Las Virgenes Municipal Water District
FSA Study on Artificial Intelligence

FINAL REPORT

August 2021

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Abbreviations

AI	Artificial Intelligence
C	Celsius
Carollo	Carollo Engineers
DDMO	Data Driven Model Optimization
DOC	dissolved organic carbon
gfd	gallons per square foot per day
IPR	indirect potable reuse
kWh	kilowatt-hour
LRV	log removal values
LVMWD	Las Virgenes Municipal Water District
MAPE	mean absolute percent error
MC	maintenance clean
METI	Ministry of Economy, Trade, and Industry
Metropolitan	Metropolitan Water District
MF	microfiltration
mg/L	milligrams per liter
mgN/L	milligrams nitrogen per liter
ML	Machine Learning
NWRI	National Water Research Institute
PMMoV	pepper mild mottle virus
RAS	return activated sludge
RMSE	root mean square error
RO	reverse osmosis
Tapia WRF	Tapia Water Reclamation Facility
TMP	transmembrane pressure
UF	ultrafiltration
UV AOP	ultraviolet advanced oxidation process
Yokogawa	Yokogawa Electric Corporation

Glossary

Artificial Intelligence (AI) – Systems that mimic human problem-solving by receiving data, learning from data, and taking action to achieve an objective.

Log Removal Values (LRV) – Removal of contaminants, typically pathogens, from water, expressed as the negative based 10 logarithm of the fraction remaining. For example, 90% removal is 1 LRV, 99% removal is 2 LRV, and so on.

Machine learning (ML) – Algorithms that build a model based on training data to make predictions based on new data.

Microfiltration (MF) – Filtration that can remove particles down to a minimum size in the range of 0.1 to 5.0 µm.

Pepper Mild Mottle Virus (PMMoV) – A plant pathogenic virus that affects many species of agricultural peppers but is not harmful nor contagious to humans.

Permeability – Flow through an RO unit, divided by membrane area and transmembrane pressure.

Return Activated Sludge (RAS) – Bacteria that are settled out after the biological treatment stage of a water reclamation facility, then pumped to an earlier stage of the water reclamation facility. This maintains the desired amount of bacteria within the water reclamation facility to biodegrade contaminants and remove nutrients.

Reverse Osmosis (RO) – A water purification process that removes ions and other contaminants from water by applying pressure across a selective, partially permeable membrane to overcome osmotic pressure.

Secondary Effluent – Water that has passed through the primary settling, biological treatment, and secondary setting stages of a water reclamation facility. Secondary effluent has not yet passed through *tertiary* treatment processes such as filtration or disinfection.

Transmembrane Pressure (TMP) – The difference in measured pressure on two sides (feed and permeate) of a membrane.

Ultrafiltration (UF) – Membrane filtration that can remove particles down to a minimum size in the range of 0.02 to 0.1 µm.

Ultraviolet Advanced Oxidation Process (UV AOP) – A family of water treatment processes that simultaneously expose contaminants to ultraviolet radiation and powerful oxidants. For example, hydrogen peroxide (H_2O_2) is commonly added, which reacts under ultraviolet radiation to form the powerful oxidant hydroxyl radicals ($\cdot OH$).

Water Reclamation Facility (WRF) – A facility that treats wastewater from homes and business to stringent water quality standards so that the water can be beneficially used such as for maintaining ecologically desirable flow in a river, irrigation, or further purification for potable reuse.

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EXECUTIVE SUMMARY

The Las Virgenes Municipal Water District (LVMWD) and Carollo Engineers (Carollo) received a grant from the Metropolitan Water District (Metropolitan) for funding to devise and implement Artificial Intelligence (AI) and Machine Learning (ML) control algorithms at the LVMWD-Triunfo Joint Power Authority's Demonstration Facility (Demo) and the Tapia Water Reclamation Facility (Tapia WRF). The Demo was commissioned in June 2020 and work has been ongoing since that time, with data collected for AI/ML through December 2020. The total project budget was approximately $70,000.

The primary goals of the study include:

- To reduce energy consumption associated with biological and advanced treatment processes while maintaining water quality.
- To support operators as they are asked to achieve stringent water quality targets with increasingly complex treatment processes.

These goals were achieved by:

- Evaluating performance data from the Demo, which purifies tertiary effluent from the Tapia WRF with microfiltration (MF)/ultrafiltration (UF), reverse osmosis (RO), and ultraviolet advanced oxidation (UV AOP).
- Evaluating performance data from the biological nutrient removal system at the Tapia WRF, a conventional activated sludge wastewater treatment plant with tertiary filtration and chloramine disinfection.
- Using AI/ML to predict the performance of the membrane systems from the Demo and the biological treatment process from the Tapia WRF.

This project focuses upon two critical issues that California faces, energy and water. Through AI/ML implementation in water reuse, utilities across the state can reduce energy use in their biological and advanced treatment processes and create more reliable high-quality water.

The results described in this report build on both the original grant and previous AI/ML research that Carollo has conducted with the Yokogawa Electric Corporation (Yokogawa) and the National Water Research Institute (NWRI). This project was led by the LVMWD with support from Carollo and Yokogawa. Carollo and Yokogawa routinely collaborated with each other as well as with the LVMWD staff throughout the course of the project to gather data and share testing results. Findings of the study include the following:

- General Demo performance:
  - Extensive water chemistry sampling across the Demo demonstrates that the high-quality purified water meets all regulatory requirements for indirect potable reuse (IPR).
  - The performance of the MF/UF system was stable throughout the operational period without coagulant additional and at fluxes tested up to 50 gallons per square foot per day (gfd).

  - Pathogen monitoring:
    - Pepper mild mottle virus (PMMoV) log removal values (LRV):
      - 3.9 to 6.1 LRV across UF and 2.6 to 3.5 LRV across MF.
      - ~2 LRV across RO (limited by low PMMoV concentrations in the RO permeate).
    - Protozoa LRV across the MF/UF systems consistently exceeds ~4.5.
- Demo facility AI:
  - The initial AI model was able to predict the rise in MF/UF transmembrane pressure (TMP) over a 2-week period, which closely matched actual operational data.
  - A subsequent model revision allowed prediction of the entire month of December after training the model on the 40 gfd data set from November – the TMP data was predicted very well, but adjustments to the prediction parameters are needed to improve prediction of TMP recovery due to membrane cleaning. The AI underpredicted the effects of cleaning (i.e., the prediction was conservative, creating a safety margin).
    - Permeability predicted by the model was lower than actual operating data, including the recovery of permeability due to cleanings. This is advantageous as it means that predictions currently have a safety margin.
    - The capacity for model optimization and refinement and the improved accuracy of model predictions over time demonstrate significant promise for AI as a forecasting and operational tool for MF and UF membrane systems.
- Tapia WRF BioWin Modeling:
  - The plant-wide BioWin model (for the Tapia WRF activated sludge system) was initially updated to reflect the baseline operating condition (prior to the blower control change in June 2020). Coordination with operations staff supported further refinement and model calibration.
  - Aeration and return activated sludge (RAS) control could be further optimized to save on energy costs while maintaining and/or improving effluent water quality.
  - Installation of a secondary effluent ammonia probe would provide the online data that would further support process control/optimization.
- Tapia WRF Data Driven Model Optimization (DDMO):
  - DDMO demonstrated potential blower optimization (>10 percent energy savings) while maintaining effluent nitrogen concentrations less than discharge permit limits.
  - DDMO demonstrated that artificially setting the target effluent ammonium (NH_4-N) concentration to 1.0 milligrams nitrogen per liter (mg-N/L) (instead of 2.5) results in only a 3 percent higher energy cost.
  - A DDMO demonstration of blower control is planned for the summer of 2021.

The results of this study highlights the ability for AI/ML to improve operating efficiency with anticipated energy savings and benefits to water quality. This study's focus on common treatment processes such as aeration basins and MF/UF provides broad applicability to other utilities regionally, across the state, and nationally that either currently or intend to develop potable reuse. This project set the stage for future phases of work, now funded by other groups (e.g., the USBR) to further define and implement AI/ML solutions for biological and potable reuse treatment.

Conducting a full-scale DDMO demonstration will further refine the DDMO model and will also prove the effectiveness of the system under real-world operational scenario. This testing must occur during the irrigation/reuse season as opposed to the winter months when the Tapia WRF is discharging and must meet discharge water quality limits. Initially planned for November 2020, the demonstration was not logistically feasible before the end of the irrigation season in 2020 and was postponed until irrigation season 2021, which is funded by other grants. Planning includes defining solutions for efficiently transferring operational data and control setpoint updates on a frequent basis during the demonstration period. Through this testing, the team will not only further validate initial results of the DDMO simulations, but the team will also establish a protocol for data transfer which will serve as an important basis for the future implementation of AI projects.

In 2021, the LVMWD-Carollo-Yokogawa team was awarded two additional grants to continue to advance this work – a new grant from the Ministry of Economy, Trade, and Industry (METI) as well as a grant from the U.S. Bureau of Reclamation. Each of these grants will support advancement of the AI algorithms for potable reuse processes and also build upon the scope of this project to develop a user interface and data transfer to support the eventual implementation of these AI tools. Without the original funding and support from MWD and LVMWD, these other grant opportunities may not have been successful.

Section 1

INTRODUCTION

1.1 Background

In August of 2018, the Las Virgenes Municipal Water District (LVMWD) and Carollo Engineers (Carollo) submitted a grant application to the Metropolitan Water District (Metropolitan) under the Future Supply Actions (FSA) Funding Program. The grant requested funding to implement and test Artificial Intelligence (AI) and Machine Learning (ML) control algorithms as part of the LVMWD-Triunfo Joint Power Authority's Demonstration Facility (Demo) project, with the goal of determining if AI/ML could provide intelligent system control that would increase resilience and reliability of the new advanced water treatment facility (AWTF), which could further protect public health and reduce operating costs. The grant application was approved by Metropolitan. This project builds on previous research conducted with the Yokogawa/NWRI/Carollo team with the following goals:

- To reduce energy consumption associated with biological and advanced treatment processes while maintaining water quality.
- To support operators as they are asked to achieve stringent water quality targets with increasingly complex treatment processes.

These goals were achieved by:

- Evaluating the performance of the Demo, which purifies Tapia Water Reclamation Facility (Tapia WRF) tertiary effluent with microfiltration (MF)/ultrafiltration (UF), reverse osmosis (RO), and ultraviolet advanced oxidation process (UV AOP).
- Evaluating the performance of the Tapia WRF (a conventional activated sludge wastewater treatment plant with tertiary filtration and chloramine disinfection).
- Using AI to evaluate and predict the performance of the membrane systems from the Demo and the biological treatment process from the Tapia WRF.

This project provides critical value on two critical issues that California faces, energy and water. Through AI/ML implementation in water reuse, utilities across the state can reduce energy use in their biological and advanced treatment processes and create more reliable high-quality water.

The results of this study/grant are summarized in this report.

1.2 Project Team

This project was led by the LVMWD, with support from Carollo and from Yokogawa. Darrell Johnson with LVMWD is the point of contact for this grant.

Section 2

PROJECT COST AND SCHEDULE SUMMARY

The project started in June 2020 and has been ongoing since that time. The overall project schedule is presented in Table 1.

Table 1 Overall project schedule.

Date(s)	Milestone
June 2020	Project kickoff. Demo commissioned; start of ongoing water quality testing.
July 2020	Start of AI training data collection.
August 2020	Start of MF/UF test plan implementation, conducted in monthly cycles. Start of ongoing update to BioWin and DDMO accuracy analyses.
October 2020	Comparison of AI-predicted October performance vs. real October performance. Start of October/November AI training data collection.
December 2020	Comparison of AI-predicted December performance vs. real December performance.
January 2021	End of data collection for the study.
June 2021	Final Report completed.

The total project budget was approximately $70,000. Approximately 36 percent of this amount was allocated to Yokogawa, who acted as a subconsultant for Carollo. The project was finished on time and on budget.

Section 3

STUDY RESULTS AND ANALYSIS

3.1 Demo Performance

The Demo was commissioned in late June 2020 and has been consistently operating and producing high quality purified water and valuable performance data. Figures 1 and 2 show the exterior and interior of the Demo, respectively. Grab sample and online monitoring systems demonstrate the high level of performance achieved with the treatment process transforming tertiary recycled water to potable water quality. MF/UF membrane operational data has been provided on a routine basis to Yokogawa to support ongoing AI analysis of the MF/UF membranes.

Figure 1 Exterior of LVMWD Pure Water Demonstration Facility.

Figure 2 Interior of LVMWD Pure Water Demonstration Facility.

A summary of relevant Demo operational details, providing important operational and performance information incorporated into the AI analysis includes:

- Water Quality:
  - Extensive water chemistry sampling has been conducted across the Demo, documenting the high-quality purified water that meets all regulatory requirements for indirect potable reuse (IPR).
- Operational performance conditions:
  - The MF/UF test plan was followed in monthly cycles, where either the target flux or maintenance clean (MC) frequency was adjusted, followed by a month of observation. Between each monthly cycle, recovery cleans were conducted on the MF/UF system. The MF/UF setpoints analyzed for August 2020 through December 2020 were:
    - August 2020 – 30 gallons per square foot per day (gfd), Twice Weekly MCs – Recovery Clean (RC) at end of August.
    - September 2020 – 35 gfd, Twice Weekly MCs – RC at end of September.
    - October 2020 – 35 gfd, Weekly MCs – RC at end of October.
    - November 2020 – 40 gfd, Weekly MCs – RC at end of November.
    - December 2020 – 40 gfd, Weekly Maintenance Cleans – Recovery Clean at end of December.

