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Hybrid water treatment cost prediction model for raw water intake optimization

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ABSTRACT

In order to reduce the total cost of a dual source drinking water treatment plant operation, a comprehensive hybrid prediction model was built to estimate the necessary chemicals dosage and pumping energy costs for alternative source selection scenarios. Correlations between the water quality parameters and the required treatment chemicals were estimated using historical data and the expected pH variations associated with each chemical addition, which was based on the Caldwell–Lawrence diagram. The pumping energy costs were also estimated using a data-driven approach that was based on historical plant data. The research has practical implications for water treatment operators seeking to minimize plant operational costs through selecting raw water intake volumes for their treatment plant based on multiple source options and offtake tower gate levels. Future research seeks to better link current and future water treatment dosage cost predictions directly to water quality measurements taken from vertical profiling systems.

1. Introduction

1.1. Water treatment process

The delivery of safe drinking water (i.e. without harmful chemicals or waterborne pathogens) is an essential task for any bulk water supplier. The treatment of raw water from lakes, rivers, or wells is, therefore, required in order to meet the drinkability criteria defined by different national regulators.

In a conventional water treatment plant (WTP), the process of treating water usually consists of the following five steps: (1) raw water is adjusted for alkalinity and pH with the addition of hydrated lime and carbon dioxide; (2) particulate matter congregates together with the addition of aluminum sulphate and other coagulants such as polymers and then the water flows over a cascade that mixes chemicals and raw water with the coagulants; (3) water is slowly mixed in the clarifiers where larger particles settle down to the bottom and are periodically removed (sedimentation); (4) water is directed from the clarifiers to the filters (e.g. anthracite and sand filter) in order to entrap any smaller particles that survived the clarification process; and (5) sodium hydroxide is added to adjust the final pH/alkalinity, sodium hypochlorite for disinfection and fluoride for fluoridation (Sarai, 2006). Sometimes, as an alternative to sedimentation, dissolved air flotation can be effectively used in those WTP receiving waters from lakes that overturns once/twice each year leading to algae blooms, or taste and odours problems (Kawamura, 2000).

Estimating the monetary cost associated with water treatment is fundamental to a practical planning approach for potable water supply (Abdullahi, 2013). The operation of a WTP, nevertheless, is significantly different from most other industrial operations, as raw water quality constantly changes according to the season, wet weather events, or anthropogenic activities in the catchment. The water treatment cost is clearly related to the amount of the chemical dosage needed to adequately improve the sourced water quality, however the creation of accurate cost estimate predictions is challenging due to the variance in water quality parameters in the raw water (Abdullahi, 2013). Therefore, although it is clear that an accurate algorithm is a prerequisite to predicting the chemical dosage for optimum treatment, it must be based on water quality data that often does not exist for most WTP's (Mirsepassi, 2004). Typically, chemical dosages are estimated with jar tests, which are expensive and time-consuming (Maier et al., 2004). Moreover, jar tests are not ideal for handling sudden changes in water quality that

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can occur, which require a prompt adjustment of chemical dosing. However, recent advancements in the field of environmental monitoring technologies such as vertical profiling systems (Rouen et al., 2005), or data storage and analytics, greatly enhanced the potential for the creation of decision support systems for WTP operators seeking to make urgent water treatment decisions.

1.2. Review of reported optimization models

In recent years, a number of optimization models have been developed for different stages of water and wastewater treatment processes. Mathematical data-driven models, in particular, appear to be more prevalent in the literature than process-based models. Their main virtues include their simplicity, relative precision and cost-effectiveness. Additionally, data-driven simulations tend to be faster than process-based (e.g. hydraulic) models, which often require outputs from multiple component models to be combined in order to provide useful predictions, making them less feasible for treatment optimization (Regneri et al., 2010). On the other hand, mathematical models can be effective in situations where a solution is needed urgently (e.g. because of an outbreak of a waterborne contagious disease), since the sample analysis procedure can be time consuming (Al-Ali et al., 2011). In general, data mining techniques have been found to be promising for modelling industrial applications (Kusiak and Wei, 2011). In relation to the water industry, Savic et al. (1999) provided comprehensive review of data mining and analytics techniques applied to urban and surface water engineering problems. More than a decade has passed since their study, and a significant amount of new research has been completed that has improved these existing techniques and also added a range of novel water treatment management applications.

A good part of previous research has focused on Wastewater Treatment Plant (WWTP) optimization and costs reduction rather than on the potable water treatment processes improvement. For WWTP applications, there are a few examples of process-based models. For example, McCorquodale et al. (2005) used physical modelling to investigate the optimization of the hydraulic conditions of a high-purity oxygen-activated sludge. Also, Seggelke et al. (2005) optimized the dynamic control of a treatment plant inflow by using an online simulator running parallel to the real WWTP operation; this provided model information to a prognosis tool which determines the best inflow options.

