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# Modeling Ultra Filtration Systems for Direct-to-Potable Reuse of Wastewater

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**Abstract:** Wastewater treatment facilities rely on achieving performance standards regardless of critical components degradation and water source variability. The need for reliable and continuous water production has often been resolved by volume and equipment redundancy, which is neither efficient nor sustainable. Recent advances in machine learning and adaptive control can offer a solution to overcome resources redundancy. In this work, we will develop and test an approach for modelling the power and generated feed for the ultra-filtration (UF) unit. The proposed modeling utilizes variable data across multiple units in a direct potable reuse (DPR) system. The main contribution of this paper is providing a nonlinear model structure that enables transient membrane pressure (TMP) forecasts over time horizons spanning the filtration phases collected over days. Our results show that the proposed model provides reliable forecasts. The proposed models were tested on dynamic data, in which dynamic changes were deliberately introduced.

**Keywords**: Ultra-filtration; direct potable reuse; membranes; power consumption; transient membrane pressure.

## INTRODUCTION

Realistic dynamic models are crucially needed to enable effective optimization of water treatment plants. To achieve this, online data need to be collected and processed to update the dynamic model of the plant. Our aim is to jointly optimize the operational settings of the entire plant across all the treatment system units. In this paper, we introduce two models for estimating and forecasting the consumed power and transient membrane pressure for the ultra-filtration unit in a direct potable reuse (DPR) pilot system. Demonstration on the DPR pilot achieves multiple objectives. First, it allows us to vary the influent quality, which is not possible to do with full-scale plants. Second, we can demonstrate the proposed model on distinct process units, thus supporting the claim of generality. Ultra-filtration (UF) is a crucial component in water treatment plants due to its high efficiency. UF is a water treatment process in which water passes through a semipermeable membrane to filter suspended solids and high-molecular-weight particles. UF often removes most organic molecules and viruses without requiring any chemicals except for membrane maintenance. The continuous need for maintenance in UF is to prevent membrane fouling with solids, algae, and microbes. In this work, we utilized both linear and nonlinear process models based on online data to forecast the power consumption and the transient membrane pressure (TMP) of the UF unit. The proposed models are tested on the pilot-scale system data to evaluate the reliability of the model forecasts.

## RELATED WORK

Membrane filtration, such as microfiltration (MF), ultrafiltration (UF), nanofiltration (NF), and reverse osmosis (RO), is prevalent in wastewater pretreatment processes. As a result, the topic of membrane fouling has been extensively studied in literature. Forecasting membrane fouling is

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crucial for fouling control and mediation. In [1], the authors provide a long short-term memory (LSTM) model to assess variations in filtration performance and identify fouling mechanisms in nanofiltration (NF) systems. In [2], thermal hydrolysis (TH) is integrated into an anaerobic membrane bioreactor (AnMBR) to promote sludge solubilization, methane bioconversion, and membrane fouling mitigation. Artificial neural networks (ANNs) are widely used to predict membrane fouling in membrane bioreactors (MBRs) and show great potential [3]. Other models utilize pressure, salt rejection, and other operating parameters to predict the membrane fouling mechanisms for water and wastewater treatment in [4]. Classical mathematical models are also employed to predict the occurrence and development of membrane fouling, as in [5].

