to solve key process plant problems while meeting performance objectives for a given unit operation. In addition to its predictive capability, machine learning can be utilized to develop soft sensors and report system status when operational data is missing, or sensor health is declining. Additionally, ML based modelling can also be applied to predict equipment failures in advance and prevent unnecessary down time.

The dewatering plant in this case study was able to reduce its chemical and energy expenses by 10-20%, optimize real-time operational schedules, decrease equipment downtime, and improve equipment life.

INTRODUCTION

AI driven digital twins can be used to solve key process issues and meet performance objectives for a given system. A digital twin of a system is a virtual representation or model of a physical asset, which updates itself in real-time via two-way data connection with SCADA or DCS (Distributed Control System).

Data driven models are predictive AI models utilising Model Predictive Control (MPC) philosophy. These models predict and recommend future operating control set points / schedules for the operators to ensure optimum state of the process at all times. Through the use of AI, any process plant schematic (Water / Wastewater network and Water treatment plants) can be converted into an interactive and real-time predictive model that takes into account various disturbance variables to achieve optimum outcomes.

The technological focus of this paper will be dewatering operations optimisation at a utility scale wastewater treatment plant. AI driven digital twin utilising data driven and physics based models were used to achieve steady operations, reduce chemical usage, improve final sludge cake quality and reduce overall cost of sludge treatment per dry ton.

HIGHLIGHTS

- Combinations of data driven and physics based models can be used to accurately determine dosing rate and state of the system under various operatign scenarios
- A reaction curve can be used to calculate and recommend real-time polymer dosing set points to optimize dosing rate at various feed conditions
- Soft Sensors can be developed using ML Models by utilising available historical Lab based and online quality data
- Utilitzing operational data to prevent equipment breakdown and plant stoppages

PROCESS OVERVIEW & OUTCOMES

Pacific Northwest Wastewater Resource Recovery Facility – Dewatering Optimization Project:

The Pacific Northwest Wastewater Resource Recovery Facility (WRRF) is a nationally acclaimed, state-of-the-art facility. It cleans on average, 22 MGD of wastewater and discharges it into an adjacent river. As part of the process, WRRF also treats the sludge for reuse. Sludge treatment consists of thickening, digestion, dewatering, and phosphorus recovery. The dewatering facility is made up of two centrifuges 1 duty and one standby, where polymer is added to facilitate dewatering of the sludge. Schematic of the dewatering process is indicated in Figure1. Figures 2 and 3 indicate a typical operator dashboard to monitor KPIs and receive predictive recommendations.

For its imported electricity, the facility is subject to a variable tariff structure (day, night, weekday, weekends). The facility operates to maintain sufficient storage in the centrate tanks to feed the phosphorus recovery facilities and treat and discharge solids as they age over a 15-20 day digestion period.

Machine Learning models were developed based upon historical data from various data sources like total solids sensors, flow monitors, water quality sensors, and chemical control feed pumps, real-time operational decisions were made and improved upon with the use of machine learning. Figure 4 is a heat map identifying the correlations between various signals to select important features for the development of machine learning models.

<u>Polymer Dosing Optimization:</u> Seasonal operational trends were discovered and identified in historical data and were used to cluster and then simulate unique operational scenarios. A polymer reaction curve (Figure 5) was generated for the machine learning models so that it can select best operating conditions for these clusters. Utilizing the system performance curve machine learning (ML) was utilized to select best dosing points and sludge feed rate to reduce overall polymer use while maintaining and/or improving sludge quality (percent capture).

<u>Centrifuge Operational Timing Optimization:</u> The centrifuges where operated to maintain centrate quality and storage for use in phosphorus recovery facility. This happened as needed when the phosphorus recovery facility had capacity and was not offline for maintenance due to poor centrate feed quality. By switching to a centrate TSS polymer dosing strategy, quality can be maintained to avoid operational shutdowns downstream of the centrate. Using forecasting tools and predictive modelling; the digital twin can forecast when to turn on and off centrifuges to take advantage of the variable energy tariff structure, create operator schedules, and maintain centrate storage.

