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Research article

Statistical monitoring of a wastewater treatment plant: A case study

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ABSTRACT

The efficient operation of wastewater treatment plants (WWTPs) is key to ensuring a sustainable and friendly green environment. Monitoring wastewater processes is helpful not only for evaluating the process operating conditions but also for inspecting product quality. This paper presents a flexible and efficient fault detection approach based on unsupervised deep learning to monitor the operating conditions of WWTPs. Specifically, this approach integrates a deep belief networks (DBN) model and a one-class support vector machine (OCSVM) to separate normal from abnormal features by simultaneously taking advantage of the feature-extraction capability of DBNs and the superior predicting capacity of OCSVM. Here, the DBN model, which is a powerful tool with greedy learning features, accounts for the nonlinear aspects of WWTPs, while OCSVM is used to reliably detect the faults. The developed DBN-OCSVM approach is tested through a practical application on data from a decentralized WWTP in Golden, CO, USA. The results from the DBN-OCSVM are compared with two other detectors: DBN-based K-nearest neighbor and K-means algorithms. The results show the capability of the developed strategy to monitor the WWTP, suggesting that it can raise an early alert to the abnormal conditions.

1. Introduction

Wastewater treatment processes, that aim to remove pollutants from wastewater so that it can be safely reused or discharged, are extremely important for community health and environment. Treated wastewater can be recycled and re-distributed as non-potable water for cleaning, agricultural, and industrial purposes, or safely discharged back into the environment without inducing any serious effects (Grant et al., 2012). Discharges from WWTP must meet the discharge permit limits and the national effluent discharge quality standards to protect the environment and public health (Siegrist, 2017). From a practical point of view, and environmentally speaking, it is often more beneficial to recycle and reuse the treated wastewater rather than to discharge it (Castellet and Molinos-Senante, 2016). For example, the reuse of treated wastewater is increasingly becoming a necessity in water-stressed countries, such as countries in the Middle East region, as it offers substantial water - resource savings, while simultaneously providing significant financial benefits, as the costs related to the recycling process are much lower than those of desalting seawater (Dolnicar and Schäfer, 2009; Côté et al., 2005).

To achieve the efficient operation of wastewater treatment plants (WWTPs), some key variables involved in the process, such as dissolved oxygen, nitrogen, phosphorus, and pH, need to be accurately monitored and controlled (Boujelben et al., 2017; Kazor et al., 2016). A good understanding of the WWTP dynamics is required for reliable monitoring and control activities. However, the dynamical behavior of WWTPs is usually complex and uncertain due to nonlinearity, variations in the physical properties in terms of the environmental conditions, strong interactions between the process variables involved, and wide variations in the flow rate and concentration of the composition of the influent of WWTPs. These many factors increase the difficulty of monitoring and control tasks.

Increased attention to modeling wastewater processes has led to the development of several models capable of describing the biological processes involved in WWTPs (e.g., ASM1, ASM2, ASM2d and ASM3) (Henze et al., 2000; Mannina et al., 2011; Plattes et al., 2006). However, these models have complex structures and are comprised of relatively large numbers of parameters that must be identified, making them unsuitable for monitoring purposes. For example, the model ASM1 is comprised of 13 nonlinear differential equations, which involve 19 parameters that are hard to estimate (Dochain and Vanrolleghem, 2001). This high level of model complexity represents a heavy computational burden for the simulation and design process (Vanrolleghem et al., 1999).

Keeping a WWTP running correctly and safely, and generating the desired product quality remains a major challenge in environmental

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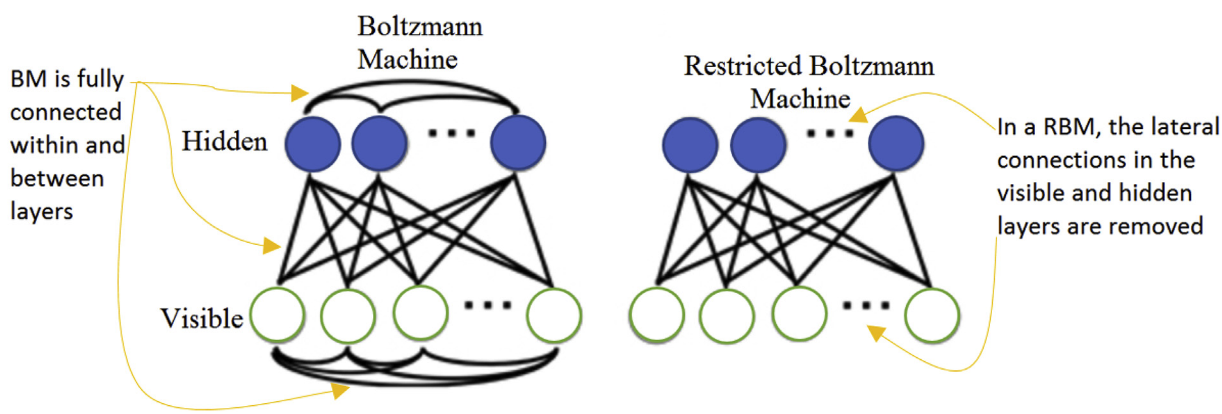

Fig. 1. Schematic presentation of a restricted boltzmann machine (RBM). Left: A general Boltzmann machine. Right: An RBM with no visible-to-visible or hidden-to-hidden connections.