  - The hotter temperatures experienced until October resulted in the temperature corrected flux being approximately 5 gfd lower than the operational flux set point. Cooler temperatures at the end of 2020 resulted in the temperature corrected values converging.
    - Even with cooler temperatures, the performance of the MF/UF system was stable throughout the operational period without coagulant addition and at fluxes tested up to 45 gfd.
- Pathogen monitoring:
  - Preliminary sampling was conducted for pepper mild mottle virus (PMMoV), which is indigenous to wastewater at high concentrations.
  - PMMoV sampling has indicated that virus LRV across the low-pressure membrane systems of 3.9 to 6.1 for UF and 2.6 to 3.5 across MF. Removal of PMMoV by RO was about 2 LRV, limited by low RO permeate PMMoV concentrations.
  - Some initial PMMoV samples were subject to quality control issues which have since been resolved with improved sampling methods.
  - Protozoa LRV, as indicated by pressure decay testing, has been stable across the MF/UF systems with typical LRVs exceeding 4.5.

3.2 Demo Facility AI

On a routine basis, Carollo provided Yokogawa with operational data to support AI algorithm development, focused on the MF/UF systems. The preliminary analysis focused on the flux, TMP, and MC intervals with the goal of optimizing the MC frequency based on flux. The AI model used inputs as illustrated in Figure 3.

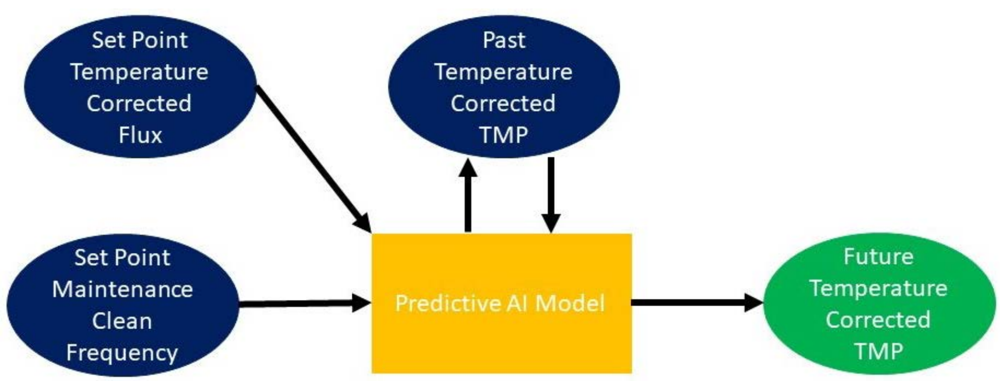

Figure 3 AI modeling approach currently trialed for TMP prediction.

Results of this analysis for temperature corrected operating fluxes of 26 and 30 gfd before October 2020 are presented in the following figures.

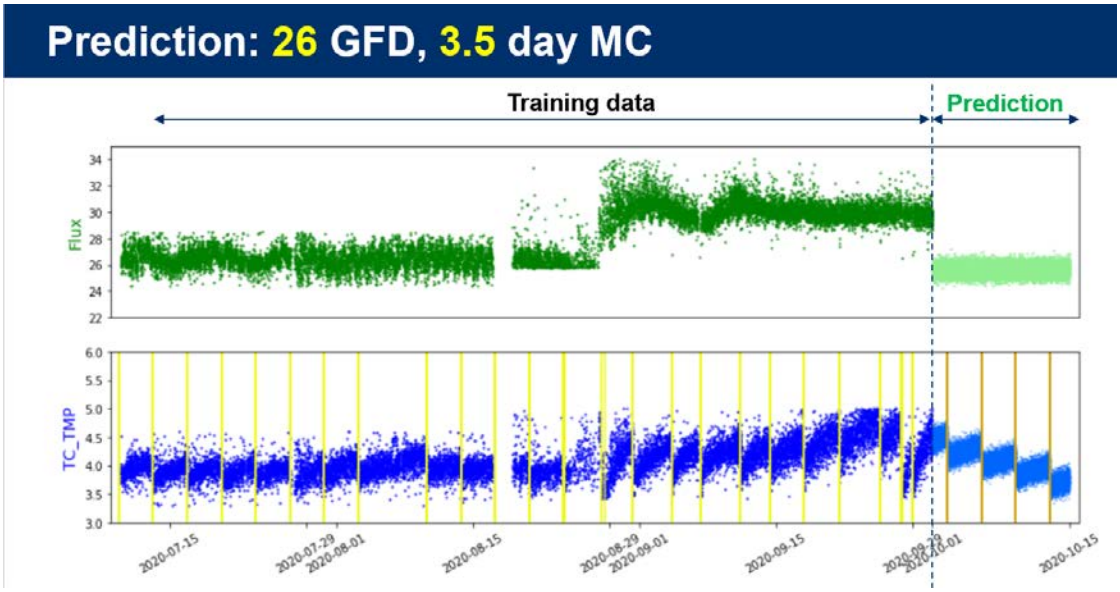

Figure 4 AI-predicted decreasing TMP over the prediction period suggests that the MC interval could be increased for a temperature corrected flux of 26 gfd.

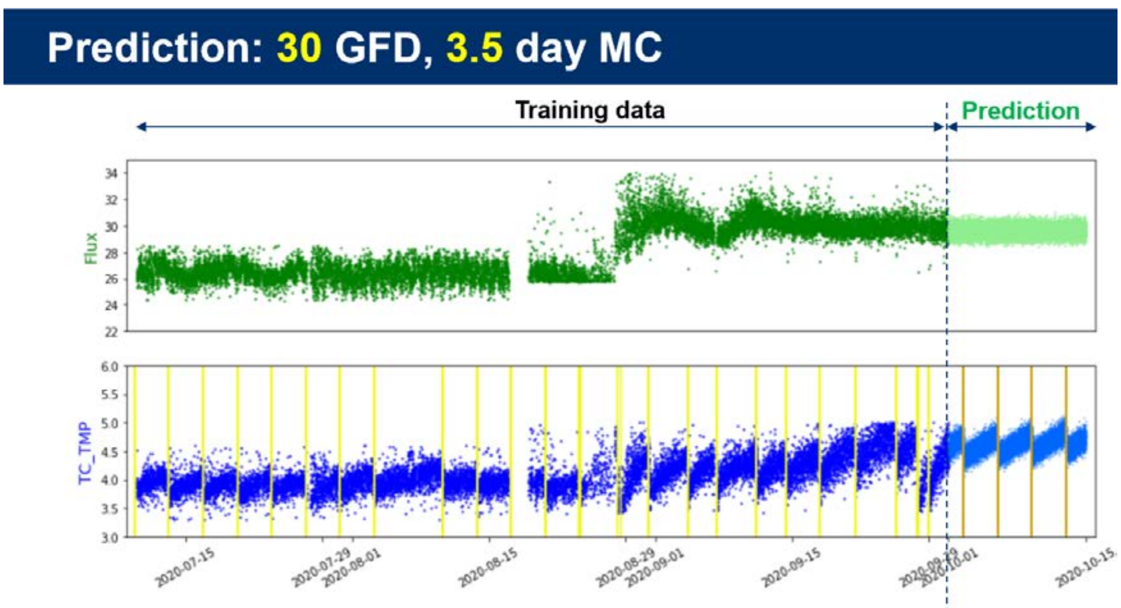

Figure 5 AI-predicted consistent TMP over the prediction period suggests that the MC interval is appropriate for a temperature corrected flux of 30 gfd.

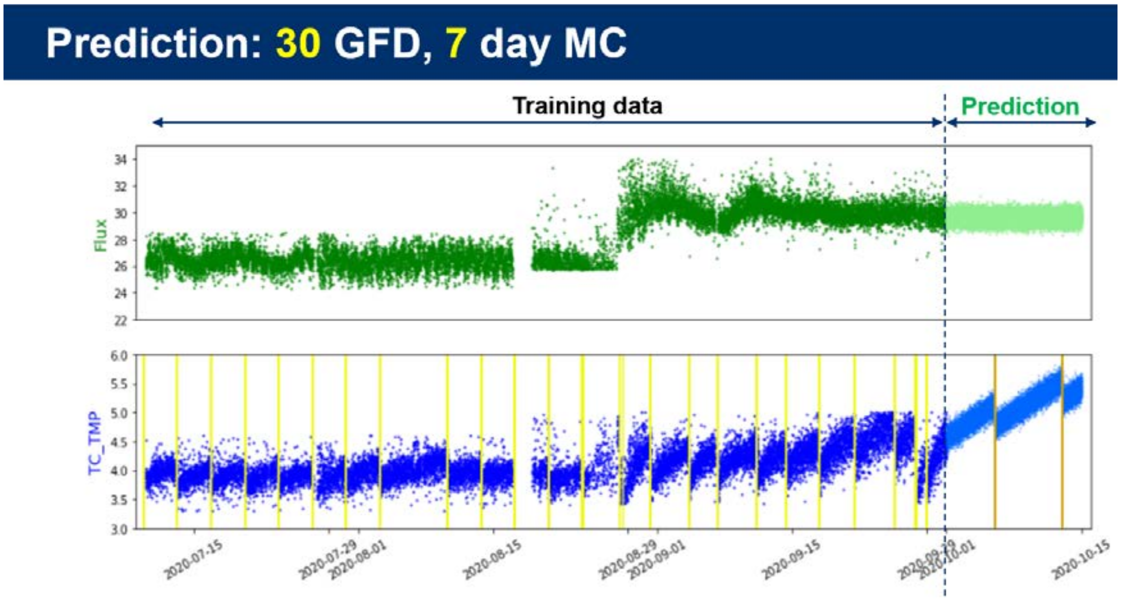

Figure 6 AI-predicted consistent TMP over the prediction period suggests that the MC interval should be decreased for a temperature corrected flux of 30 gfd.

The TMP predictions for early October were validated against recorded operating data as they coincided with an operational change. Prior to October, when the modeling took place, the test condition for a temperature corrected flux of 30 gfd with a 7-day maintenance cleaning interval had not been tested. Hence, it should be noted that the predictions were being made outside of the model calibrated range. In addition, the maintenance clean schedule was not established prior to modelling, and as a result, the predicted and actual maintenance cleans occur on different days, which impacted results by a fixed error.

A comparison of the actual operating flux, temperature-corrected flux and model input temperature-corrected flux is shown in Figure 7. Data were expressed as a 5-minute rolling averages and were filtered prior to averaging to ensure that non-operational data (i.e., backwash or maintenance clean values) were not included.

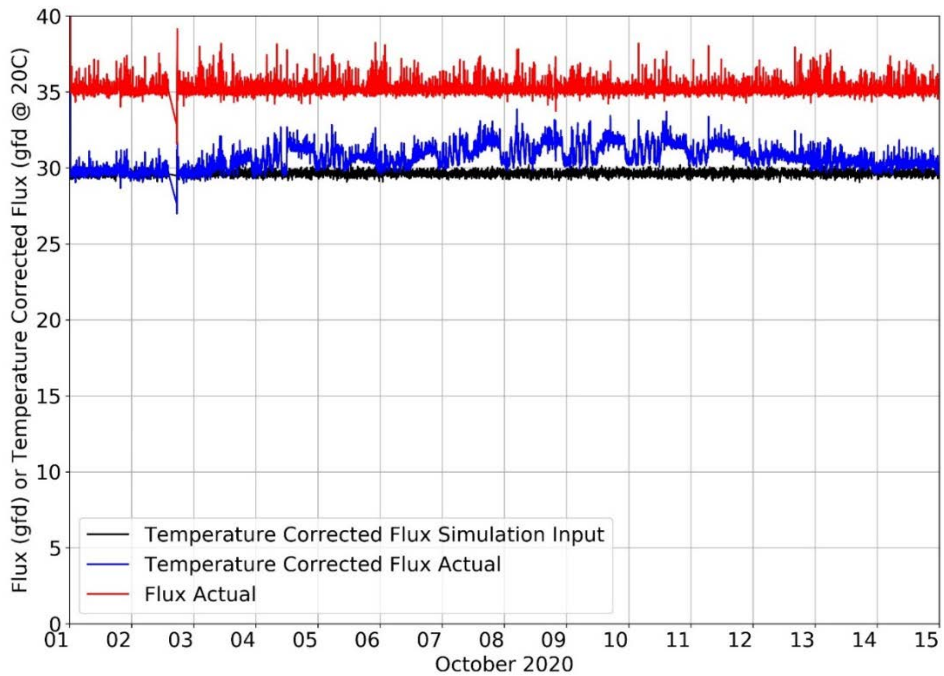

Figure 7 Comparison of model input temperature corrected flux (black), actual temperature corrected flux (blue), and operational flux (red) for the modeled period.

From Figure 7 the following observations can be made:

- The operational flux is approximately 5 gfd higher than the temperature corrected flux due to a feed water temperature typically higher than 25 degrees Celsius (C).
- The operational flux is the control variable and is more stable than the temperature corrected flux which varies according to feedwater temperature.
- Cyclic feedwater temperature variations have been noted and are due to the filling and drawdown cycles of the upstream Tapia WRF effluent reservoir.
- Operational data is more variable than simulation inputs. Nevertheless, actual temperature corrected flux was within 2.5 gfd (8.5 percent) of the simulated input throughout the predicted period.

Based on the information in Figure 7, it was recommended that normal operating flux (i.e., not temperature corrected) is used as a future model input as it is the more stable control variable.

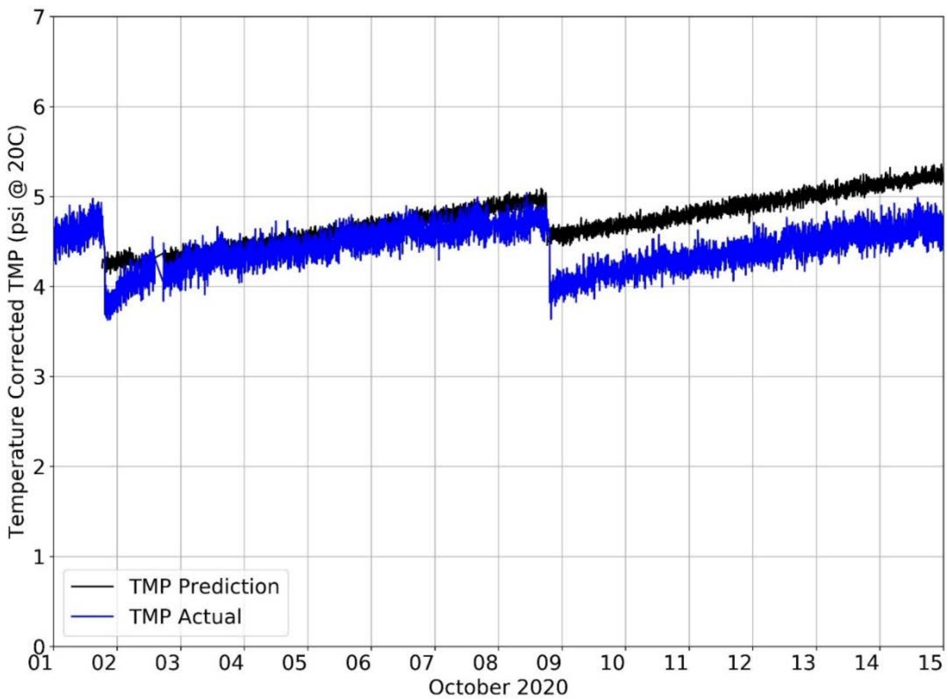

Figure 8 Comparison of model output temperature corrected TMP (black) and actual temperature corrected TMP (blue) for the modeled period. Step decreases on the 2nd and 9th of October are due to MC events.