## OBJECTIVES

In this work, a demonstration-scale DPR system was maintained and operated for our experimental purposes. The DPR system is located at the Colorado school of Mines (Denver, CO, USA) and comprised of six processes, namely (1) ozonation, (2) biological aerated filter (BAF), (3) ultra filtration (UF), (4) granular activated carbon (GAC), (5) ultra-violet (UV), and (6) chlorine contact. **Figure 1** depicts a flow diagram of the DPR demonstration system. Each unit is equipped with sensors to track key variables and selected pipe parity metrics and to assure redundancy to facilitate prognostic sensor management. The feed to the DPR systems is generated by a water reclamation facility and has highly variable quality due to daily and seasonal water source quality changes, water use patterns during the day, and plant operating conditions. The utilized DPR system adjusts rapidly to changing conditions to continuously need produce very high-quality water for potable use. Water quality sensors continuously measure turbidity, pH, nitrate, ammonia, total organic carbon (ToC), and ozone levels. Additional sensors investigate the reliability of fault management tools. Actuators, such as pumps and valves, ensure the operational flexibility on the DPR trailer to match that of the industrial plant. The scheme of the DPR pilot is depicted in **Figure 2**. Real images of the inside of the DPR are shown in **Figure 3.** In this work, we utilize the sensor collected data from the DPR system to develop empirical dynamic models for estimating the power consumption and the TMP of the UF unit to support automated control actions.

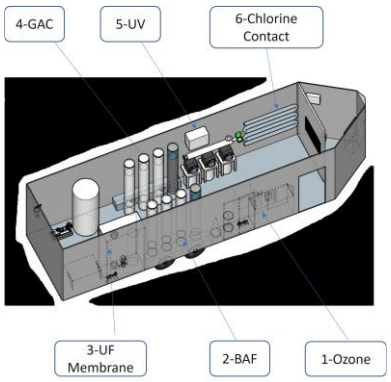


***Figure 1*** *DPR pilot*

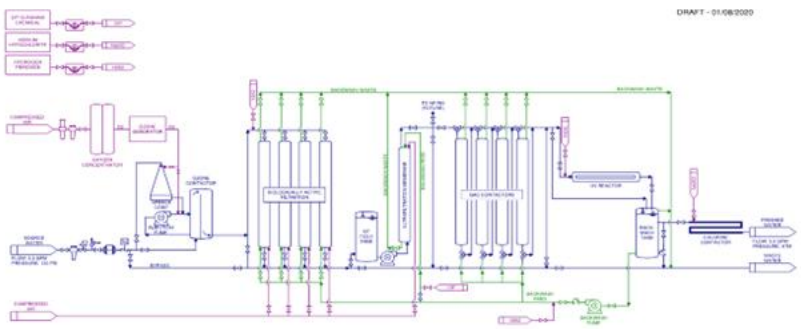

***Figure 2*** *Scheme of the DPR pilot, including six processes: biologically active filtration (BAF), ozonation, ultra-filtration (UF), granulated activated carbon (GAC), UV treatment, and chlorination*

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***Figure 3*** *Real images from the DPR trailer*

## POWER MODELING

In the following, we will elaborate on our approach for power modeling of the UF unit. We used **Equation 1** to model the UF power using both the TMP and UF feed flow rate (FFR). First, we normalize the TMP, flow rate, and true measured power. In the data, we have more than 300 filtration cycles for the UF unit, which are used to estimate the parameters A, B, C, D, E, and F in **Equation 1** for each cycle. More specifically, we employ linear regression to estimate the value of power consumption by using the measured values for TMP and FFR.

$$Power = A + B \cdot TMP + C \cdot FFR + D \cdot TMP^2 + E \cdot TMP^2 + F \cdot TMP \cdot FFR \quad (1)$$

In **Figure 4**, we show the root mean square error (RMSE) between the measured and estimated

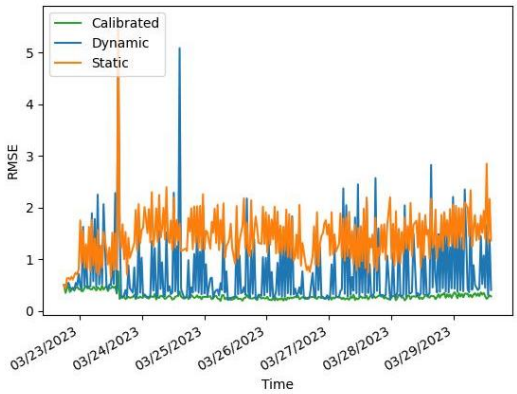


***Figure 4****: Power model RMSE for calibrated, dynamic, and static models*

power using three error estimation methods. The first method is the calibrated one, in which the coefficients of the regression model are estimated for each filtration cycle. The second method for error estimation is the dynamic approach, where the coefficients from the previous cycle are used to estimate the current cycle. The third method is static, in which the coefficients from the first cycle are used to estimate all future cycles. From **Figure 4**, it is clear that the RMSE of the dynamic model is less than the static model, which shows that dynamic model is performing better and more realistic than the calibrated model.