<u>Reduction in Centrifuge Breakdowns:</u> At times the centrifuges during operations would trip and shut down, causing the facility to shut off, and require maintenance, or restarting procedures. Through the analysis of centrifuge's historical operational data, it was observed that specific sludge total solids in the influent at set torque limits and polymer dosing rate resulted in an overloading scenario. This overloading scenario created high vibrations, that eventually caused the centrifuge to shut down and require a complete wash down prior to restarting. By monitoring centrifuge vibrations, the machine learning model can consider influent total solids predictions into its recommended operations mode and reduce the amount of unexpected equipment shutdowns and increase the useful life of the centrifuge.

<u>Soft Sensing Technology:</u> The system monitored influent total solids, temperature, flow rates, pH, and ambient weather conditions such as precipitation and humidity for influent characterisation in real time. For polymer dosing control and quality control, effluent total solids, centrate TSS and air index, along with total wet solids weight was monitored in real time. Merging daily lab sampling data and numerical physics based models, the model is able to predict centrate TSS and effluent total solids with high enough fidelity to monitor sensor health. When the sensors indicate abnormal readings, the system is able to generate approximate operating values close enough to actual lab recorded values to continue to operate and maintain facility operations. System then triggers calibration activities when it detects sensor anomalies. While the sensor is down, or lab facilities backed up, the model can be used to approximate conditions and characteristics.

<u>CONCLUSION</u>

Combinations of data driven and physics-based models can be used within cohesive workflows to facilitate operations. The dewatering plant in this case study was able to reduce polymer dosing and energy expenses by 10-20%, optimize operational schedule whilst considering facility operational needs, and decrease equipment downtime and improve equipment life. In combination with model predictive control, machine learning can be utilized for its soft sensing technologies for system insights where operational data may be missing, or sensor health is declining. Overall, the utilization of data driven models with physics based models can be used to develop operational performance management systems that are able to optimise total chemical / energy costs as well as improve equipment reliability and uptime.