sustainability (Skrjanc and Teslic, 2008; Lee et al., 2003; Steyer et al., 1997). Therefore, monitoring in WWTPs has received special attention from researchers and practitioners in the field of safety engineering. Many methods have been developed for improving fault detection in WWTPs. Wang et al. (2017) proposed a statistical approach based on combined principal components analysis (PCA) and multiple regression to model a WWTP. Dias et al. (2007) applied an artificial neural network (ANN) and neural fuzzy models for monitoring and predicting WWTPs. Wilcox et al. (1995) also used ANN model to monitor and control an anaerobic WWTP. Other researchers focused on using time series analysis approaches to model and monitor WWTPs (Huo et al., 2005; Novotny et al., 1991; Capodaglio et al., 1992). Other approaches used latent variable (LV) methods, such as PCA and projection latent structures (PLS), for monitoring and predicting parameters of the influent and effluent of WWTPs. Amaral and Ferreira (2005) applied a PLS regression for activated sludge process (ASP) monitoring. PLS methods have been applied to predict the deterioration of sludge sedimentation properties by monitoring the parameters affecting effluent quality and filamentous bulking in ASPs (Mujunen et al., 1998). PCA and its extensions have been widely used for statistical modeling and monitoring of WWTPs (Liu et al., 2014; Huang et al., 2012; Villez et al., 2008; Lee et al., 2004; Rosén and Lennox, 2001; Lee and Vanrolleghem, 2003).

The main objective of this paper is to enhance the operation and performance of WWTPs through the development of an innovative monitoring strategy. This paper presents a flexible and efficient fault-detection approach based on deep learning to monitor WWTPs. A fault detection strategy capable of dealing with the complex nonlinear dynamics of WWTPs has been proposed. This approach integrates a deep belief network (DBN) model and a one-class support vector machine (OCSVM), and simultaneously takes advantage of the powerful feature-extraction capability of DBNs and the superior predicting capacity of OCSVM. The DBN model, which is a powerful tool with greedy learning features, accounts for the nonlinear aspects of WWTPs, while OCSVM reliably detects the faults in a WWTP dataset. The DBN model, which consists of multiple layers of restricted Boltzmann machines (RBMs), is built via unsupervised greedy layer-wise training using the data collected from a WWTP. Here, WWTP monitoring is addressed as an anomaly-detection problem based on the one-class support vector machine (OCSVM) classifier, trained unsupervised on fault-free data obtained from the DBN model. The central role of the OCSVM classifier is to separate fault-free from faulty data by building a hyperplane. We test the proposed DBN-OCSVM method on practical data collected from a pilot-scale membrane bioreactor (MBR) at the Mines Park Water Reclamation Test Site, a decentralized wastewater treatment facility in Golden, CO.

The remainder of this paper is organized as follows. Section 2 gives a brief overview of machine-learning generative models and the OCSVM algorithm. In Section 3, the proposed DBN-OCSVM fault-detection approach is presented. In Section 4, the performances of the proposed methods are illustrated in a real data application, and Section 5 concludes with a discussion.

2. Preliminary material

Over the past two decades, several approaches to fault detection based on shallow learning have been investigated, such as training different classifiers by support vector machines (SVM), AdaBoost, and neural networks in supervised learning with one or two layers (Jabeen et al., 2017; Raduly et al., 2007; Ribeiro et al., 2013). However, shallow-learning approaches are not suitable for representing dependencies among multiple variables, are inefficient when dealing with high-dimensionality data, and have a limited ability to model complex functions, leading to unsuitable generalized models. To overcome these limitations, deep-learning approaches have been developed. In a deep-learning approach, several layers are stacked to describe complex functions (Hinton, 2012). In other words, the output of each layer represents the input of the next layer. Using this structure, the classification and learning of complex input information can be achieved. Restricted Boltzmann machines and deep belief networks are powerful deep architectures that overcome most of shallow-learning limitations (Hinton and Salakhutdinov, 2006; Hinton, 2007; Bengio, 2009). In this section, a brief overview of these two models is presented.

2.1. Restricted Boltzmann Machines (RBMs)

RBMs are stochastic neural networks (Smolensky, 1986) (see Fig. 1) that consist of m visible units ($v \in \{0,1\}^m$) and n hidden units ($h \in \{0,1\}^n$). There are no visible-to-visible or hidden-to-hidden connections, although v and h are fully connected (see Fig. 1). These models are trained using contrastive divergence learning procedure based on Gibbs sampling (Hinton, 2012). The learning procedure is comprised of many Gibbs sampling steps (propagate: sample hidden given visibles; reconstruct: sample visible given hidden; repeat) and selecting the weights with the minimum reconstruction error (Salakhutdinov and Hinton, 2009; Bengio, 2009; Hinton et al., 2006).

RBMs are particularly energy-based models and have been used as generative models for several types of data (Bengio, 2009), such as text, speech, and images. The energy of join configuration is defined by (Mohamed et al., 2012):

$$Energy(v, h) = -\sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij} v_i h_j, -\sum_{i=1}^{m} b_i v_i - \sum_{j=1}^{n} c_j h_j, \tag{1}$$

where W_{ij} is the weight matrix between the visible variable v_i and the