From Figure 8 (above) the following observations can be made:

- The general reduction of TMP following a maintenance clean was more than that predicted by the model. It is suggested that analysis of permeability recovery achieved by maintenance clean may be a more effective predictor of TMP change following a maintenance clean and this resulted in higher discrepancies when predicting data further into the future (i.e., greater than 1 week or more than 1 MC).
- In general, the rise of TMP over time predicted by the model was similar to the rise noted in actual data which is promising when it is considered that the prediction extrapolated over two weeks into the future.
- It should also be noted that the prediction evaluated was outside of the model's validated range and that some error should be anticipated.

The comparison of predicted permeability is shown against actual permeability for the modeled period in Figure 9.

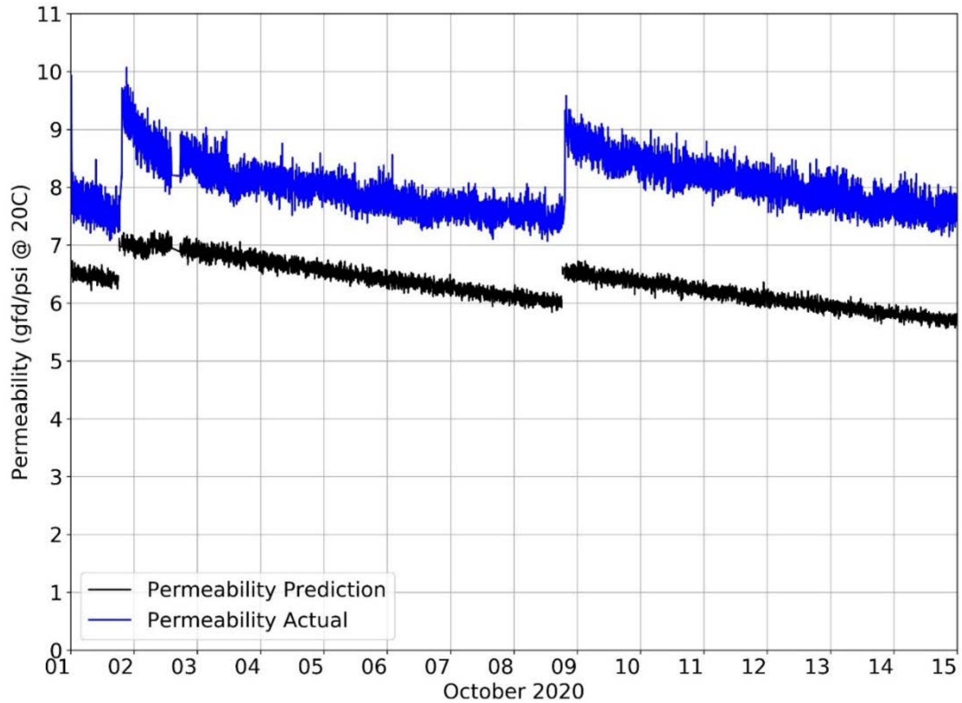

Figure 9 Comparison of model output temperature corrected permeability (black) and actual temperature corrected permeability (blue) for the modeled period. Step increases on the 2nd and 9th of October are due to MC events.

From Figure 9 the following observations can be made:

- The TMP slope for the AI prediction matches the actual data.
- Similar to the TMP model, the effectiveness of MCs to recover permeability has been under predicted by the AI model but the general trend in decline is similar.
- The permeability predicted by the model is lower (i.e., more conservative) than the actual operating data. This is advantageous as it means that predictions currently have a safety margin.

Initial modeling results demonstrated that there did not appear to be large deviations in performance over the two-week model prediction period and the predicted results included a safety margin.

Based the initial results, the next step in the analysis was to update the AI model with new data from October and November 2020. The recommendation was made to evaluate membrane permeability, instead of TMP, to account for small fluctuations in flux (due to system control tuning) that impact the sensitivity of the AI algorithm results. In addition, it was recommended that normal operating flux (i.e., not temperature corrected), was used as the control input. The system flux was increased by approximately 5 gfd every 30 days with a recovery clean prior to each flux increase. The data analysis and predictions are shown in the following figures.

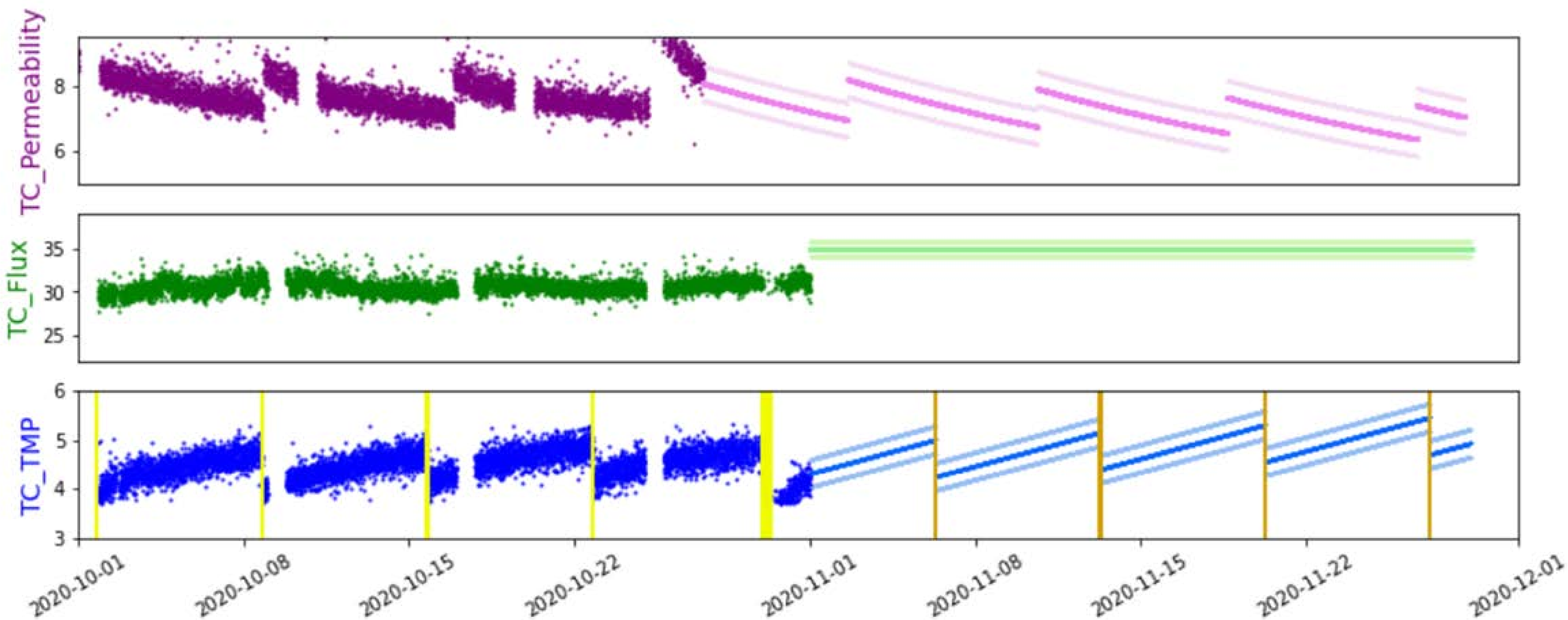

Figure 10 Update of Pure Water Demo AI model with October 2020 data for prediction of November 2020 data.

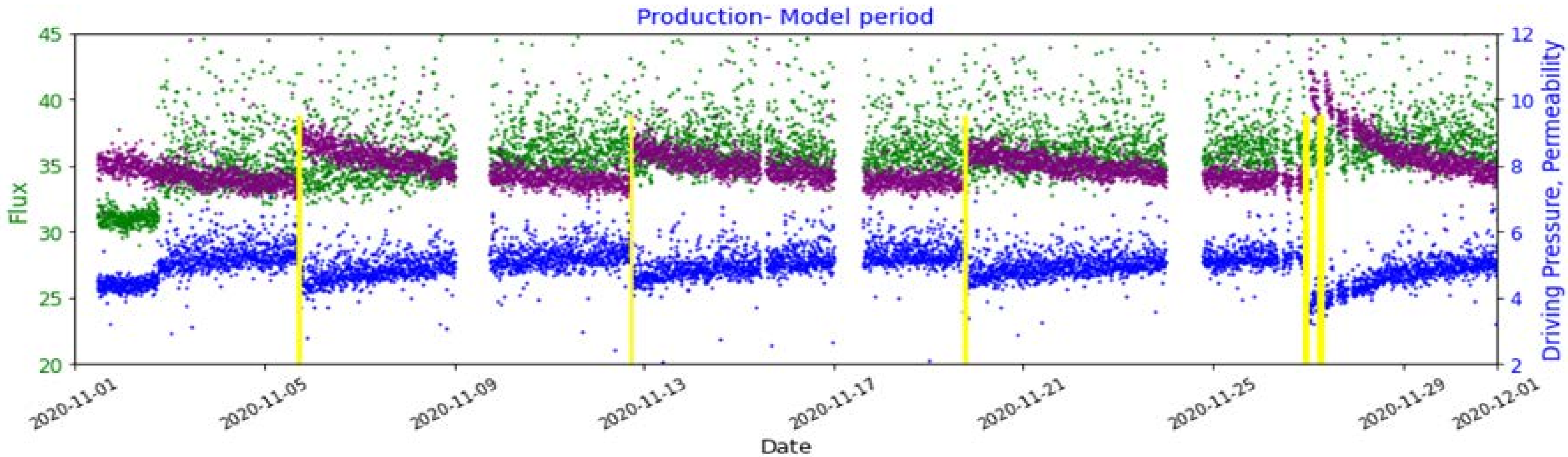

Figure 11 Plot of November 2020 model training data after outlier analysis.

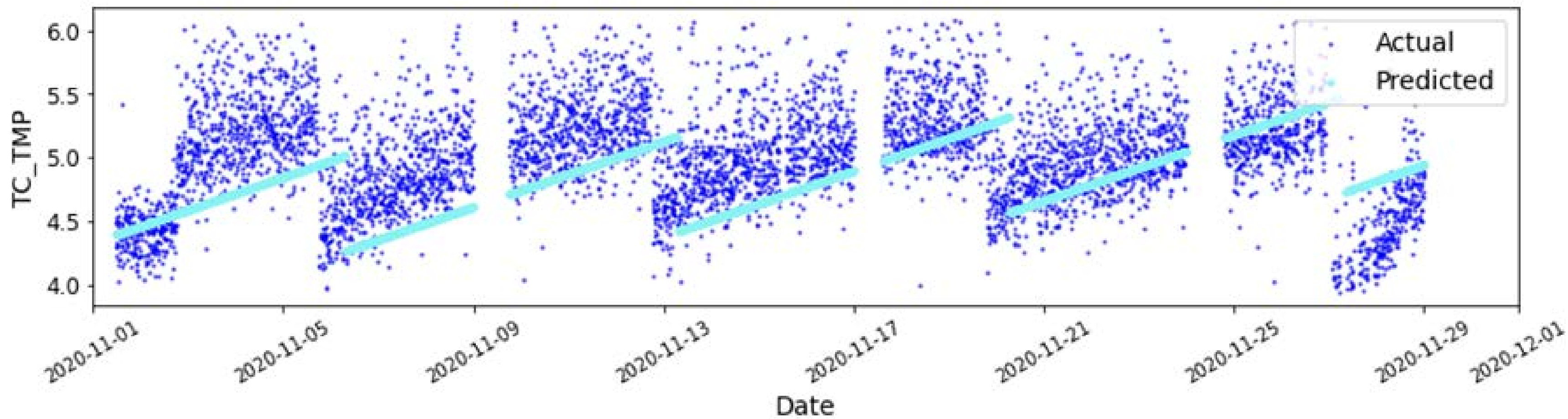

Figure 12 Comparison between actual (blue dots) and modelled (light blue lines) TMP for November 2020 training data.

Due to system issues, the MF/UF was operated at a flux set point of 40 gfd and a 7-day cleaning interval throughout December 2020. Yokogawa provided an estimate of the temperature corrected TMP for the entire month of December, using November 2020 as the training data set. The December flux, measured and predicted temperature-corrected TMP, and predicted and measured permeability are shown in Figure 13, Figure 14, and Figure 15, respectively.