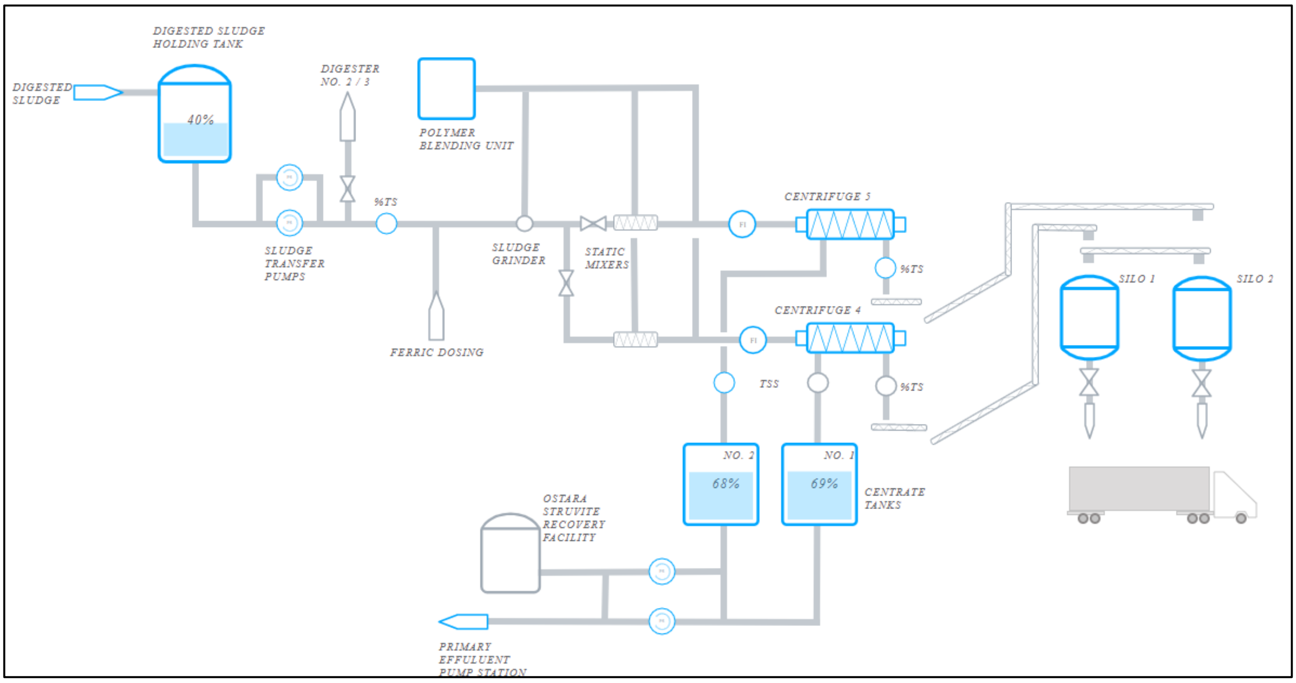

Figure 1 Schematic representation of the dewatering facility

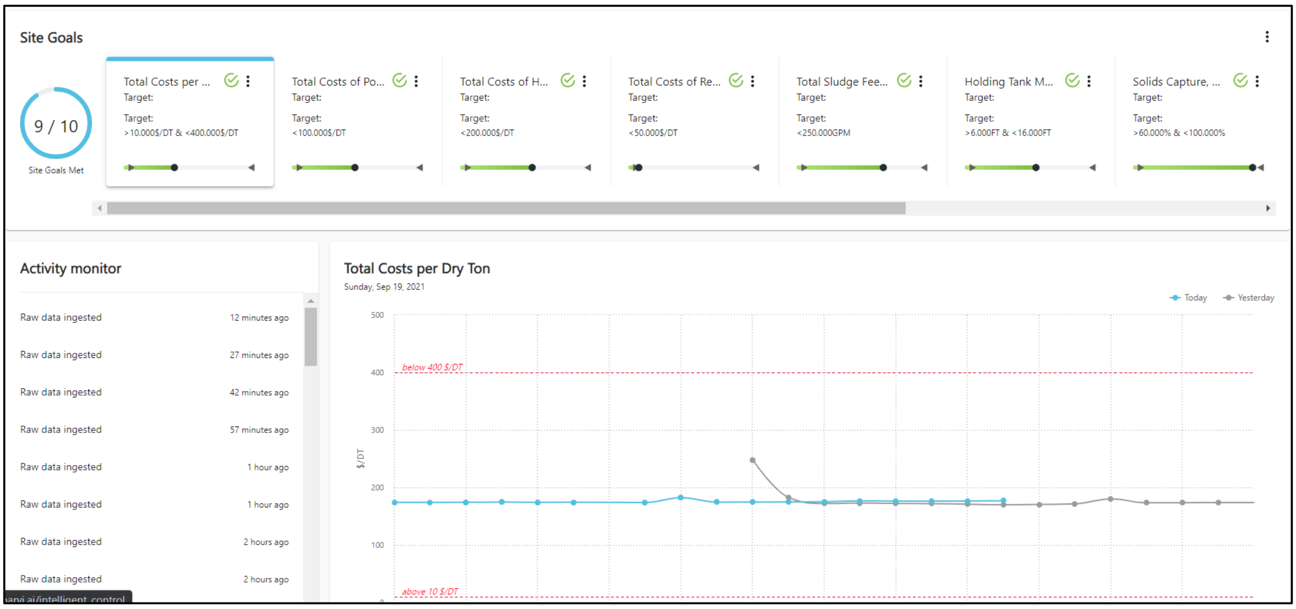

