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An intelligent detection method for bulking sludge of wastewater treatment process

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ABSTRACT

Prediction of bulking sludge is a matter of growing importance around the world. In this study, to detect bulking sludge of wastewater treatment process (WWTP), an intelligent detection method, using a self-organizing recurrent radial basis function neural network (SORRBFNN) and a cause variables identification (CVI) algorithm, was developed to detect the fault points and the fault variables of bulking sludge. For this intelligent detection method, first, the structure and parameters of SORRBFNN were updated by an information-oriented algorithm (IOA) and an improved Levenberg-Marquardt (LM) algorithm to improve the prediction accuracy of the sludge volume index (SVI) from the water qualities. Second, the CVI algorithm was designed to allow a quick revealing of the cause variables of bulking sludge with high accuracy. And the intelligent detection method was tested on the measured data from a real WWTP. Experimental results confirmed the attractiveness and effectiveness of the proposed intelligent detection method.

1. Introduction

The activated sludge process is the most commonly applied technology for wastewater treatment process (WWTP). In the activated sludge process, one of the most important steps is the secondary clarification, whereby the activated sludge is separated from the treated effluent water [1,2]. In the secondary clarification, excess filamentous bacterial growth will cause operational problems known as filamentous bulking [3]. Bulking sludge, which settles slowly and compacts poorly, is one of the most frequent operational problems in the activated sludge process [4–6]. To avoid the phenomenon of bulking sludge, the applied research of detection method is one of the important tools in monitoring the process of wastewater treatment plant [7,8].

To fully understand the exact cause of filamentous bulking, several methods have been reported recently in literature to describe the filamentous bulking by modeling the kinetic properties of filamentous bacteria [9,10]. Wagner et al. introduced a practical mathematical approach to model the filamentous bulking by using computational fluid dynamics [11]. Since the process operators of WWTP were dynamic, the nonlinear dynamic behavior of the processes was hard to be remained in this mathematical model. In [12], Amaral et al. proposed an image analysis method to provide the morphological data of bulking sludge. The results showed that this method can detect the phenomenon of bulking sludge. In addition, Jenne et al. described a fully automatic image analysis procedure for detecting the reliable characterization of floc and filament features of the activated sludge composition [13]. These image analysis methods are offline, as well as the hardware equipment is expensive. Moreover, the prediction results of these methods rely on the quality of the images [14,15]. In recent years, several hypotheses on bulking sludge are formulated in the hope of finding a general explanation for this problem. For example, diffusion-based selection [16], kinetic selection theory [17], and storage selection theory [18] are proposed to explain bulking sludge. Unfortunately, none of them leads to a definitive solution. Most of the theories still lack experimental verification.

Since it is difficult to estimate the overflow capacity of a clarifier with the above methods, some sedimentation parameters (such as the sludge volume index (SVI), defined as "the volume in ml occupied by 1 g activated sludge after settling the aerated liquor for 30 min"; the diluted SVI (DSVI), defined as "the apparent volume of diluted sludge samples after a 30 min sedimentation") have been performed to quantify the settling characteristics of the sludge. SVI of 150 ml/g is most commonly considered as a threshold for bulking

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sludge [19]. It is measured that the DSVI value of 120 ml/g and above suggests a poorly settling sludge [20]. In [21], a dynamic autoregressive exogenous (ARX) model was investigated as a function of organic loading and digital image analysis information to predict the evolution of SVI. Bagheri et al. developed hybrid artificial neural network-genetic algorithm models (multi-layer perceptron artificial neural network (MLPANN) and radial basis function artificial neural network (RBFANN)) to predict SVI in [22]. In these models, the operation parameters, including pH, dissolved oxygen (DO) concentration, temperature, total suspend solid (TSS), chemical oxygen demand (COD) and total nitrogen (TN), were selected as the inputs. And the genetic algorithm was utilized to optimize weights and thresholds of the MLPANN and RFBANN models. Moreover, Yu et al. developed an intelligent method for predicting bulking sludge based on the artificial neural network and grey Markov model [23]. The results demonstrated that the proposed intelligent method can obtain the real-time prediction of bulking sludge. A self-organizing radial basis function neural network (SORBFNN) was utilized to predict the evolution of SVI in [24]. Furthermore, some other methods were used to predict the SVI values to detect the bulking sludge in [25,26]. In these above methods, only the SVI values were used to detect the bulking sludge. The quantification of the single sedimentation parameter is often case specific, and there is no broad consensus over the definition. The neural networks used in these above methods are feedforward. The main drawback of feedforward neural networks is that they are essentially static input-to-output maps and their capability for representing nonlinear systems, especially complex and/or time-varying, is limited [27,28].