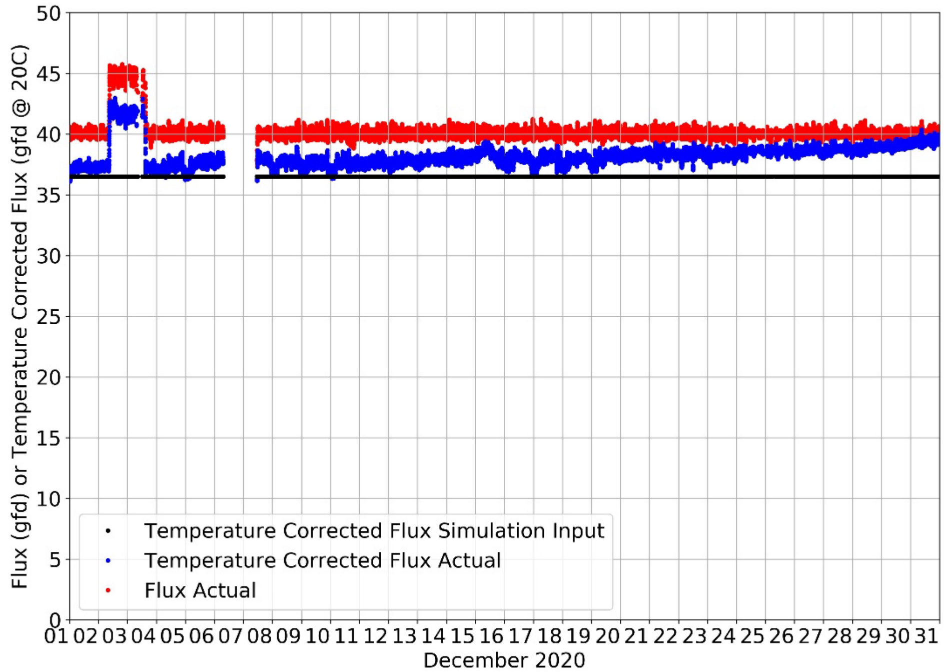

Figure 13 Comparison of model input temperature corrected flux (black), actual temperature corrected flux (blue), and operational flux (red) for the revised December model.

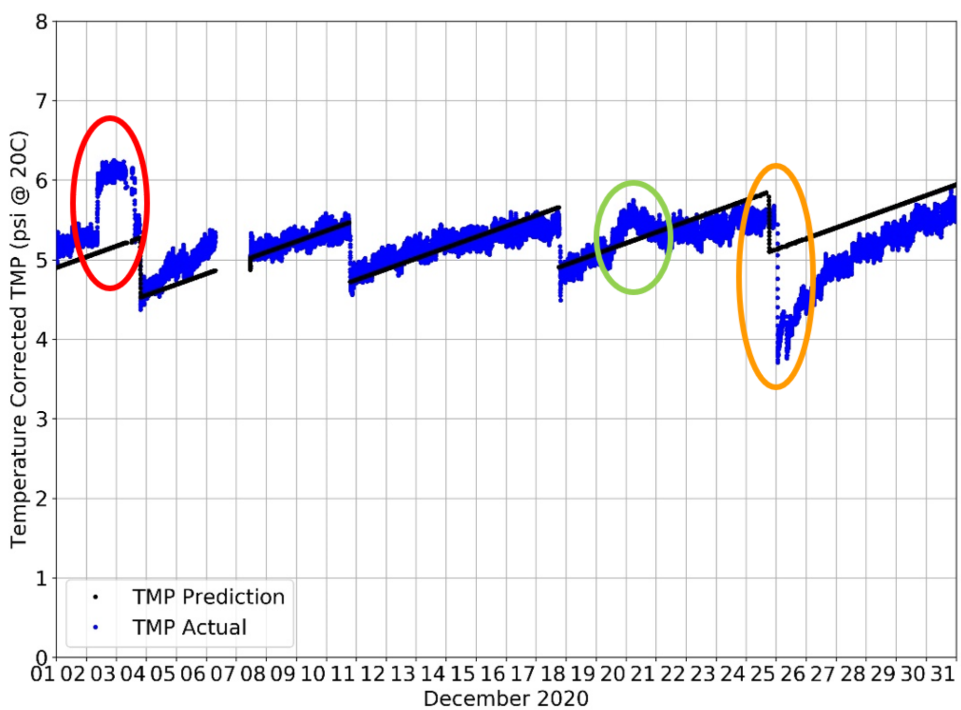

Figure 14 Model output (black) and actual (blue) temperature corrected TMP for the revised December model. Outlier events were an unscheduled flux increase (red) and a recovery clean (orange). Unknown outlier behavior also occurred (green).

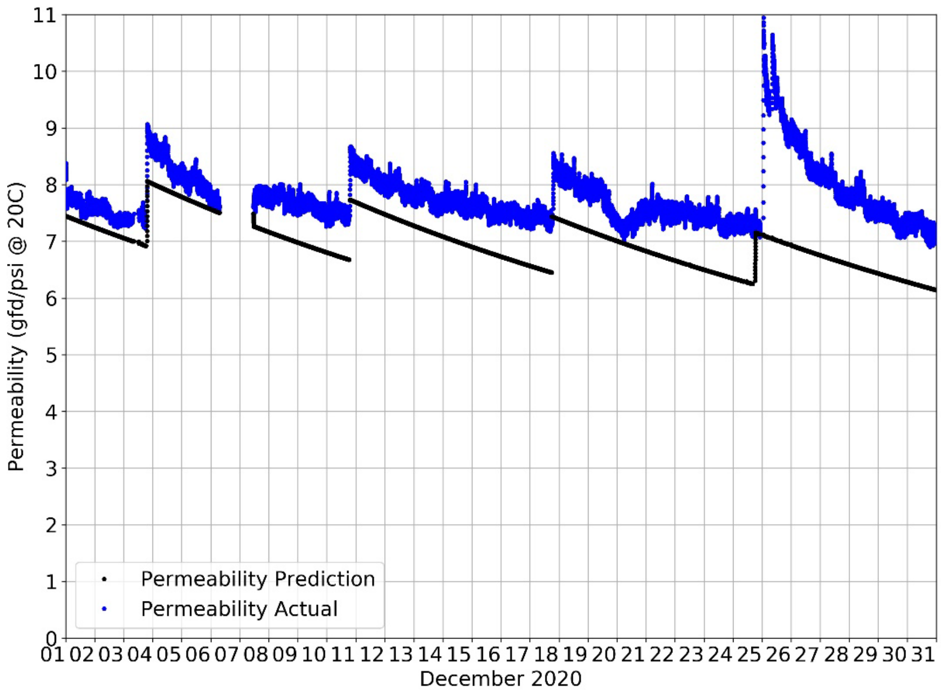

Figure 15 Model output temperature corrected permeability (black) and actual temperature corrected permeability (blue) for the revised December model.

The revised AI predictions for the December period were significantly improved. The following observations were made:

- The model was used to predict operating data set points for which it had been trained.
- TMP agreement was excellent with prediction of both the TMP rate of increase and absolute value, with the exception of three outliers (Figure 14).
  - Outlier 1 was due to an unscheduled flux increase that was not modeled and is not relevant (red circle).
  - Outlier 2 was due to an RC (orange circle) and indicated that there are potential model improvements for predicting TMP recovery by a recovery clean, relative to a lower strength and duration MC, which the model now appears to successfully predict.
  - Outlier 3 (green circle) could not be isolated to a specific cause. However, it is of note that discrepancies between the model performance and actual data could be used to detect operational events that require further investigation.
- Flux and temperature corrected flux began to converge towards the end of December coinciding with lower daily temperatures (Figure 13). It is likely that the discrepancy between actual temperature-corrected flux and predicted temperature-corrected flux were in part responsible for increasingly divergent permeability predictions further towards the end of December (Figure 15).
  - It is recommended to consider modeling the flux without temperature correction and to potentially use long term trends of ambient vs. feedwater temperature to learn and better predict future temperature corrected flux.
- As for the first set of validated forecasts, permeability prediction was conservative, which is advantageous for sustainable operational recommendations.

The following conclusions can be made based upon the AI modeling conducted in 2020:

- TMP predictions are possible with the AI model developed for the Pure Water Demo MF/UF system.
- The predictions are conservative (i.e., they underpredict performance), which provides a safety margin for operations.
- It is important to align the predicted and actual maintenance clean frequency for AI model accuracy.
- Flux without temperature correction is a controlled variable and should be used instead of temperature-corrected flux to predict TMP.
- Investigation of long-term trends in ambient temperature and feedwater temperature may help to forecast temperature-corrected flux (and permeability) more accurately.
- Temperature-corrected permeability may be more appropriate as the key AI parameter for this process since it is more stable than TMP, due to the fact that it is normalized for variation in flux.

Future development of AI for potable reuse include the advancement of the existing MF/UF process optimization as well as creating new algorithms for processes such as ozone/biofiltration or other advanced treatment processes. Expanding the scope of analysis to include key process indicator water quality characteristics (i.e., feed water turbidity and dissolved organic carbon [DOC]) and opportunities to optimize power demand and chemical feed will be a key component in developing a portfolio of AI algorithms that can be deployed for potable reuse systems. The long-term goal for updating the MF/UF AI algorithm is illustrated in Figure 16.

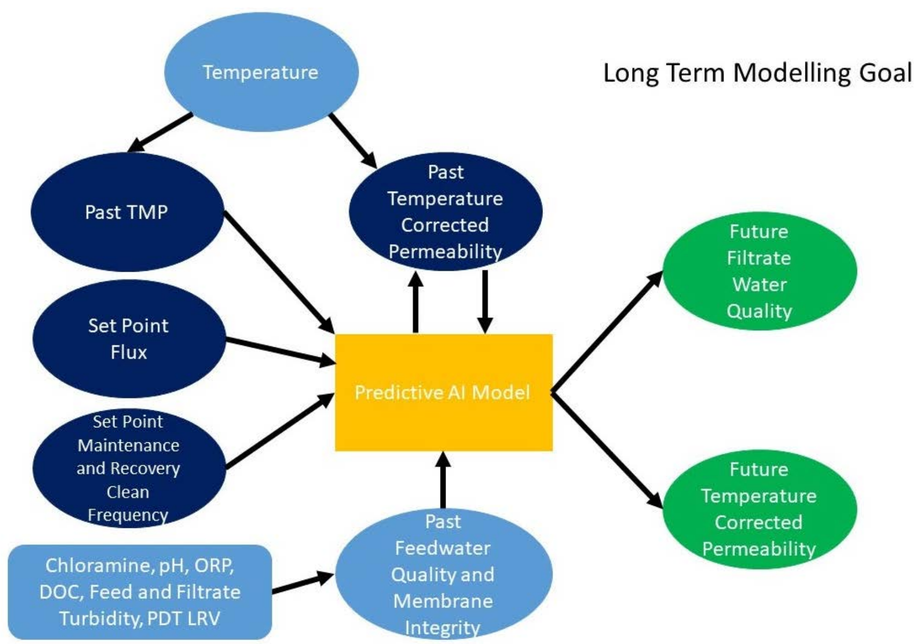

Figure 16 Proposed long-term goals for AI modeling that incorporate an assessment of both production efficiency (permeability) and water quality.

3.3 Tapia WRF BioWin Model and AI

The Tapia WRF has a four-stage Bardenpho configuration for biological nutrient removal with two trains in parallel (Figure 17). Tapia WRF secondary treatment has six basins, three for each parallel train. In each train, the first basin is unaerated (anoxic) for denitrification. The second basin is aerated (aerobic) for nitrification. There is internal recycle from the second basin to the first to send the resulting nitrate to the anoxic zone for denitrification. The third basin has an initial anoxic zone for further denitrification followed by aerated aerobic zone for further nitrification. The basins for one train are labelled 3, 2, 1 and for the other train are labelled 4, 5, 6 (Figure 18). Thus, basins 3 and 4 are anoxic/unaerated and basins 1, 2, 5, and 6 are aerobic/aerated.

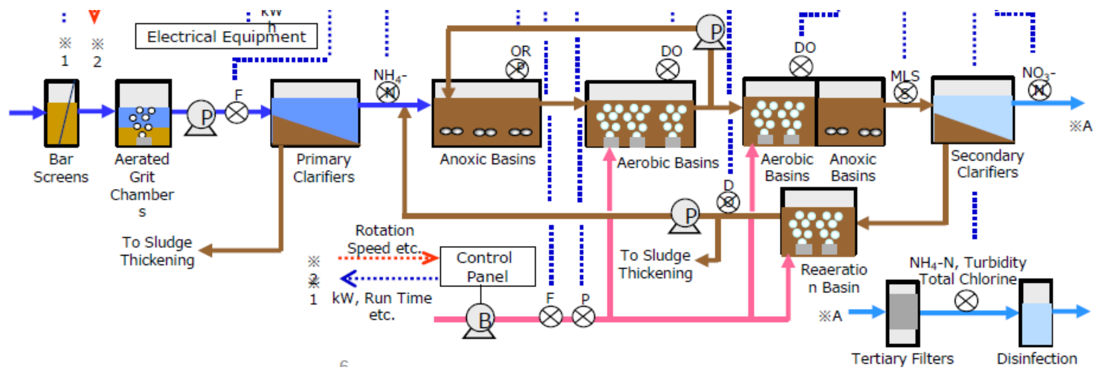

Figure 17. Tapia WRF – Process Flow Diagram.

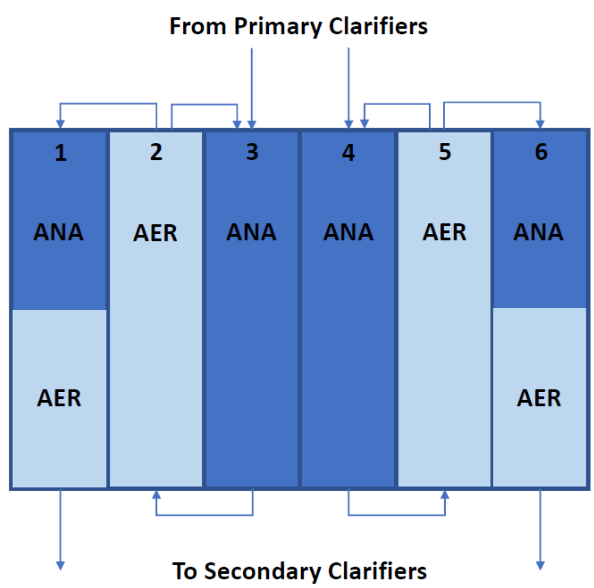

Figure 18. Diagram of Tapia WRF basin numbers.

