EMPIRICAL MODELING OF A REVERSE OSMOSIS SYSTEM

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REFERENCE: *Proceedings of the 2017 Georgia Water Resources Conference*, held April 19-20, 2007, at the University of Georgia

Reverse osmosis systems (RO) play an increasing role in supplying potable water through direct and indirect reuse, and treating low quality sources. The Orange County Water District, California operates a 75 MGD RO that treats secondary WWTP effluent for its Groundwater Replenishment System. The RO comprises 45 membranes in 15 parallel 3-stage units, and requires periodic chemical cleanings to restore permeability due to fouling that occurs in two phases. Phase 1 fouling is caused by initial particle deposition, whereupon Phase 2 brings long-term biofilm and inorganic scale growth. OCWD wants to increase the duration of "runs" between cleanings to reduce costs, and supplied a six-year process dataset to be mined for useful information. The dataset comprised 179 runs and 62 hydraulic and water chemistry parameters.

The investigative approach involved developing dynamic models of membrane fouling using multilayer perceptron artificial neural network models (ANN), with the goal of quantifying causes and effects among foulants, anti-foulants, and fouling indicators. Data for specific flux, the traditional fouling indicator, was sparse and exhibited extensive superposed hydraulic disturbances unrelated to fouling. An alternative fouling indicator (P′) was calculated from five RO pressures. P′ is the portion of the feed pressure that modulates the permeate (cleaned water) flow rate. An ANN with only two inputs, P′ and the feed flow rate, accounted for 97% of permeate flow variability. Modeling P′ behavior caused predominantly by fouling required filtering the dataset to remove hydraulically-induced variability. P′ was then modeled using ensembles of water quality parameters represented as spectral signal components. Sensitivity analyses identified the most predictive components. Runs were divided into Phases 1 and 2, and the phases were modeled separately. The strongest predictors of P′ during Phase 1 were total chlorine, ammonia, TDS, electrical conductance, and boron; and total chlorine, ammonia, turbidity, and TOC during Phase 2.

Program reference: 6.6.4