Wastewater effluents & Optimizing Aeration Process

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Abstract

Moving and treating wastewater is energy intensive and often ignored during the wastewater treatment plant operation process due to the main emphasis on water quality. In this research, one of the most energy intensive processes of wastewater treatment, namely aeration process is optimized with consideration of water quality as well as energy aspects. The computational models developed in the present research indicate with less energy consumption, still an acceptable water quality level can be achieved. Case studies depicting few energy saving scenarios are also investigated.

Keywords
Wastewater treatment, Data mining, Energy optimization, Artificial Intelligence, Aeration

1. Introduction
1.1 Background
Wastewater treatment includes different methods and processes that are used to clean wastewater from certain contaminants. In the United States, wastewater treatment facilities collect, treat, and release about 4 billion gallons of treated effluent per day from an estimated 26 million homes, businesses, and recreational facilities nationwide. Large facilities and processes such as wastewater treatment plants (WWTPs) accounts for more than 4% of the US electricity consumption [1]. Minimizing the energy use of WWTPs by just 10% could lead to an annual savings of $400 million or more [2]. Due to the environmental regulations, wastewater industries are primarily concerned with meeting the water quality standards without paying much attention on the energy consumption aspects. The design of most operational wastewater treatment plans is based on kinetic models such as ASM1, ASM2 & ASM3 developed by international Water Association(IWA). Although the design is based on these well studied models, the operation of WWTPs are often based on intuition and experience. This fact alone leaves improvement opportunities in terms of process optimization and better resource allocation.
The energy consumption in WWTPs is mainly attributed to the mechanical systems [3], such as the pump and air support systems for moving and treating wastewater. The air support system consists of a group of air blowers that provides oxygen to the aeration tanks for removing organics and converting ammonia. Both of the pump system and the air support system are typically 0.5-MW class mechanical equipment and accounts for more than 70% of the electricity consumption of WWTPs.

So far, in wastewater treatment plants, much effort and money is invested in operating and maintaining dense plant-wide measuring networks. Such networks primarily serve as input for the supervisory control and data acquisition (scada) systems to satisfy the stringent effluent quality constraints. However, with the proliferation of information technologies (IT), it is now possible to perform long term data archiving for analysis. The steadily growing amount of plant data fosters the avenues for plant wide analysis. Often such data contains hidden information about the process, equipment's which require systematic analysis. Although there has been studies to improve efficiency in wastewater treatment plans, very few has used real data and various datamining techniques to obtain optimal performance and give a comprehensive measure to compare different datamining techniques on aeration process. As a contribution, this research gives a comparison between performance of different datamining techniques and their sensitivity on operational data. This research also presents a methodology for energy saving techniques without decreasing effluent water quality.

1.2. Wastewater Treatment

The industrial data used to perform the analysis was obtained from Detroit Water and Sewerage Department (DWSD). Detroit Wastewater Treatment Plant located at 9300 W. Jefferson Avenue in Detroit, Michigan is the largest single-site wastewater treatment facility in the United States. It serves approximately 35% of the population of the State of Michigan, providing treatment of wastewater. DWSD distribute, treat and collects approximately 1.5 billion Gallons of water and wastewater per day (BGD) to be finally discharged into Detroit River. The collected wastewater enters the plant and passes through bar screens. As the first stage of treatment process, large items, such as rags and sticks, are screened out for later disposal. After screening, the influent wastewater enters the wet well and get pumped to primary clarifiers. In 1 to 2 hours of retention time, scum floats to the surface and is removed by a skimmer while larger particles deposit at the bottom of the clarifier where it would be collected, treated and disposed later. Then, the wastewater is delivered by intermediate pumps to adjacent aeration tanks. In each aeration tank pure oxygen is provided by centrifugal blowers and through diffuser to bottom of thank. During normal operations, a required quantity of the sludge from the secondary clarifiers, called Returned Activated Sludge (RSL), enters the aeration tanks through sludge pumps. When the RSL and the wastewater are mixed, microorganisms in the activated sludge use oxygen provided by the fine bubble diffusers located on the bottom of the aeration basins to break down the organic matter. The remaining sludge from the secondary clarifiers and the sludge from the primary clarifiers are either pumped to the anaerobic digesters to produce biogas or fed to the incineration process and the final remaining is transported to the land field. Next, wastewater enters cylindrical clarifiers for the secondary treatment. In secondary treatment microorganisms which consumed all of the biological content of the wastewater, through gravity, settles down to the bottom of secondary clarifiers. The settled sludge is collected, some returned back to the aeration basins for continuous supply of microorganisms and the rest is treated for other application such as landfilled disposal. The effluent water from secondary clarifiers is disinfected through chlorination and then discharged into the Detroit River.