During the August through October period of work, both an updated BioWin model and machine learning analysis for the Tapia WRF process was started. Prior to this project, the most recent version of the Tapia WRF BioWin model was completed in 2007. The project team gathered comprehensive operational data in July covering the September 2019 through June 2020 period. The Tapia WRF BioWin simulation configuration included the following assumptions (confirmed with Tapia WRF operations staff):

- Aeration tank dimensions and configuration based on 2018 *Process Air Improvements* project drawings.
- Each of the three passes represented as two complete-mix bioreactor elements.
- Biological selector channels out of service.
- Assumed typical settled sewage (primary effluent) carbon, nitrogen, and phosphorus wastewater fractions.
- Assumed default fine-bubble diffuser model parameters.
- May 17-23 selected as the performance data used for BioWin calibration to match DDMO selected period.
- 1-min data aggregated to calculate hourly- and daily-average values.
- IWA diurnal flow and load pattern tool used to estimate diurnal flow rates and COD, TKN, and TP concentrations for dynamic simulation.

Once the model was configured, the process variables were calibrated based on the operational data provided. The figures below show some of the key parameters and processes included in the updated BioWin model.

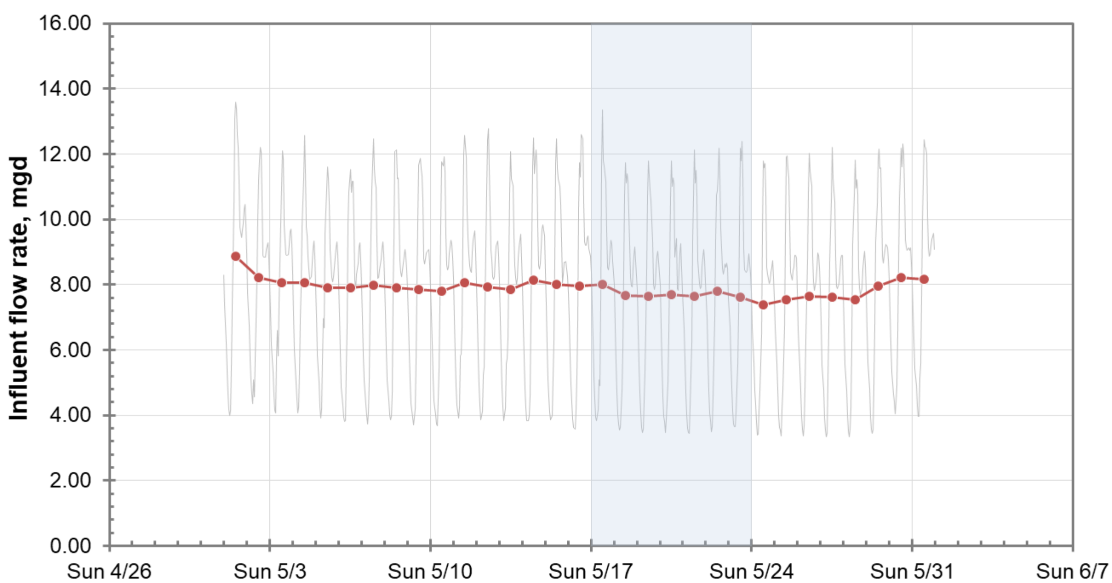

Figure 19 Tapia WRF influent flow (highly variable on a diurnal basis).

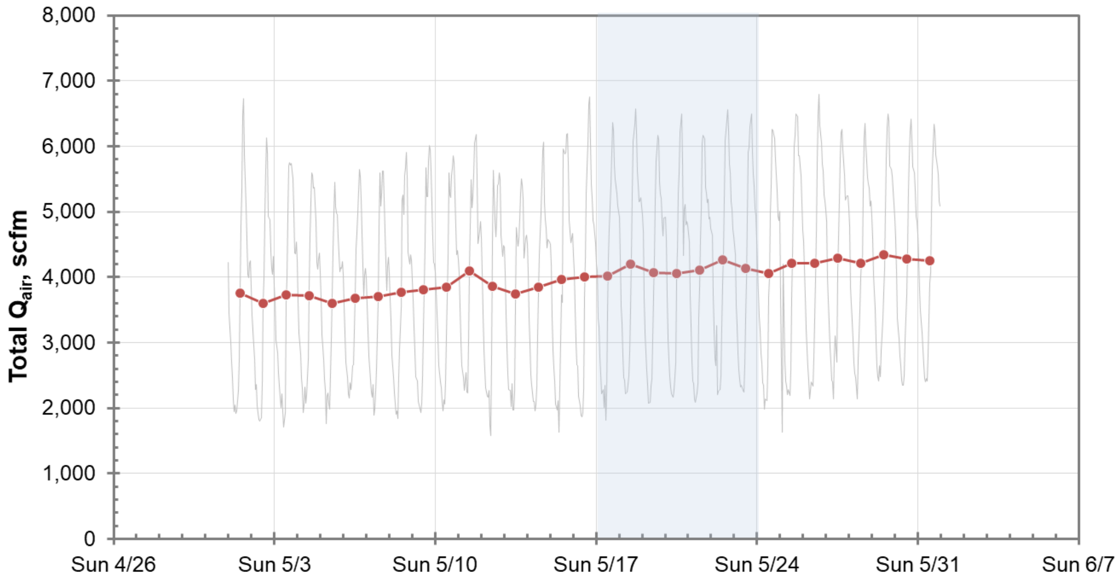

Figure 20 Tapia WRF total aeration flow (highly variable based on original DO setpoint control strategy)

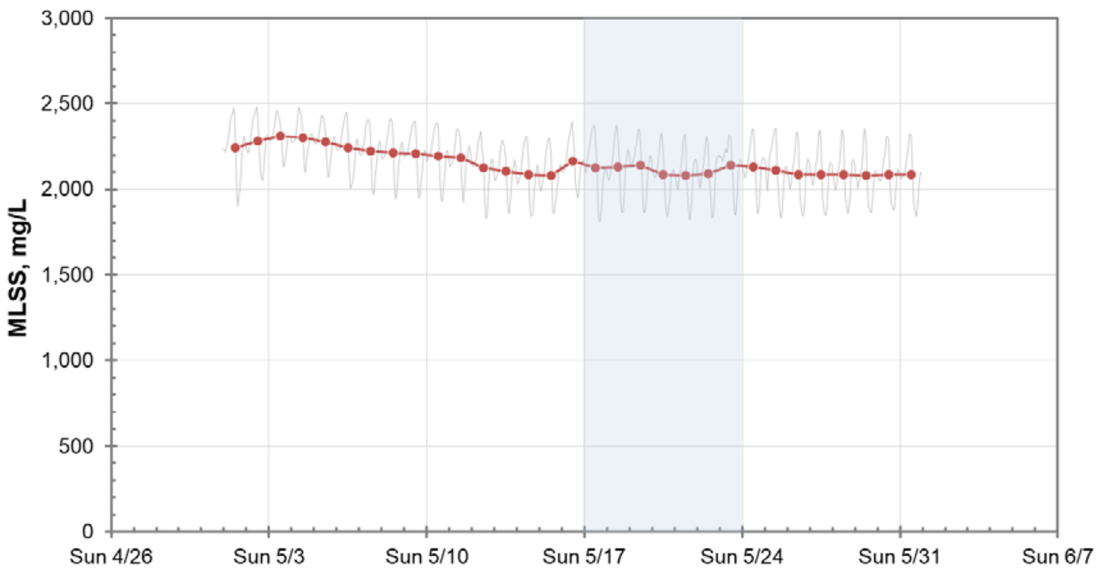

Figure 21 MLSS concentration.

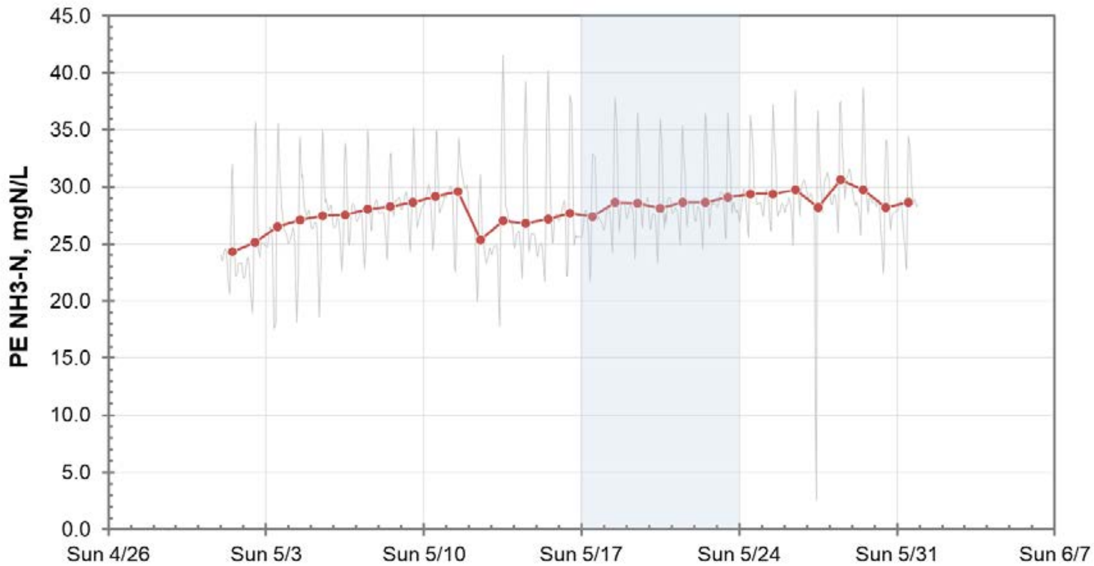

Figure 22 Primary clarifier effluent ammonia.

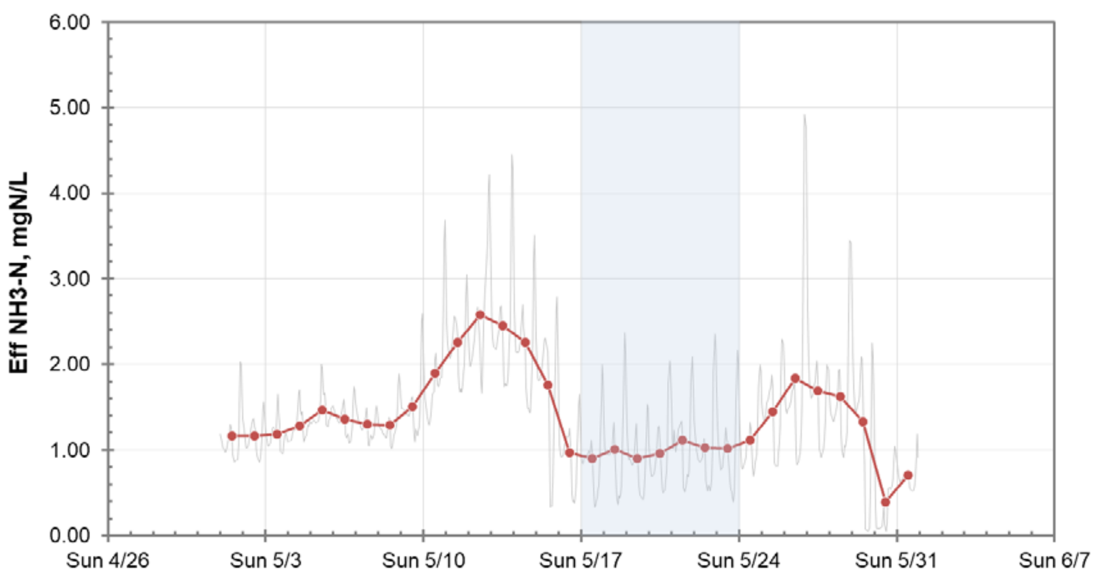

Figure 23 Tertiary effluent ammonia (mg/L as N). Note that this parameter is measured at the tertiary effluent so additional aqueous ammonia used for chloramine disinfection is included in this measurement (an ammonia probe on the secondary clarifier effluent is recommended to provide the necessary data to support future optimization of the aeration process).

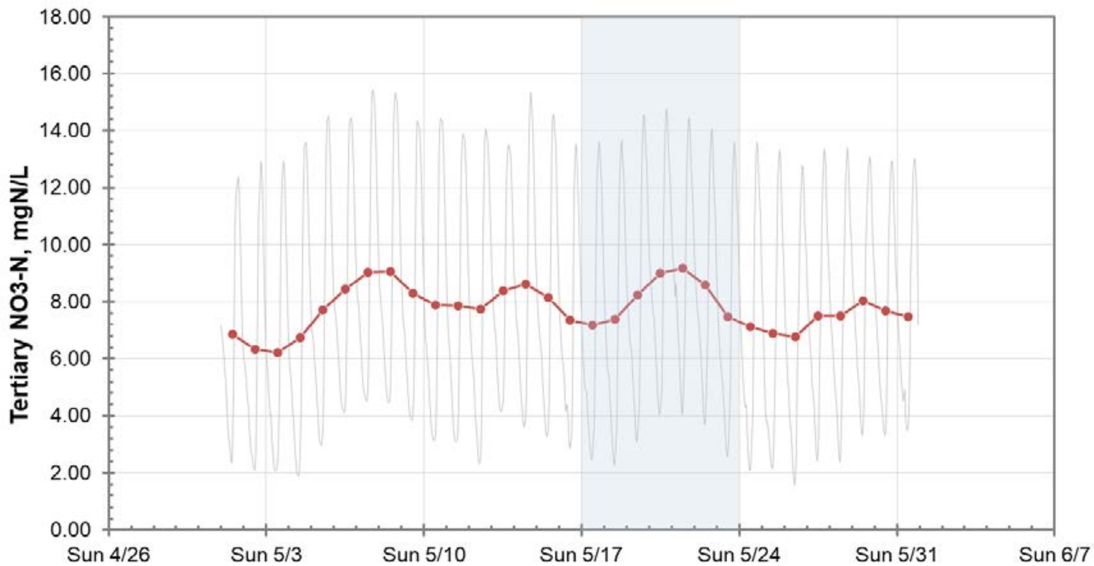

Figure 24 Tertiary influent (secondary effluent) nitrate (mg/L as N).

Table 2 Summary of steady-state BioWin parameters compared to actual plant data.