Interestingly, there are many examples of formulated data-driven models that have surfaced in recent years. For instance, Baruch et al. (2005) built three adaptive neural network control structures to regulate a biological wastewater treatment process. Another neural network-based control system was developed by Lee et al. (2005) to efficiently operate small plants with significant variance in the influent loadings. They used an internet-based remote monitoring system that input oxidation–reduction potential (ORP) as the main sensor for the control. Interestingly, Gillot et al. (1999) created a novel economic index that considered both WWTP fixed and variable costs in order to compare and decide on potential lowest cost treatment scenarios for a WWTP. The integration of variable costs was deemed crucial for more clearly identifying treatment options that could deliver cost savings. Both Bozkurt et al. (2015) and Hakanena et al. (2013) developed similar optimization models that could be used for multi-objective WWTP design and operation. Al-Ali et al. (2011) provides another example of a data-driven statistical model that could correlate biogeochemical and chemical oxygen demand with total suspended solids and other anions of the wastewater samplings from a drug factory. Beyond WWTP, Alcolea et al. (2009) developed an optimization tool for desalination plants that attempted to achieve the multiple objectives of reduced environmental impacts and minimized the operational costs (Alcolea et al., 2009).

For potable water systems, Chen et al. (2014) recently built an interesting hybrid model that optimized the source selection proportions of a water resource system that included both surface and groundwater. The groundwater flow was simulated with a physical model and incorporated into an artificial neural network to run the optimization. One of the first WTP optimization models was attempted by Baruch et al. (2005) for an Iranian plant; however, the optimization tool covered turbidity and total organic carbon removal only, with the chemicals optimization being conducted by jar tests. Similarly, a Decision Support System (DSS) was built by Slavik et al. (2010) to assess different reservoir raw water management strategies. Even though the model is very comprehensive, and also considers such aspects as flood risks, the water quality (and thus treatment cost) is assessed by means of organic load and turbidity parameters only. The model does not consider the extra treatment costs associated with the day-to-day variations of other relevant water quality parameters (e.g. pH, alkalinity, or peaks in manganese). Interestingly, Rietveld et al. (2010) developed a number of optimization models for a drinking WTP aimed to improve the operation of treatment sub-processes and, thus, reduce the costs.

In the Rothberg, Tamburini and Winsor (RTW) model, more details are provided to support water operators (Rothberg et al., 1993; RTW, 1996). This model is a spreadsheet-based tool designed to help users assess the effects of chemical additions on the stability of water, and to predict changes in the water quality parameters, such as pH, alkalinity, or calcium carbonate precipitation potential. The RTW model is often used by water engineers to develop corrosion control strategies, optimize coagulation, determine pH impacts on the precipitation of metals, and evaluate the chemical dosage options and their economics.

A quite relevant body of work, in terms of chemical dosages and treatment cost prediction modelling was undertaken by Abdullahi and his colleagues. Firstly, he determined the amount of alum (Abdullahi and Odigure, 2006), then the amount of chlorine (Abdullahi and Abdulkarim, 2010) and, finally, the amount of lime (Abdullahi et al., 2012) required for water treatment, using mathematical models and the existing interrelationships between the parameters. It must be acknowledged that an alum prediction model, based on historical jar tests, had already been built by van Leeuwen et al. (2001), while Artificial Neural Networks modelling was used by Maier et al. (2004) to predict optimal alum doses and, thus, potentially avoid the jar tests.

Abdullahi (2013) was able to put all the models together and, by using a new, integrated data-mining approach, he was able to estimate the WTP operational costs. The new model covers energy, administration, maintenance, and chemical costs. However, it should be noted that the only modelled chemicals are lime, alum, and chlorine using the findings of his previous studies in 2006, 2010 and 2012.

In the Mudgeeraba WTP, location of this study, more chemicals are used (e.g. carbon dioxide and sodium hydroxide) which also cause pH variations during the process, and must be taken into account in order to properly adjust the final pH of the treated water. Also, one of the two water sources that can be drawn from is derived from a reservoir that has a lower elevation than the WTP, while the second reservoir provides gravity fed raw water to the WTP. Therefore, for this study, the cost of all the estimated chemicals as well as the pumping costs must be calculated for each water reservoir source selection scenario.

Due to the amount of historical water treatment data available to the researchers and the literature presenting the successful development of several data-driven models for similar applications, the authors embarked on this study to apply data-mining and