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Research on Intelligent Detection System for Predicting Membrane Pollution

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Abstract: Membrane bioreactor (MBR) is a new sewage treatment system that organically combines membrane separation technology and biological treatment technology. The key problem restricting the development of MBR is membrane pollution. This paper summarizes the main causes of membrane pollution and common treatment methods, and puts forward a new method of membrane pollution prevention - intelligent detection system. The intelligent detection system can be divided into four modules: data acquisition module, real-time data transmission module, online prediction module and real-time display module, which are used to monitor the actual situation of sewage treatment, thus reducing membrane pollution and improving.

Keywords: MBR; Membrane Pollution; Intelligent Detection System; Partial Least Squares Method.

1. Introduction

MBR (Membrane Bio-Reactor) is a new type of wastewater treatment system that organically combines membrane separation technology and biological treatment technology [1-3]. A key factor that restricts the development of MBR is membrane pollution. Membrane pollution directly leads to the decline of membrane flux (referring to the amount of fluid passing through unit membrane area in unit time), which greatly shortens the service time of membrane, resulting in the decline of MBR performance and the increase of operating power.

2. Prevention and control methods of membrane pollution

2.1. Membrane pollution influence parameters

Membrane fouling is a key factor affecting MBR efficiency, and membrane flux is an important indicator of membrane fouling. The decline of membrane flux is affected by many factors, including sludge particle size, sludge concentration, soluble microorganisms, suspended solids in mixture and water pressure. The main influencing parameters of membrane flux are as follows:

(1) Sludge concentration

One of the most critical factors for the decline of membrane flux is the sludge concentration. The membrane pollution is negatively correlated with the sludge concentration index. When the sludge concentration is low, the adsorption capacity of sludge to organic matters decreases, the deposition of organic matters on the membrane surface increases, and the membrane pollution increases [4].

(2) Sludge particle size

The particle size of sludge is also an important factor that determines the membrane pollution, which is negatively correlated with the particle size of sludge [5]. When the particle size of sludge is small, it is easy to immerse in the membrane surface. After many times of deposition, the resistance of filter cake layer will increase and the membrane pollution will increase.

(3) Soluble microorganism

Soluble microorganisms have a negative correlation with membrane pollution. Compared with extracellular polymers, soluble microorganisms are easier to accumulate in MBR. With the increase of soluble microbial concentration, membrane pollution is more serious.

(4) Sludge viscosity

Sludge viscosity is positively correlated with membrane fouling. Tao [6] and others believe that the increase of sludge EPS production will increase the viscosity of activated sludge, resulting in serious membrane pollution.

(5) Zeta potential of sludge

Zeta potential of sludge is an important parameter to characterize sludge electrification performance, and membrane fouling is negatively correlated with zeta potential of sludge [7].

(6) Hydrophilicity and hydrophobicity between membranes

The hydrophilicity and hydrophobicity between membranes is an important factor affecting membrane fouling, which is negatively correlated with the hydrophilicity and hydrophobicity between membranes.

2.2. Common control methods

The key factor causing membrane pollution is membrane flux, so the prevention and control of membrane pollution are mostly carried out around solving the problem of membrane flux. Among them, chemical cleaning and physical cleaning are the most widely used. Physical cleaning includes online air cleaning and online backwash. This is a relatively simple cleaning method [8,9]. The existing equipment blower and backwash pump are used for direct cleaning. If the physical cleaning effect is not good, chemical cleaning should be used. Chemical cleaning is to add chemicals for cleaning, Acidic agents (hydrochloric acid, sulfuric acid, citric acid, etc.) for organic pollution and alkaline agents (sodium hypochlorite, caustic soda, etc.) for inorganic pollution are better than physical cleaning [10].