Parameter	5/17 - 5/23 average	Steady-state simulation	
MLSS, mg/L	2,111	2,213	+4.8%
RAS TSS, mg/L	5,619	5,504	-2.0%
WAS solids load, klb/d	6.22	5.99	-3.7%
SE NH3-N, mgN/L	0.99	0.18	-0.81 mgN/L
SE NO3-N, mgN/L	8.15	7.56	-0.59 mgN/L
$Q_{air,\ Pass\ 2}$, scfm	3,137	3,432	+9.4%
$Q_{air,\ Pass\ 3}$, scfm	986	829	-15.9%
$Q_{air,\ total}$, scfm	4,123	4,261	+3.3%

Notes:
klb/d thousand pounds per day mg/L milligrams per liter scfm standard cubic feet per minute

Table 3 Summary of steady-state and Dynamic BioWin parameters compared to actual parameters.

Parameter	5/17 - 5/18 average	Steady-State Simulation		Dynamic Simulation (daily average)	
MLSS, mg/L	2,111	2,213	+4.8%	2,125	+0.7%
RAS TSS, mg/L	5,619	5,504	-2.0%	5,790	+3.0%
WAS solids load, klb/d	6.22	5.99	-3.7%	6.28	+1.0%
SE NH3-N, mgN/L	0.99	0.18	-0.81 mgN/L	1.08	+0.09 mgN/L
SE NO3-N, mgN/L	8.15	7.56	-0.59 mgN/L	7.82	-0.33 mgN/L
$Q_{air,\ Pass\ 2}$, scfm	3,137	3,432	+9.4%	3,192	+1.8%
$Q_{air,\ Pass\ 3}$, scfm	986	829	-15.9%	966	-2.0%
$Q_{air,\ total}$, scfm	4,123	4,261	+3.3%	4,158	+0.8%

A steady-state simulation was able to match activated sludge solids inventory, but not effluent ammonia concentration. Dynamic simulation was able to match flow-weighted daily average effluent ammonia concentration:

- The relative proportion of RAS flow to primary effluent flow throughout the day causes significant diurnal change in aeration tank and reaeration tank solids inventory. The total solids inventory does not change significantly throughout the day, but a portion of the solids inventory shifts from the aeration basins to the RAS basins and back as the RAS flow and primary effluent flows change. This shift can affect aeration basin nitrification and denitrification performance.
- BioWin DO setpoint control achieves "perfect" control for process simulations, which is not representative of actual operating conditions that can be affected by actual performance of aeration air control valves, dissolved oxygen probes, and aeration air blowers.

The project team elected to utilize Yokogawa's statistical predictive model DDMO to optimize dissolved oxygen and chemical usage to meet target effluent water quality parameters while maintaining a reasonable margin of safety. The DDMO software is slightly different than the AI algorithms used for the UF analysis but has a proven track record for this type of system optimization analysis. DDMO is a modeling software that can create a model from operation data automatically using statistical methods. DDMO extracts relationships among variables from data to generate characteristic equations. DDMO automatically adjusts these equations in response to changes in plant operations to derive optimal manipulated values such as airflow rate or DO.

DDMO provides continuous modeling of actual performance data, looking back up to one week while predicting targeted water quality and process parameters 10 hours into the future. In the characteristics of DDMO analysis for the Tapia WRF, linear characteristic equations were developed to optimize the airflow rate and DO setpoints based upon the known characteristics of the facility. The derived numerical formulas are redefined and automatically convert mathematical formulas that calculate optimum values.

After the raw data was sorted and analyzed, the DDMO model was developed based on a 1-week learning period (5/15/20 to 5/21/20) and a 1-week evaluation period (5/22/20 to 5/29/20). Figures 24 through 33 illustrate the initial DDMO evaluation which was set to optimize energy consumption (i.e., reduce airflow) while maintaining effluent ammonia, nitrate, total nitrogen, and turbidity within the discharge limits.

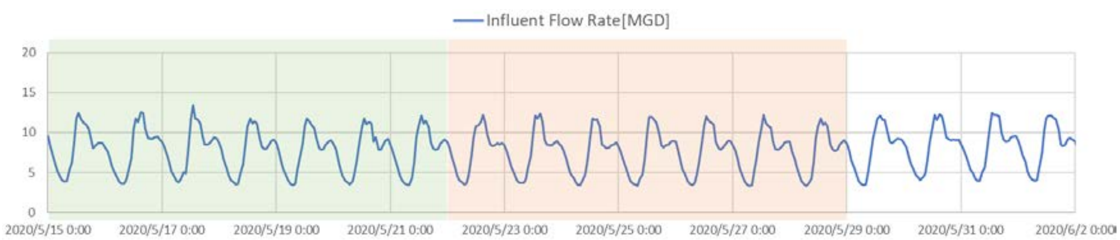

Figure 25 Example plot of the DDMO learning and evaluation period for the Tapia WRF influent flow rate.

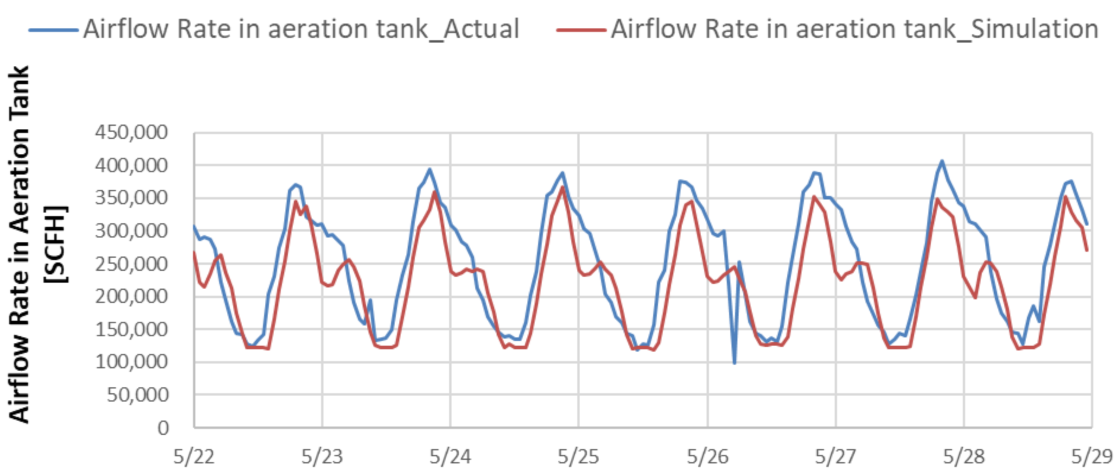

Figure 26 Actual and DDMO-optimized air flow rates for the evaluation period.

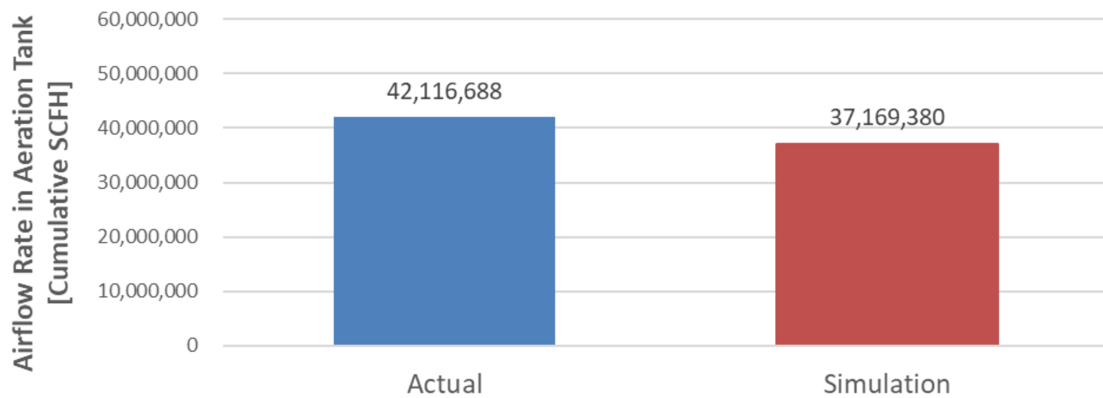

Figure 27 Actual and simulated air flow (cumulative scfh) for evaluation period.

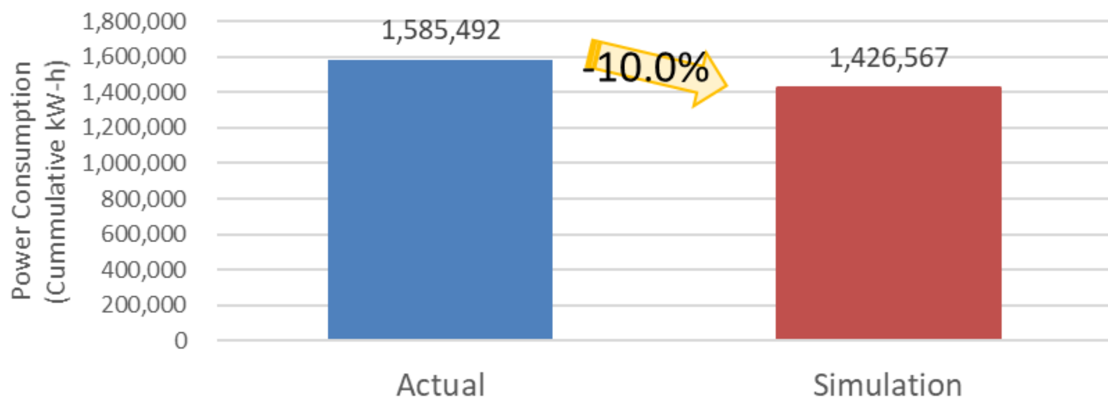

Figure 28 Estimated cumulative (kW-h) power consumption for the actual and simulated air flow rates during the evaluation period.

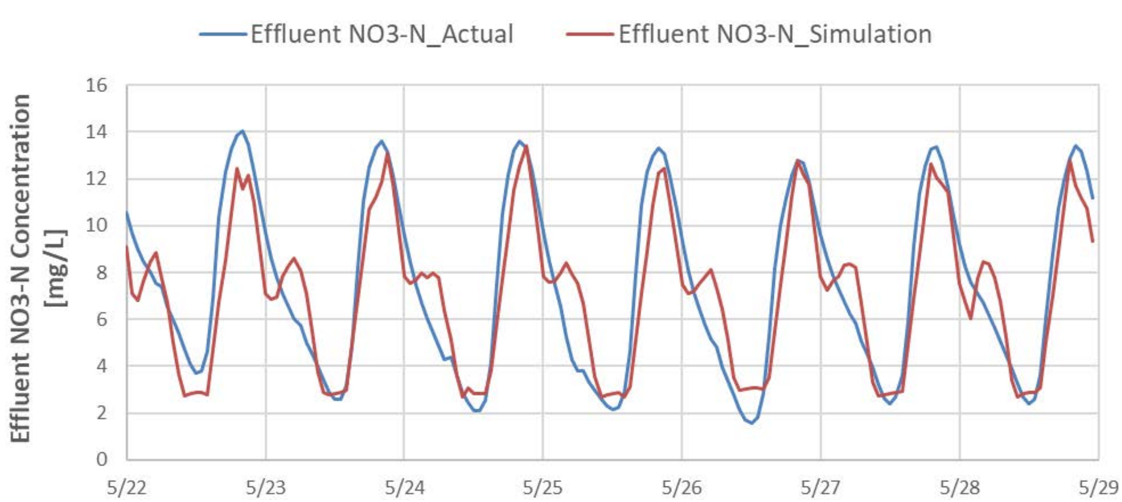

Figure 29 Actual and simulated effluent NO_3 concentrations for evaluation period.

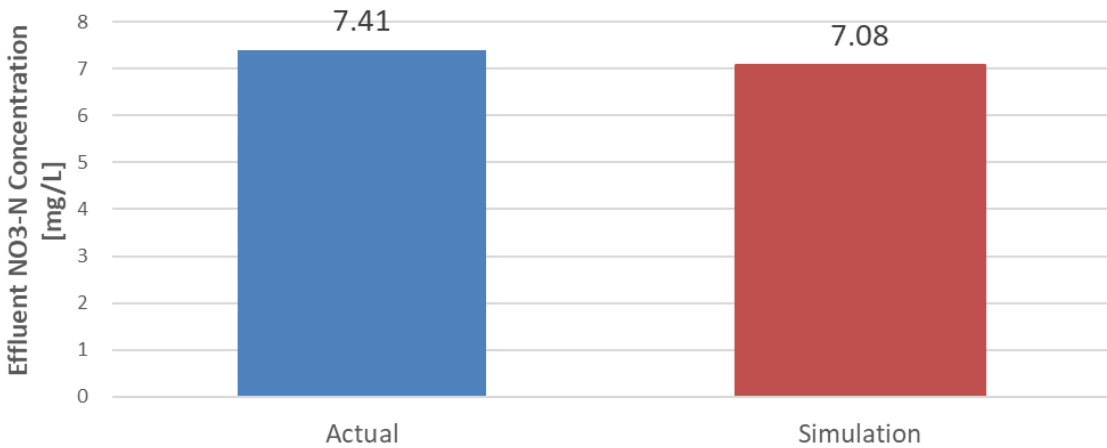

Figure 30 Actual and simulated effluent NO_3 concentrations (average) for evaluation period.