Figure 2: Monitoring Dashboard for Site Goals in Real Time

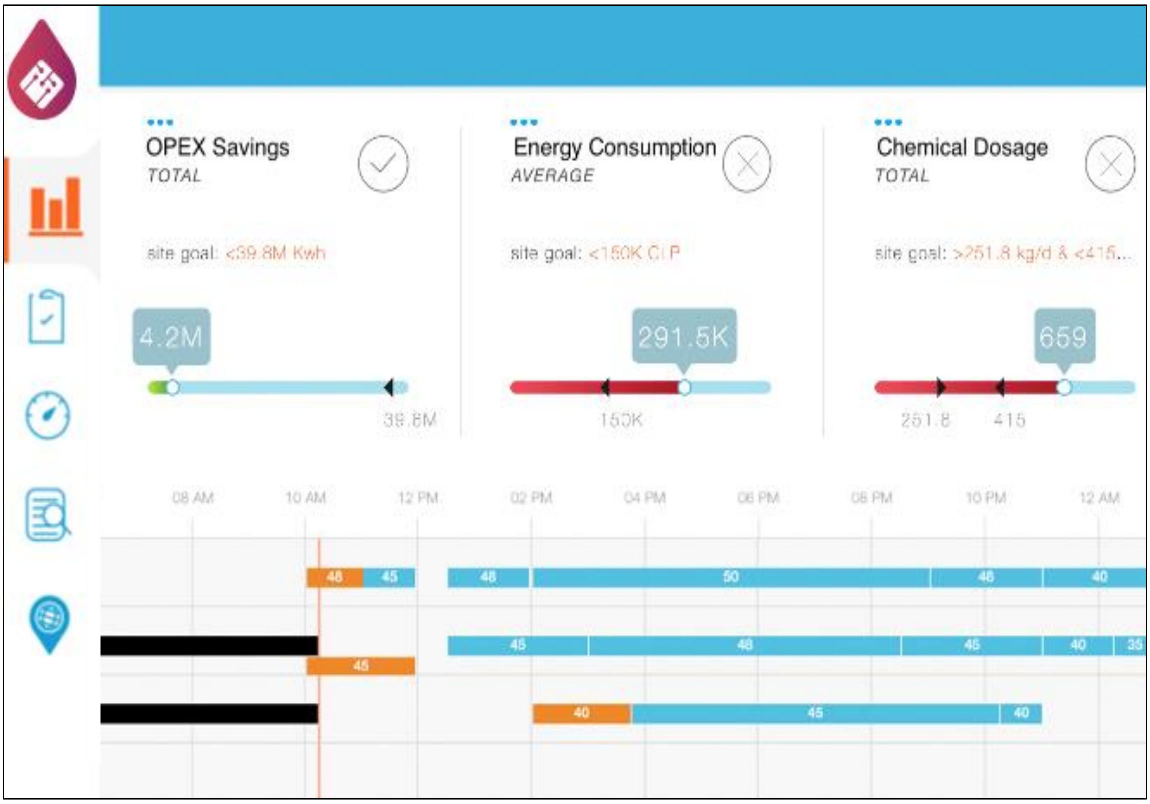

Figure 3 Predictive recommendations and control schedules for optimum performance.