3. Intelligent detection system for me--mbrane pollution

3.1. Intelligent detection system settings

The intelligent detection system is used for online monitoring of membrane permeability in a real sewage treatment plant using MBR technology [11]. The MBR sewage treatment process includes anaerobic tank, anoxic tank and aerobic tank. First of all, pre-treatment is carried out to screen and precipitate the pollutants in MBR. The biological reaction tank includes anaerobic tank, anoxic tank and aerobic tank. On the basis of the MBR system, the MBR system is equipped with a collection sensor and mixer for process variables to ensure the full mixing of the mixture full mixing of the mixture. Acknowledgment.

The data of water treatment can be obtained by connecting the intelligent detection system with sensors. The intelligent detection system consists of four parts: data acquisition module, real-time data transmission module, online prediction module and real-time display module. The data acquisition module is used to obtain the value of process variables from the sensor. The real-time data transmission module is used to transfer data from the sensor to the local programmable logic controller (PLC). Due to its small size and convenient installation, the protocol converter is used as the communication channel of the data transmission module. The online prediction module aims to predict the pollution through the membrane flux based on soft computing [12-15]. The real-time display module has an extremely effective role, allowing the system administrator to monitor the membrane pollution status online and take appropriate actions.

3.2. PLSR parameter selection

PLSR (Partial Least Squares Regression) is a linear regression modeling method, which can make a richer and more detailed interpretation of the model [16] This paper selects PLSR method to screen variables, with the purpose of selecting the factors that have the strongest impact on the output parameters and screening out the factors that have the smallest impact on the output parameters, so as to reduce the dimension of the data set, reduce the calculation amount and improve the accuracy of membrane pollution detection[16-18].

(1) preprocess the analysis variables to obtain the standardized order of magnitude.

$$u_i = Xw_i \ , v_i = yc_i \tag{1}$$

$$X = \sum_{i=1}^{n} u_i \, p_i^T + E, \quad y = \sum_{i=1}^{n} v_i \, q_i^T + G \tag{2}$$

In formula (3-1), and are the eigenvectors of the largest eigenvalues of the symmetric matrices X and Y, and the first pair of principal components of X and Y are calculated according to the eigenvectors of the largest eigenvalues. Regression modeling of principal components of X and Y according to formula (3-2)

(2) The linear regression equation is constructed after the internal relationship is established through PLSR.

The linear regression equation between and is shown in equations (3-3) and (3-4), where is the regression coefficient between and.

$$u\hat{}_i = u_i t_i \tag{3}$$

$$b_i = \frac{u_i^T b_i}{t_i^T t_i} \tag{4}$$

(3) The predicted fitting value of the new sample is obtained, and the number of extracted components is determined by the cross-degree criterion.

$$y\hat{}_j^{\propto} = x_j b^{\propto} + c^{\propto} \tag{5}$$

$$Q_h^2 = \frac{\sum_{j=1}^{h} (y_j - y\hat{}_i^{h})^2}{\sum_{j=1}^{h} (y_j - y\hat{}_i^{h-1})^2} \tag{6}$$

The prediction fitting value formula of the new sample j (j=1,2...... M) based on all samples is shown in formula (3-5), where is the process vector of sample j, is the regression coefficient variable, and is the offset. The final number of extracted components is determined by the cross-validity criterion according to Formula (3-6), where h is the extracted fraction. When<0.075, the model meets the accuracy requirements, the algorithm will be stopped.

4. Conclusion

Membrane bioreactor has been widely used to treat wastewater from wastewater treatment plants [19]. In the application of sewage treatment, rapid and accurate membrane flux prediction can monitor the situation of sewage treatment in real time, monitor the change of MBR in advance, and timely replace or clean the membrane when the membrane flux decreases, which can better predict the performance of MBR sewage treatment [20]. The intelligent detection system used in this paper can monitor the conditions of various parameters in MBR in real time, and can predict the situation of membrane pollution in advance. In addition, the system is cheap, with light calculation burden, and can be widely used

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References

[1] Ming, Feng, Tay, et al. The feasibility of nanofiltration membrane bioreactor (NF-MBR)+ reverse osmosis (RO) process for water reclamation: Comparison with ultrafiltration membrane bioreactor (UF-MBR)+RO process[J]. Water Research A Journal of the International Water Association, 2018.