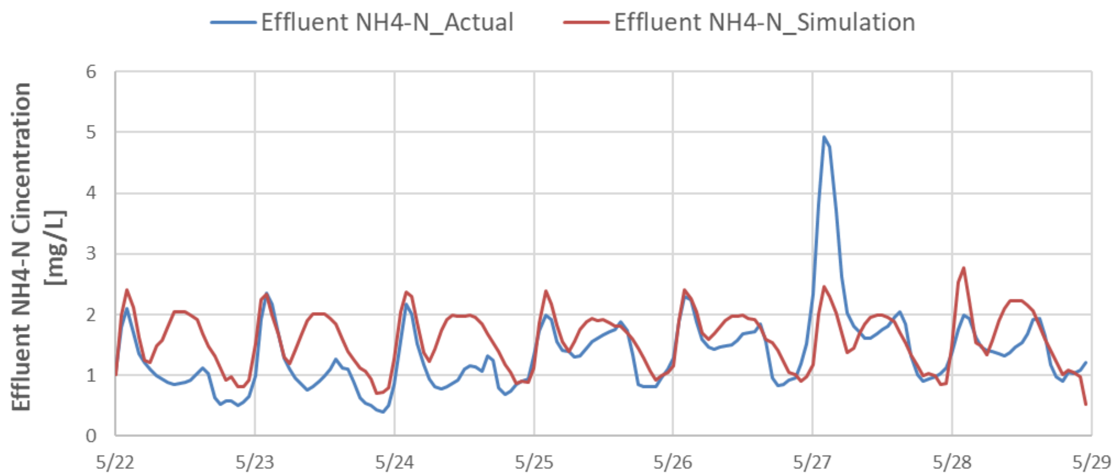

Figure 31 Actual and simulated effluent NH_4 concentrations during evaluation period.

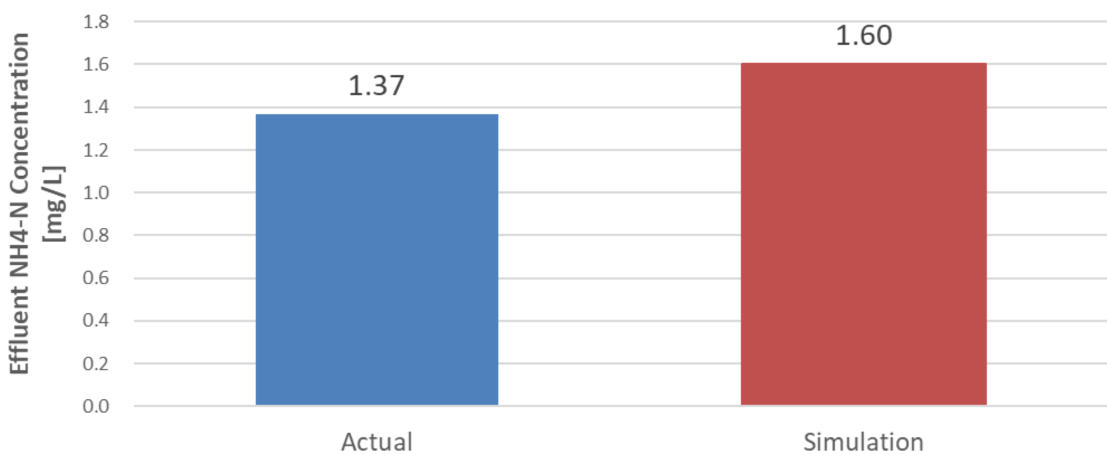

Figure 32 Actual and simulated effluent NH_4 concentrations (average) for evaluation period.

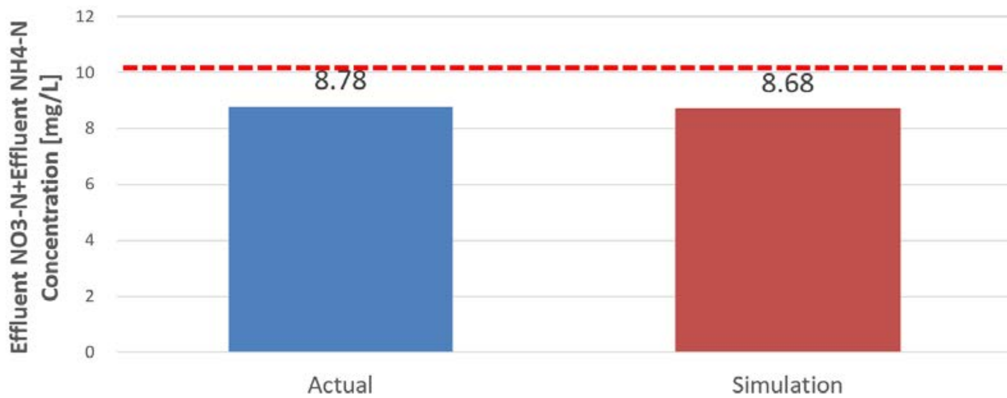

Figure 33 Actual and simulated effluent total nitrogen concentrations (average) for evaluation period.

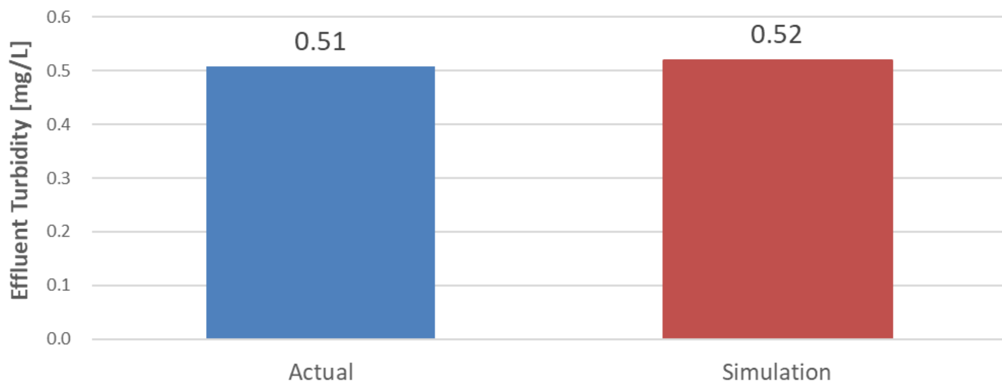

Figure 34 Actual and simulated effluent turbidity (average) for evaluation period.

In addition to the DDMO simulation results targeted to optimize energy consumption, an alternate simulation scenario was also run to reduce the effluent ammonia to the greatest extent possible. As expected, to achieve this target parameter goal, the air flow rate was increased leading to greater energy demand (estimated by DDMO to be 2.7 percent). The additional aeration also limited the denitrification process, and the effluent nitrate was predicted to exceed the maximum effluent limit (8.9 mg/L compared to the limit of 8.0 mg/L).

3.3.1 DDMO Accuracy Analysis

During the November through January period of work, both the BioWin and DDMO analyses for the Tapia WRF process were updated. As part of this follow-on, there was a greater focus placed on quantitative indicators for accuracy of the model. The mean absolute percent error (MAPE), correlation, and root mean square error (RMSE) are statistical values calculated for actual vs. DDMO simulated water quality parameters such as ammonia, nitrate, and turbidity. MAPE values less than 20 percent represent a model capable of good forecasting while RMSE correlations approaching 1.0 also demonstrate model accuracy when compared to the actual Tapia WRF data. RMSE were normalized from 0 to 1, based on the minimum and maximum values for each observed parameter. Examples of the actual data and DDMO model prediction as well as model accuracy (MAPE and correlation) are shown in Figure 35 and Figure 36 for ammonia and nitrate, respectively. The RMSE for effluent ammonia, nitrate, turbidity and total chlorine are shown in Figure 37 and effluent chlorine is shown in Figure 37.

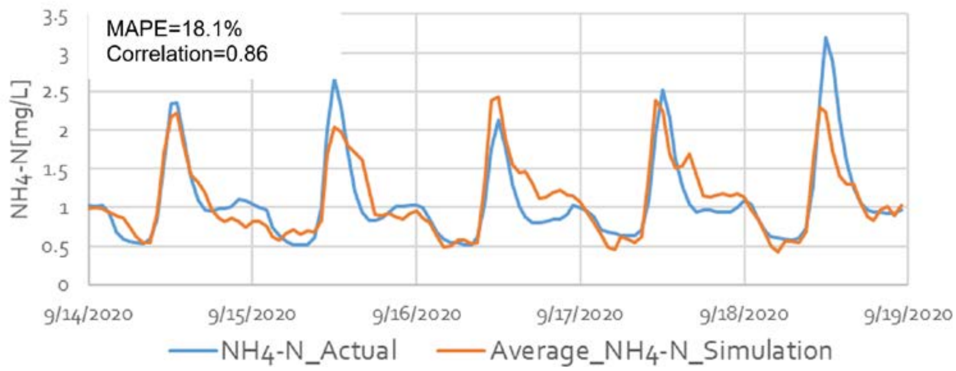

Figure 35 Actual (blue) and simulated (orange) effluent NH_4 concentrations during the May 2020 evaluation period.

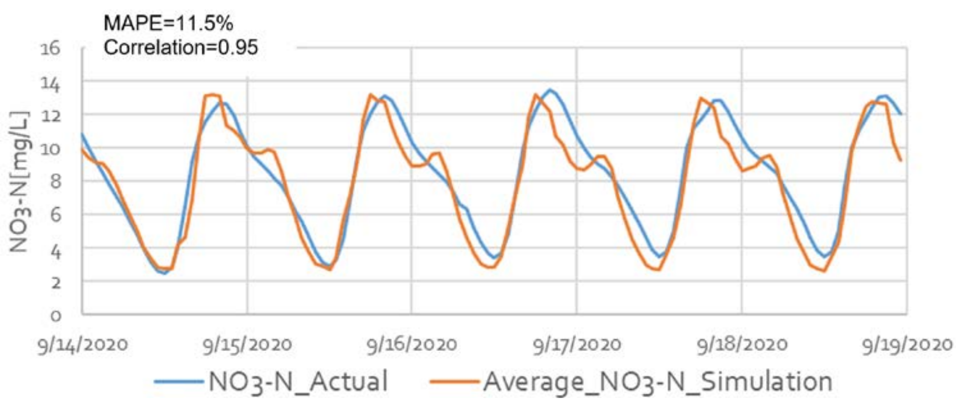

Figure 36 Actual (blue) and simulated (orange) effluent NO_3 concentrations during the September 2020 evaluation period.

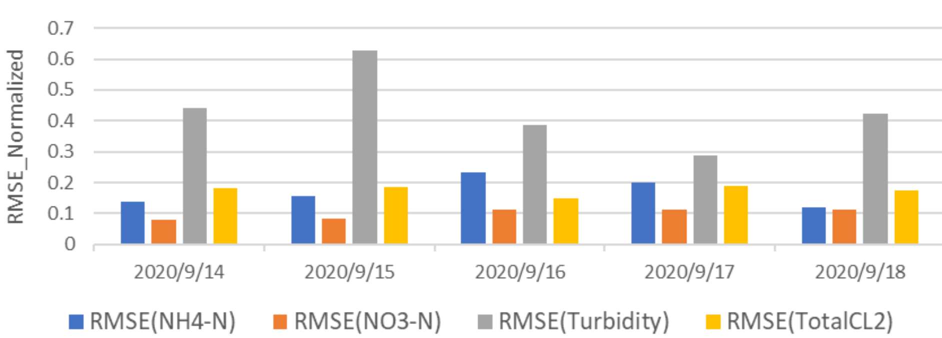

Figure 37 Normalized RMSE for each day during the phase 2 prediction period for effluent ammonia (blue), effluent nitrate (orange), effluent turbidity (grey) and effluent total chlorine (yellow). Lower values indicate a better prediction performance.

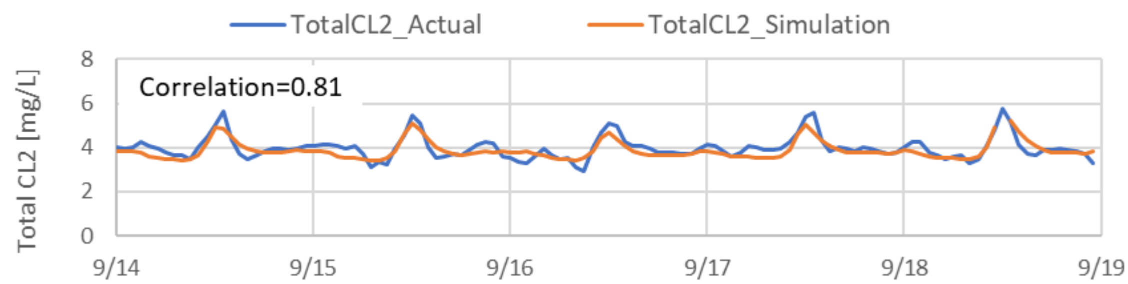

Figure 38 Actual (blue) and simulated (orange) effluent total chlorine concentrations during the September 2020 evaluation period.

The model accuracy analysis demonstrated that:

- Effluent ammonia was predicted well, with RMSE < 0.3, correlation = 0.86 and MAPE = 18.1%.
- Effluent nitrate was predicted very well with RMSE < 0.2, correlation = 0.95 and MAPE = 11.5%.
- Effluent total chlorine was predicted well with RMSE < 0.3 and correlation = 0.81.
  - Daily increases in total chlorine appeared to coincide with ammonia troughs and appeared to be captured by the model (Figure 26).
- Effluent turbidity was not predicted well with RMSE >0.3 and correlation = 0.3.
  - Inclusion of coagulant dosing as a DDMO input variable may result in improvements in filtrate turbidity estimates.

3.3.2 DDMO Results

Once the learning and calibration evaluations were updated for the new data set, DDMO was updated to achieve the same energy optimization scenario as previously shown in the May 2020 data. The results of this analysis are show in Figures 38 through 41.