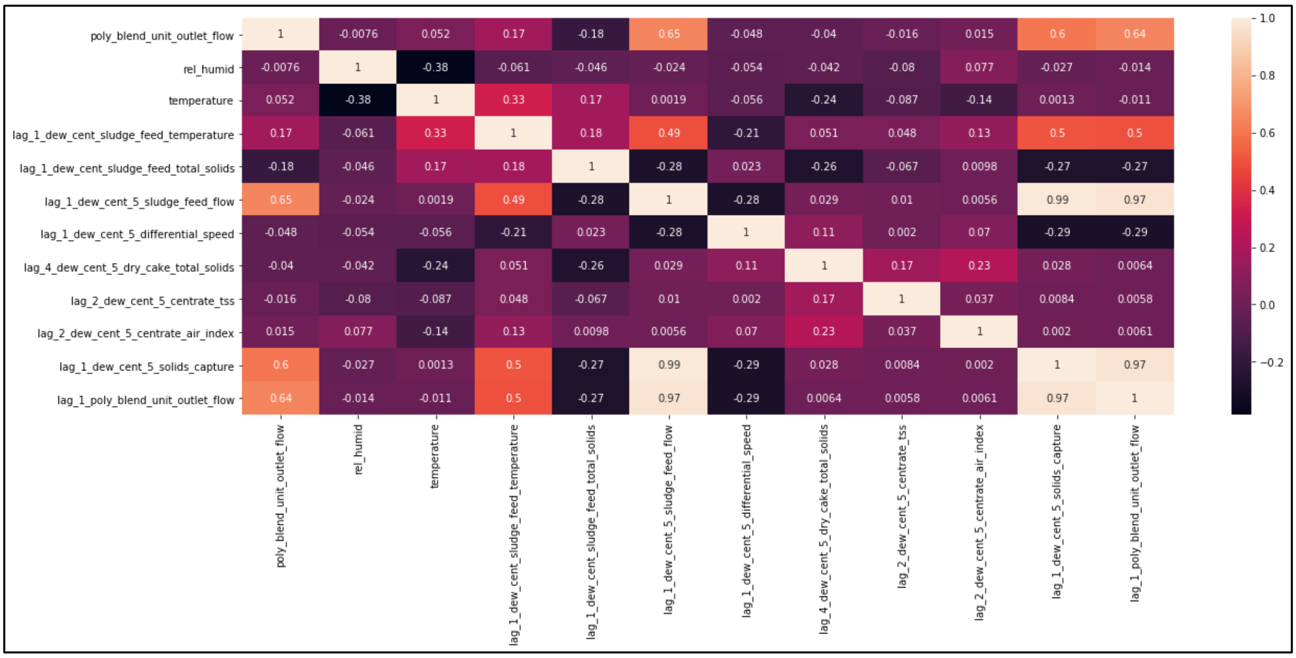

Figure 4 Correlation Heat Map Indicating Interrelation of Various Operating Parameters based on Historical Data

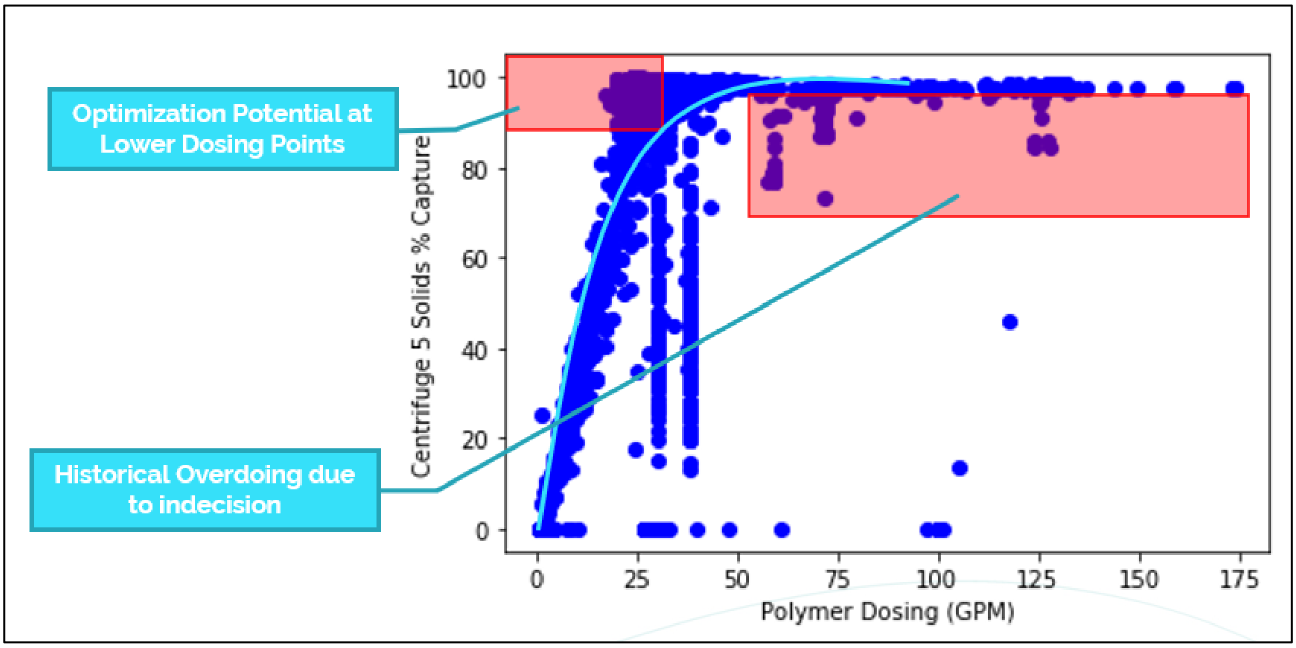

Figure 5 Polymer reaction curve indicating polymer dosage vs solids removal efficiency