## TRANSIENT MEMBRANE PRESSURE MODELING

In the following, we will elaborate on our approach for TMP modeling for the UF unit. We used **Equation 2** to model the UF TMP at time $k+1$ and time step $i$ using both the TMP at time $k$ and UF permeate flow rate (PFR) set point at time $k$.

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$$TMP(K+1,i) = A * PFR(k,i) * dt(k,i) + \big(1 - B * dt(k,i)\big) * TMP(k,i) + C * PFR(k,i) * TMP(k,i) * dt(k,i) \quad (2)$$
$$for\ i = 1, 2, \dots, 9\ \ s.t.\ TMP(0,i) = theta(i)\ and\ dt(k) = t(k+1) - t(k)$$

First, we normalize the TMP, and feed flow rate setpoint. Because the TMP data are noisy, we cannot not assume that the initial TMP measurement *TMP(0, i)* is a good estimate of true TMP. As a result, we include the initial TMP as an additional parameter to be estimated. In the data, we have more than 220 filtration cycles for the UF unit, which are used to estimate the parameters *A, B, C,* and initial TMP in **Equation 2** for each cycle. More specifically, we employ non-linear regression to estimate the value of TMP at step *(k +1, i)* by using the measured values for TMP and permeate flow rate (PFR) at step *(k,i).* The time difference *dt(k,i)* is the difference between the time at *k+1* and time at *k* for cycle *i*. We optimize the objective function by minimizing root mean square error between the measured and predicted TMP. More specifically, we use the conjugate gradient (CG) algorithm. We vary the UF permeate flow rate set point every 60 seconds with +/- 10% to create the dynamics needed for modeling. So once the filtration stage starts, the UF runs at 5 GPM (100%) for one minute, then 4.5 GPM (90%), then 5 GPM (100%), then 5.5 GPM (110%), and so on. In **Figure 5**, we show the RMSE between the measured and predicted TMP. We use 9 cycles to train the dynamic model and used the coefficients *A, B,* and *C* to forecast the next 9 cycles. In regard to the initial TMP, we average the first 5 minutes and use it as an initial guess of the initial TMP for each cycle of the 9 current cycles. The reason we compute the static and calibrated RMSE errors is because the static RMSE is expected to have the largest RMSE and act as an upper bound. Furthermore, the calibrated RMSE is expected to act as a lower bound for the dynamic RMSE error. From the results, we conclude that the dynamic model is closer to the calibrated one, indicating that it performs well and as expected.

## CONCLUSION

In this work, we introduce two simple models based on online data to forecast the power consumption and the TMP of an UF unit. The proposed models are tested on the pilot-scale system data to evaluate the reliability of the model forecasts. The developed models can be easily updated and are anticipated to be incorporated into model-based control.

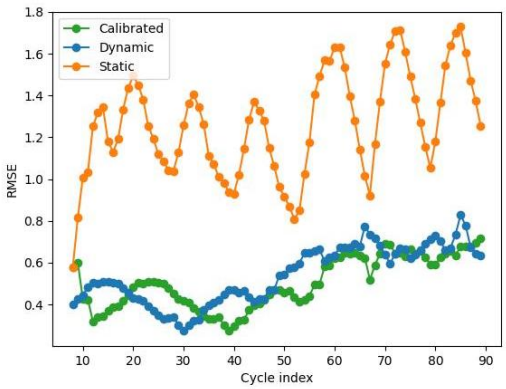


***Figure 5:*** *TMP model RMSE for calibrated, dynamic, and static models*

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