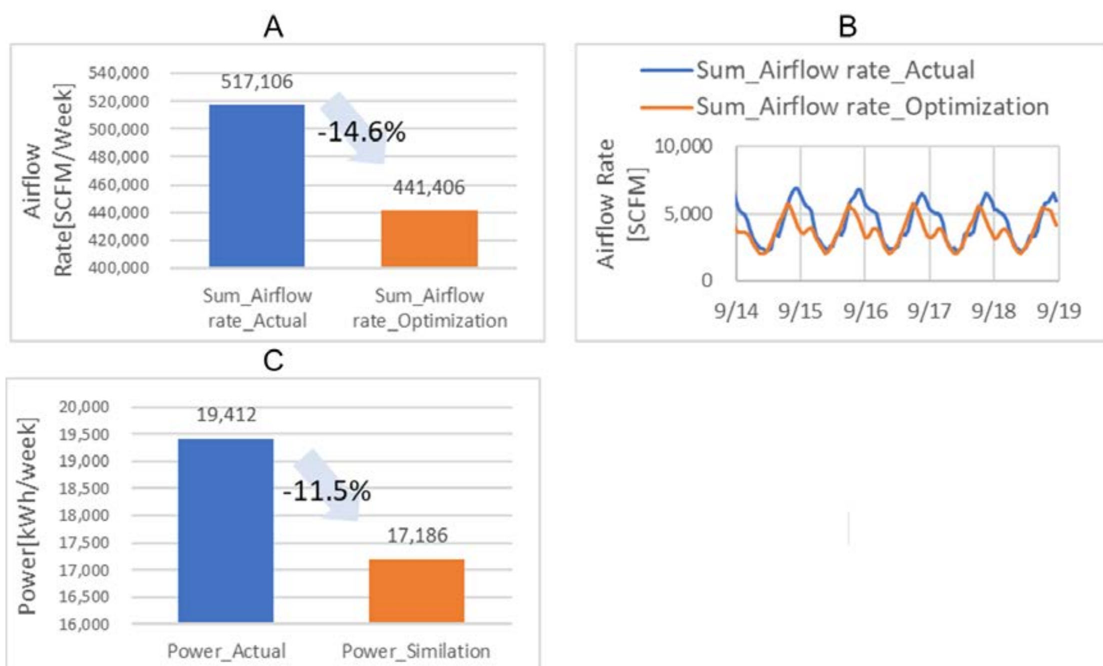

Figure 39 A) Air flow (cumulative standard cubic feet per week), B) Instantaneous airflow (scfm) and C) estimated power consumption (kilowatt-hour/week) for the Phase 2 DDMO optimization. Actual operational values are blue and DDMO optimized values are orange.

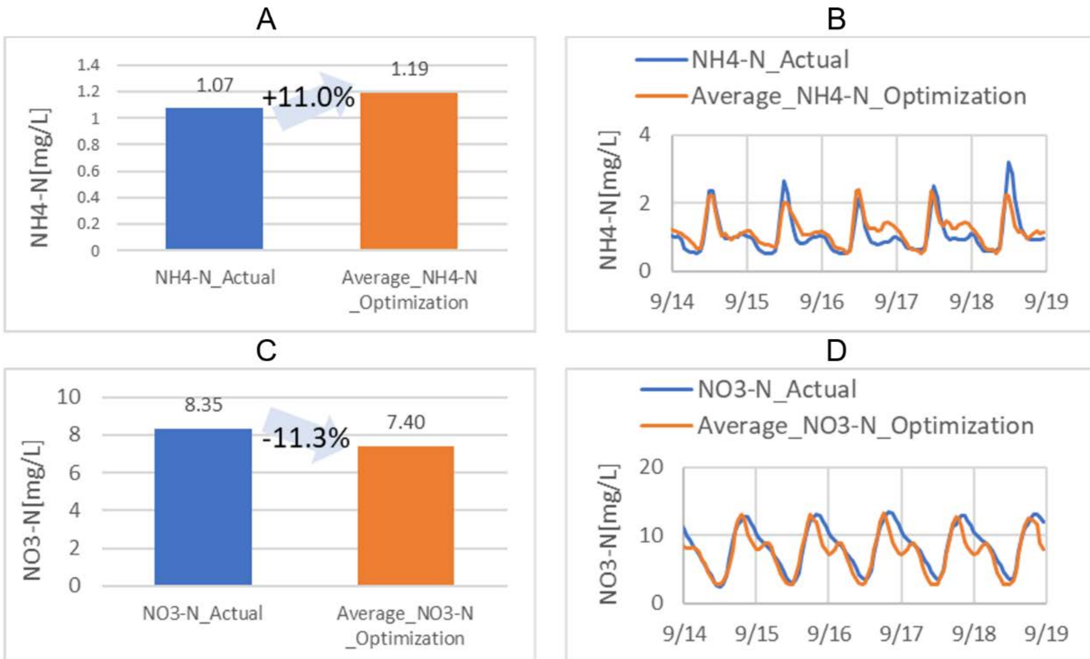

Figure 40 A) Average and B) Instantaneous effluent ammonia (mg/L). C) Average and D) instantaneous effluent nitrate (mg/L) for the Phase 2 DDMO optimization. Actual operational values are blue and DDMO optimized values are orange.

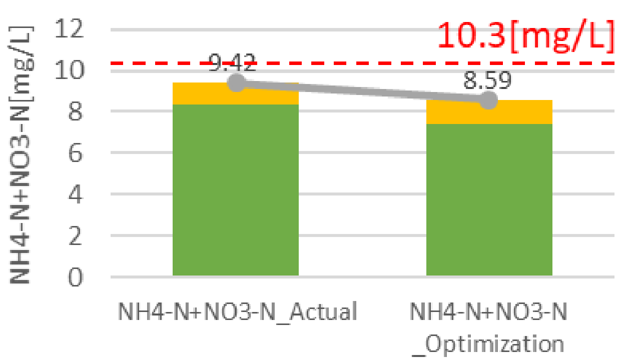

Figure 41 Actual (left) and DDMO optimized (right) effluent ammonia (yellow) plus nitrate (green) average concentrations for the Phase 2 evaluation period were maintained below the 10.3 mg/L limit.

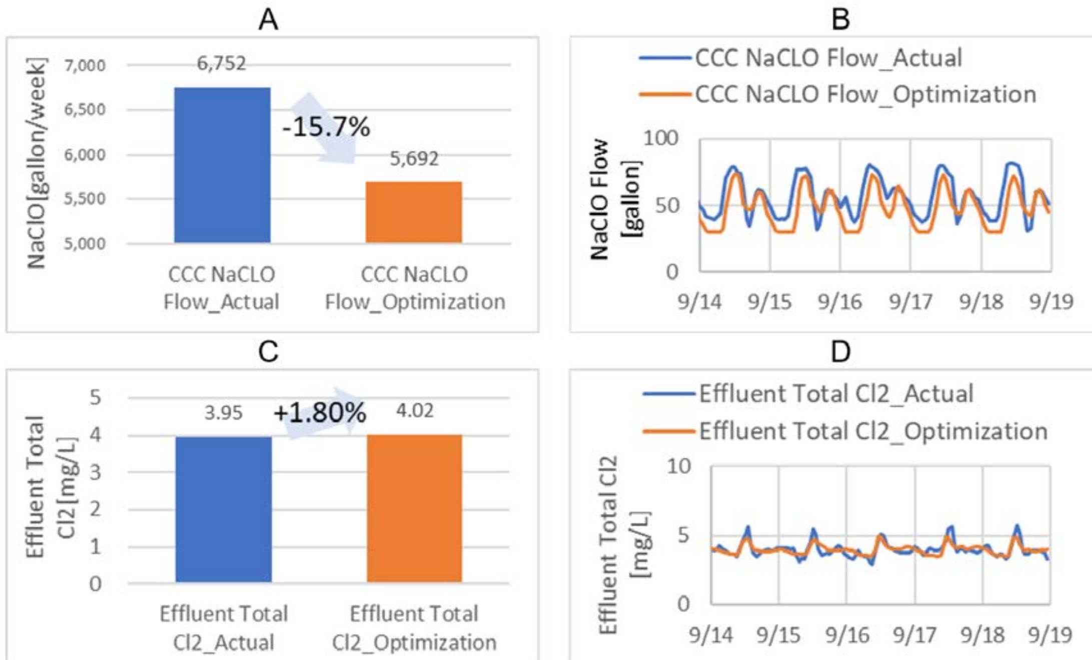

Figure 42 A) Average (gal/week) and B) Instantaneous sodium hypochlorite dosing flow (gph). C) Average and D) instantaneous effluent total chlorine (mg/L) for the Phase 2 DDMO optimization. Actual operational values are blue and DDMO optimized values are orange.

Although the Tapia WRF operations changed the blower control approach to a pressure setpoint, which was intended to smooth out fluctuations and increase efficiency, the DDMO simulation with optimized control demonstrated similar (and actually slightly better) results than the first phase of DDMO analysis (with DO setpoint control). The following observations were made during the optimization simulations of the November/December data:

- Optimized airflow resulted in an airflow reduction of 14.6 percent and estimated power reduction of 11.5 percent. Using a unit power cost of $0.14/kilowatt-hour (kWh), annual savings were estimated to be $22,750 per year (Figure 38).
- Optimized airflow resulted in a marginal increase in average effluent ammonia of 0.12 mg/L (11 percent), and a decrease in effluent nitrate by 0.95 mg/L (11.3 percent) (Figure 39). Overall, the average sum of effluent ammonia and nitrate decreased from 9.4 to 8.6 mg/L, remaining below the discharge limit of 10.3 mg/L (Figure 40).
- A preliminary analysis was conducted to simultaneously optimize sodium hypochlorite dosing based on meeting the same effluent total chlorine target. Results indicated that the DDMO optimized dosing requirement was on average 15.7 percent lower during the Phase 2 period. Assuming a sodium hypochlorite unit price of $0.79/gallon, extrapolated annual savings were estimated to be $43,500 per year (Figure 41).
  - Further investigation should be carried out to ensure that the desired chlorine residual is maintained.

An average effluent turbidity increase of 0.08 Nephelometric Turbidity Unit (NTU) (14.2 percent) was predicted as a result of the DDMO optimized conditions. However, given that this turbidity change is marginal and well within an acceptable range, as well as the fact that the learning period did not satisfactorily correlate with effluent turbidity, additional analysis, model refinement, and prediction of this parameter is recommended.

Section 4

CONCLUSIONS

4.1 Key Findings and Considerations

The following conclusions can be made based upon the information collected and analyzed in this project:

- Demo Facility AI:
  - The initial AI model was able to predict/extrapolate the rise in TMP over a 2-week period which closely matched actual operational data. Operational data is more variable than simulation inputs however the actual temperature corrected flux was within 2.5 gfd (8.5 percent) of the simulated input throughout the predicted period.
  - A subsequent model revision allowed prediction of the entire month of December after training the model on the 40 gfd data set from November. The subsequent TMP model tracked the central tendency of the actual operational data very well. However, it was noted that some improvement in the prediction of TMP recovery due to membrane cleaning was needed, in particular for higher intensity recovery cleans, which occur once per month.
  - Similar to the TMP model, the effectiveness of maintenance cleanings to recover permeability has been under predicted by the AI model but the general trend in decline is similar.
  - The permeability predicted by the model is lower (i.e., more conservative) than the actual operating data. This is advantageous as it means that predictions currently have a safety margin.
  - The capacity for model optimization and refinement and the improved accuracy of model predictions over time demonstrate significant promise for AI as a forecasting and operational tool for low pressure membrane systems.
- Tapia WRF BioWin Modeling:
  - The plant-wide model has been updated to reflect current operating conditions.
  - Aeration and RAS control could be further optimized to save on energy costs while maintaining and/or improving effluent water quality.
  - Installation of a secondary effluent ammonia probe would provide the online data necessary to support process control/optimization.

- Tapia WRF AI – DDMO:
  - DDMO demonstrated potential blower optimization (10 percent reduction in power) with effluent nitrogen maintained less than permit values (2.5 mgN/L as NH_3-N and 8 mgN/L as NO_2-N + NO_3-N).
  - DDMO demonstrated that artificially setting the target effluent NH_4-N concentration to 1.0 mgN/L (instead of 2.5) results in a 3 percent higher airflow, energy cost, and effluent nitrate concentration.
  - A demonstration of blower control with remote DDMO simulation and feedback is planned for the summer of 2021.

4.2 Lessons Learned

Successful operation depends reliable instrumentation, which is well maintained and calibrated, and strategically located within the treatment process. One of the fundamental lessons learned during this study is the importance of collecting and transmitting the right data for analysis to successfully development the AI/ML algorithms.

The stable performance and consistent LRVs of the Demo over time indicates that MF/UF systems can consistently produce water meeting IPR quality requirements. The Demo data underpredicted the performance of the MF/UF systems (particularly after membrane cleanings) in terms of TMP and permeability. The accuracy of the predictions is expected to improve over time however the current underprediction of system performance provides a margin of safety.

The Tapia WRF Biowin modeling and DDMO simulation showed that treatment performance can be improved by using AI without compromising effluent discharge limits. A future demonstration of blower control with remote DDMO feedback will further evaluate the benefits of DDMO. Overall, the data collected over the course of this study demonstrate that the AI models can effectively predict treatment performance parameters in potable reuse and wastewater treatment systems, supporting high quality product water, efficient operations, lower energy use, and operational cost savings.

Looking broadly at these results coupled with the energy and water challenges faced by California, this study demonstrates that AI/ML can reduce energy use and provide greater confidence in water quality for wastewater treatment and water reuse. Applying AI/ML regionally or state wide can provide a substantial benefit to all Californians.

4.3 Next Steps

The work presented in this report was funded by the MWD grant and additional funding was leveraged from the Japanese government (the Ministry of Economy, Trade, and Industry [METI]). The 2020 METI grant expired at the end of January 2021 and although testing at the Demo is ongoing, the work funded by both grants is considered to be completed.

The LVMWD-Carollo-Yokogawa team has been awarded two additional grants in 2021 to continue to advance this work – a 2021 METI grant and a grant from the U.S. Bureau of Reclamation. Each of these grants will support advancement of the AI algorithms for potable reuse processes and the DDMO demonstration testing. The team will also expand the scope of the project to develop a user interface and data transfer to support the eventual implementation of these AI tools.

Conducting the DDMO demonstration will further refine the DDMO model and will also prove out the effectiveness of the system in a real-world operational scenario. This testing must occur during the irrigation/reuse season as opposed to the winter months when the Tapia WRF must meet discharge water quality limits. Initially planned for November 2020, the demonstration was not logistically feasible before the end of the irrigation season in 2020 and was postponed until irrigation season 2021. Planning and coordination for this trial is underway, focused on addressing the logistical hurdles required to efficiently transfer the operational data and provide control setpoint updates on a frequent basis during the trial period. Through this testing, the team will not only further validate initial results of the DDMO simulations, but the team will also establish a protocol for data transfer which will serve as an important basis for the future implementation of AI projects.