1.3. Data Description

The available data for the analysis was collected for the period of September 2012 to October 2014 from Detroit Wastewater Treatment Plant(DWTP) as mentioned above. Data includes influent flow rate, influent pollutants, effluent pollutants, and aeration process parameters. The data is recorded at one-hour frequency, out of which two third of data is used for building the models and the one third data is used for model testing and validation. Missing, and invalid values are imputed based on the values recorded in previous time-periods.

2. Modeling and Optimization

2.1. Model Construction

For the aeration process over 35 input parameters are recorded. In order to reduce the curse of dimensionality and minimize generalization error, only relevant parameters are selected in the modeling process. A boosting tree algorithm was used to evaluate the relative importance of the process variables. Influent flow rate, returned sludge flow rate, DO concentration, and airflow rate, influent CBOD, effluent TSS, temperature and pH in the aeration tank were used to develop the model.

Considering the intense energy consumption for producing Oxygen (or the cost associated for buying the same amount of oxygen) the Oxygen flow rate provide the best measure of the energy consumption in aeration process. Since some plants use compressed air instead of Oxygen, using DO instead of Oxygen flow rate make the model more robust. Hens DO is considered as indicator main indicator of energy (as well as cost). With decreasing DO in the aeration tanks, the quality of the effluent is degraded, which is a matter of concern because it is desirable to maximize the quality of the effluent to meet federal and state requirements. Since effluent CBOD and TSS reflect treatment quality, the objective can be transformed to minimize the concentrations of CBOD and TSS in the effluent. Temperature and pH are uncontrollable variables which also affect the quality of the effluent.

2.2. Data-mining

Using data obtained from plant scada system, four well know data-mining techniques are used to obtain a set of data-driven co-relation coefficients for the model constructed in the previous stage. This model relies on recordings for the parameter evaluation instead of considering a set of assumption which traditionally usually is used in building kinetic models. Multi-adaptive regression spline (MARS), artificial neural network (ANN), random forest (RF) and k-nearest neighbor are all the methods investigated. MARS is a non-parametric approach and is independent of underlying data distribution and has very good performance on highly non-linear processes [4]. ANN is an emulation of brain which minimizes an error function obtained with maximum likelihood estimation. ANN usually has a performance on complex models [5]. RF is an ensemble method that produces a lot of classification trees while the final classification is based on majority voting of all generated classifiers. RF has good performance on complex models [6]. KNN is a clustering method with relies on distance between observations and has a very good interpretability [7].

All models have been trained on two third of data, then validated and tested on the remaining one third. Performance of all models have been compared based on Mean Absolute Error (MAE) and coefficient of determination (R2) from testing set and real readings. In general models developed using MARS and KNN have better results with MARS being the best predictor. The results are shown in tables 1 and 2 using R2 and MAE measures.

Table 1. prediction accuracy result using R2 measure

	TDP	TSP	DO	CBOD	TSS	Average	Prediction accuracy rank
MARS	0.9688	0.9485	0.9196	0.9367	0.9287	0.9405	I
RF	0.2988	0.6216	0.4603	0.5727	0.5987	0.5104	IV
NN	0.6318	0.7957	0.6808	0.7444	0.7753	0.7256	III
K-NN	0.9327	0.9754	0.8279	0.9436	0.9858	0.9331	II

Table 2. prediction accuracy result using MAE measure

	TDP	TSP	DO	CBOD	TSS	Average	Prediction accuracy rank
MARS	0.0203	0.0208	0.0229	0.0212	0.0205	0.0211	I
RF	0.0789	0.0804	0.0736	0.0842	0.0464	0.0727	IV
NN	0.065	0.0654	0.0651	0.0755	0.0421	0.0626	III
K-NN	0.0257	0.0249	0.0412	0.0357	0.0129	0.0281	II

2.3. Optimization

A multi-objective model that minimized the DO, the effluent COBD, the effluent TSS, the effluent TSP, the effluent TDP was formulated in (1). The constraint limits are obtained from the plant. Coefficients w1 to w5 are weights which enable the optimization process to set different priority. All weights are positive and less than one to guaranty all parameters remain in the optimization process.

$$F = \min(w_1 DO + w_2 CBOD + w_3 TSS + w_4 TSP + w_5 TDP) \quad (1)$$

Subjected to:

$$0 \le DO \le 6.5$$
$$0 \le CBOD \le 25$$
$$0 \le TSS \le 30$$
$$0.2 \le TSP \le 1$$
$$0.2 \le TDP \le 1$$

With modification of weights, two scenarios are created and optimized. In the first scenarios weight associated with DO is set to a lower amount comparing to other weights, the aim is to improve the water quality with no regard for cost or energy consumption. However, increasing w1 and reducing rest of the weights respectively to meet the current operational setting in the plant would result in the energy saving scenario which is the second optimization setting.

3. Results

The objective function is optimized using Simulated Annealing (SA) algorithm. The optimization is result shown in figure1 is the average of 5 iteration of SA for both scenarios. The result indicates that although cost increase while optimizing for the best water quality, it is possible to reduce DO almost without sacrificing water quality.