Motivated by the above review and analysis, an intelligent detection method, based on a self-organizing recurrent radial basis function neural network (SORRBFNN) and a cause variables identification (CVI) algorithm, was developed to detect bulking sludge in this paper. Compared with feedforward neural networks, the recurrent radial basis function neural networks (RRBFNNs) were capable of providing long range predictions even in the presence of measurements noise due to their structures [29–31]. And RRBFNNs were better for modeling the nonlinear systems [32–34]. Moreover, different from the previous works in [24] and [35], the *main contributions* of this paper can be stated as: First, an information-oriented algorithm (IOA) and an improved Levenberg-Marquardt (LM) algorithm were used to adjust the structure and parameters of SORRBFNN to improve the flexibility for predicting the values of the sludge volume index (SVI) with suitable accuracy. Second, a CVI algorithm was designed to reveal the cause variables of bulking sludge with high accuracy. Third, this intelligent detection method has been successfully applied for a real WWTP in China for detecting the fault points and the fault variables of bulking sludge. Several experimental results illustrated the efficiency of the proposed method.

The remainder of this paper is organized as follows. First, after briefly introducing the bulking sludge in WWTP and RRBFNN in Section II, the proposed intelligent detection method, based on SORRBFNN and CVI algorithm, is developed in detail in Section III. In Section IV, the proposed intelligent detection method is applied for a real WWTP. Discussions are conducted to analyze the illustration results. Finally, the conclusions are drawn in the last section.

2. Problem formation and preliminaries

2.1. Bulking sludge in WWTP

The detection method proposed in this paper was designed and tested in a real WWTP. In the event of bulking sludge, there exists an imbalance between the floc-forming bacteria and filamentous bacteria, hence preventing formation of readily settling sludge flocs. The reactors exhibit common features of industrial systems, such as nonlinear dynamics and coupling effects among the variables. These features show that the obstacles of the bulking sludge detection in WWTP are modeling challenges, uncertainties and multiple time-varying dynamics.

Filamentous bulking is an essential part of the bulking sludge in WWTP. In the activated sludge process, when there are too great numbers of the filaments and they grow out of the general confines of the floc into the bulk medium, it will result in slowly settling, poorly compacting, and bulking sludge. Meanwhile, too many filamentous always aggregate with both gas bubbles and floc particles, which may cause biological foaming. Therefore, it is urgent to design a detection method to predict the emergence of bulking sludge in real-time.

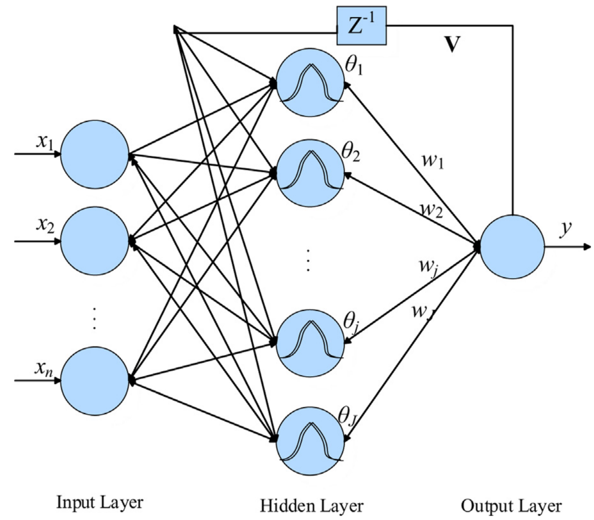

Fig. 1. The structure of RRBFNN.

2.2. Recurrent radial basis function neural network

In this paper, a three-layer RRBFNN was utilized in the intelligent detection method. The structure of RRBFNN is shown in Fig. 1. The Gaussian function is adopted as the activation function in the hidden layer due to its continuous and differential characteristics. The prior output of RRBFNN is recurrent to the hidden layer through a time delay. The mathematical description of RRBFNN is shown as follows.

In this multi-input and single-output (MISO) RRBFNN, the output of RRBFNN is:

$$y(t) = f(\mathbf{w}(t), \boldsymbol{\theta}(t)) = \sum_{j=1}^{J} w_j(t) \times \theta_j(t),\ j = 1, \cdots, J, \tag{1}$$

where $\mathbf{w}(t) = [w_1(t),\ w_2(t), \ldots,\ w_J(t)]^{\mathrm{T}}$ is the connection weights between the hidden neurons and output neuron, J is the number of hidden neurons, $y(t)$ represents the output of RRBFNN at time t, $\boldsymbol{\theta}(t) = [\theta_1(t), \theta_2(t), \ldots, \theta_J(t)]^{\mathrm{T}}$ is the output vector of the hidden layer.

3. Intelligent detection method

The design of intelligent detection, based on SORRBFNN and CVI algorithm, mainly contains three procedures (see Fig. 2): adjust the parameters by an improved LM algorithm, optimize the network size utilizing the proposed IOA method, and detect the bulking sludge and the relation variables via the CVI algorithm.