[2] Jiang Z , Gao H , Wu L , et al. Purification and recycling of municipal wastewater based on MBR process[J]. International Journal of Global Energy Issues, 2022, 44.

[3] Palharim P H , Lastre-Acosta A M , José Carlos Mierzwa, et al. Influence of low and high dosages of methyl and propyl parabens on membrane bioreactor (MBR) performance[J]. Separation Science and Technology, 2021:1-11.

[4] She Q , Wang R , Fane A , et al. Membrane fouling in osmotically driven membrane processes: A review[J]. Journal of Membrane Science, 2016, 499:201-233.

[5] Yifeng J,Shengbing H,Jianmeng C. Improved Performance of Membrane Bioreactor by Sludge Ozonation for Reduction of Excess Sludge Production[J]. Journal of Donghua University(English Edition):171-176.

[6] Mustafa A A , Furkan A M , Cicekalan B , et al. Primary and A-sludge treatment by anaerobic membrane bioreactors in view of energy-positive wastewater treatment plants[J]. Bioresource Technology: Biomass, Bioenergy, Biowastes, Conversion Technologies, Biotransformations, Production Technologies, 2022:351

[7] Tao Y X , Chun-Qing L I , Hua S U . Prediction of MBR Membrane Pollution Based on Improved PSO and Fuzzy RBF Neural Network[J]. Computer Engineering & Software, 2018.

[8] Yang M , Xie D , Ma X , et al. Mesophilic condition is more conducive to methane production yield and tylosin removal on tylosin fermentation dreg anaerobic digestion[J]. Bioresource Technology, 2021(2):125806.

[9] Mlc A , Wn B , Nbs C , et al. Sludge fractionation as a method to study and predict fouling in MBR systems. 2018.

[10] Jin L , Yu D , Dan W . Performance of membrane bioreactor (MBR) process treating wastewater containing different content of seawater[J]. Environmental Engineering & Management Journal, 2011, 10(7):887-891.

[11] Grbi L , Drueta S , Maua G , et al. Coastal water quality prediction based on machine learning with feature interpretation and spatio-temporal analysis:, 10.48550/arXiv.2107.03230[P]. 2021.

[12] Li W , Li C , Wang T . Application of machine learning algorithms in MBR simulation under big data platform[J]. Water Practice and Technology, 2020, 15(4):1238-1247.

[13] Norouzi H , Bazargan J . Using the Linear Muskingum Method and the Particle Swarm Optimization (PSO) algorithm for calculating the depth of the rivers flood. 2019.

[14] Li W , Li C , Wang T . Application of machine learning algorithms in MBR simulation under big data platform[J]. Water Practice and Technology, 2020, 15(4):1238-1247.

[15] Alfredo Bermúdez, Ulloa S B , JL Ferrín, et al. A high order projection method for low Mach number flows[J]. 2018.

[16] Yeo W S , Saptoro A , Kumar P . Development of Adaptive Soft Sensor Using Locally Weighted Kernel Partial Least Square Model[J]. Chemical Product & Process Modeling, 2017, 12.

[17] Wan S Y , Saptoro A , Kumar P . Missing data treatment for locally weighted partial least square-based modelling: A comparative study[J]. Asia-Pacific Journal of Chemical Engineering, 2020(3).

[18] Sahbeni G . A PLSR model to predict soil salinity using Sentinel-2 MSI data[J]. De Gruyter Open Access, 2021(1).

[19] Chen F , Chen C , Chen C , et al. Application of PLSR in rapid detection of glucose in sheep serum[J]. Optik - International Journal for Light and Electron Optics, 2020, 224(suppl_1):165734.

[20] Zhao T , Lo C T , Qian K . A Neural-Network Based DDoS Detection System Using Hadoop and HBase[C]// 2015 IEEE 17th International Conference on High Performance Computing and Communications (HPCC), 2015 IEEE 7th International Symposium on Cyberspace Safety and Security (CSS) and 2015 IEEE 12th International Conf on Embedded Software and Systems (ICESS). IEEE, 2015.