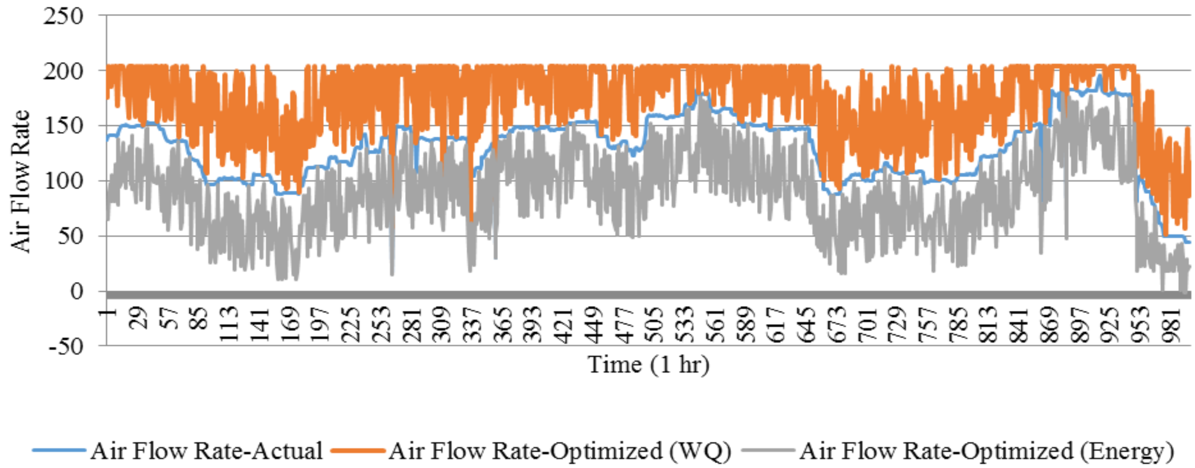

Figure 1. Comparison of observed and optimized DO scenarios

The energy optimized model is indicating that with reducing oxygen flow rate by 31.4% would lead to 5.5% decrease in the DO, 11.2% increase in TSS and 13.8% increase in CBOD. Considering that both TSS and CBOD are currently well below the limit, increasing amount virtually has no effect on the quality of effluent water. Figure 2 shows the current amount of pollutants (yellow), the increased version in energy saving scenario (green) which still is well below the limit and the limit (red). This result shows with almost one third reduction in oxygen consumption almost the same water quality output is achievable.

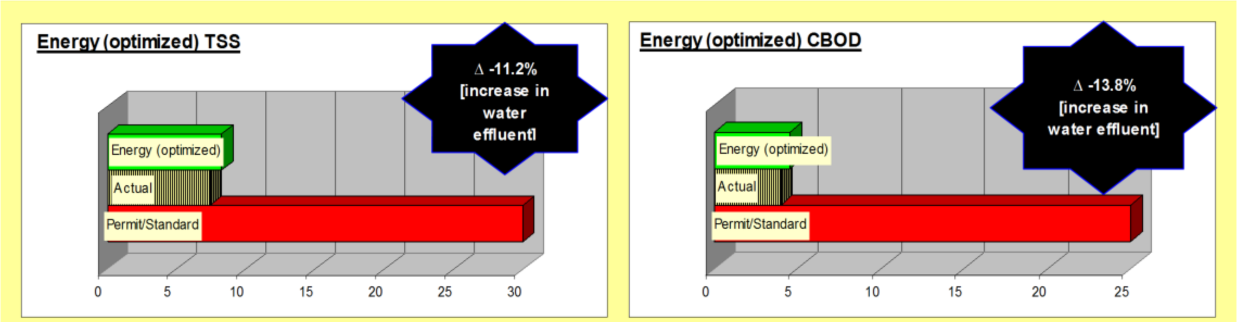

Figure 2. Comparison TSS and CBOD pollutants in energy saving scenario

The sensitivity analysis of the optimized model explores if plant can consider some deviation in their current delivery of water quality if savings in energy is possible and vice-versa. δ=0.8 (10% improvement in current setting, and δ=1.2 (20% deviation from current control setting) were analyzed along with δ=1.0 (current setting). The sensitivity analysis indicates that with δ=0.8 still 15.7% energy improvement is achievable.

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Biography

Ali R. Asadi received his undergraduate degree in Mechanical Engineering from Shahid Rajaee University. He pursued his Master's degrees in the Industrial and System's engineering and Computer Science at Wayne State University in Detroit, Michigan. Ali is focusing on data analysis and machine learning where his research mainly includes analytical aspects of energy usage. He joined Wayne state university's Industrial and System Engineering PhD program in at 2014. His research includes energy consumption analysis, electrical vehicle energy consumption, smart meter analysis, water treatment energy consumption and healthcare engineering. He is member of IIE, INFORMS and IEEE.

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