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Activated sludge process faults diagnosis based on an improved particle filter algorithm

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ABSTRACT

Maintaining the discharge standards of biologically-treated wastewater is essential in order to protect receiving water bodies from secondary pollution. If unexpected faults happen in an activated sludge process that is used as biological treatment, it would affect the quality of the receiving water body. Thus, in this paper, an improved particle filter (PF) algorithm, based on a variable frequency mutation (VFM) strategy is proposed for the process faults diagnosis. This is inspired by the frequency conversion for energy-saving application in the industrial process; an adaptive frequency conversion operator has been incorporated into the mutation operation of immune algorithm to reduce the system operating costs. Then, the resampling process of PF algorithm was replaced by particle mutation based on the previously calculated information for securing the diversity and the effectiveness of the particle; lastly, a VFM-based PF algorithm for system states estimation and fault diagnosis was established. This algorithm not only effectively increases the adaptability of the particle to changes of the system state, but also conductively solves the problems of the degeneracy in the traditional PF algorithm and the diversity weakening caused by resampling operation. Simulation results show that the algorithm can effectively improve the estimation accuracy of the nonlinear system states. The application results of faults diagnosis in the activated sludge process show that it can accurately diagnose the occurrence of faults. Therefore, the proposed method has great practical significance in wastewater treatment plants to avoid problems caused by unexpected faults.

1. Introduction

Wastewater treatment plant (WWTP) is an important infrastructure to support the ecology and improve the quality of water environment around the world (Li et al., 2017). Well-treated wastewater can be used as reclaimed water for various purposes, such as industrial/agricultural use, greening of cities, cleaning of roads, etc. However, if the treatment quality is affected by unexpected faults in the treatment processes, the effluent will not meet the reuse/discharge standards, and will cause secondary pollution in the water environment. Because of the need of continuity and irreplaceability of WWTPs, once the failure/fault occurs, it will cause serious effect to the environment. Hence, it is necessary to carry out research on fault diagnosis and supervision for WWTP's safe operation.

Monitoring complex industrial plants is a very important task in order to ensure the management, reliability, safety and maintenance of the desired product quality. As a typical complex nonlinear industrial process (Isermann and Ballé, 1997; Frank, 1996), good results for fault diagnosis of activated sludge process (ASP)-based wastewater treatment is difficult to achieve. Researchers around the world have devoted a lot of efforts into this area in the past decades. Sanchez-Fernandez et al. (2018) developed a new methodology for fault detection based on time series models and statistical process control (MSPC) to monitor dynamic and non-linear complex process. The performance of the method was validated on two benchmarks, (i) a wastewater treatment plant BSM2 (Alex et al., 2008; Nopens et al., 2010) and (ii) the Tennessee Eastman Plant. Comparison with other classical methods, principal component analysis (PCA) algorithm clearly demonstrates the superior performance and feasibility of the proposed monitoring scheme.

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A numerically efficient adaptive sensor fault diagnosis method based on recursive updating of the loading subspaces of PCA with a low computational cost has been developed by Lamiaa and Tarek (2018). They proved the diagnosis-ability of the proposed method for single sensor faults with large magnitudes. A continuously stirred tank reactor (CSTR) process simulation was considered to demonstrate the efficiency of the proposed approach. The results showed the ability of the proposed approach to adapt with the time-varying characteristics and still correctly diagnose the sensor faults even in the case of relatively moderate and small faults (Lamiaa and Tarek, 2018). A semi-adaptive fault diagnosis method based on the variational Bayesian mixture factor analysis (VBMFA) to support process monitoring was proposed and validated through a simulation study of a wastewater plant (Xiao et al., 2016). Results showed that it can significantly improve the ability of fault diagnosis under fault-free scenario, accurately detect the abrupt change and drift fault, and even localize the root cause of corresponding fault properly. Moreover, there are many other studies in this area, such as a produced water treatment pilot plant has been modeled with Multilevel Flow Modeling (MFM), for the purpose of on-line fault diagnosis for operator decision support (Nielsen et al., 2018), a parameter estimation-based methodology for fault detection in wastewater treatment systems (Mid and Dua, 2018), and an improved particle filtering (IPF)-based multiscale optimized exponentially weighted moving average chart (MS-OEWMA) to improve the fault detection in WWTP systems (Baklouti et al., 2018). Fuzzy logic is also been widely used for fault diagnosis in WWTPs (Steyer et al., 2001; Guo et al., 2018).

In recent decades, particle filter (PF) has become the mainstream method to solve the problems dealing with parameter estimation and state filtering for non-linear non-Gaussian systems. It has been widely used in variety of non-linear systems for fault diagnosis based on the calculated likelihood function value or residual smoothing value (Zhang et al., 2015). However, the problem of particle degeneration of classical PF will have a certain impact on the results of state estimation in specific applications, especially in the case of sudden change of a system state. In this paper, a model-based state estimation particle filter method for fault diagnosis of activated sludge process in WWTPs is proposed. We have incorporated the adaptive frequency conversion strategy into the PF, which is used to replace the resampling process for securing the diversity and the effectiveness of the particles. The dynamic change of the residuals are used as an indicator to detect the faults in the MATLAB simulation studies. Based on these improvements, particle degeneration has been overcome effectively as the process goes on, and the good results that were obtained from our study confirm the effectiveness of the method.

2. Materials and methods

2.1. Particle filter for state estimation

Particle filter (PF) is a method that uses a set of statistical samples to approximate the posterior probability density function, and implements recursive Bayesian estimation to estimate the system state by Nonparametric Monte Carlo method (Doucet et al., 2000; Arulampalam et al., 2002; Speekenbrink, 2016; Gordon et al., 1993).

Assume that the system state space model consists of the following system models and observation models:

$$x_k = f(x_{k-1}, u_{k-1}) \tag{1}$$

$$y_k = g(x_k, v_k) \tag{2}$$

Where, f and g are two functions; x_k is the state variable of the system at time k (assuming x_k obeys the first-order Markov process with the prior initial probability density $p(x_0)$); y_k is independent, indicating the observed value of x_k; u_k is the system noise, v_k is observation noise, which are random variables independent from the system state, and independent of each other as well.

The basic particle filter (PF) algorithm is described as follows:

1) Prediction: N particles are extracted from the transition probability density of the system states ($p(x_k|x_{k-1})$).

$$x_k(i) \sim p(x_k|x_{k-1}(i)),\ i = 1, 2, \cdots, N \tag{3}$$

2) Update: Eq. (4) is used to update the sample weights and Eq. (5) is used to normalize them.

$$w_k^*(i) = w_{k-1}^*(i) p(y_k|x_k(i)) \tag{4}$$

$$w_k(i) = \frac{w_k^*(i)}{\sum_{i=1}^{N} w_k^*(i)} \tag{5}$$

Where, $p(y_k|x_k)$ is the observed likelihood probability density of the system states.

3) Estimation: Eq. (6) is used to estimate the value $\hat{x}_k$ of x_k. The least mean square error estimation is performed here.

$$\hat{x}_k = \sum_{i=1}^{N} w_k(i) x_k(i) \tag{6}$$

4) Resampling: a multinomial resampling is performed to get a number of N new particles with equal weights.

Compared with the traditional filtering methods, particle filter (PF) has the advantages of simple principle and applicability to wider environments (Wang et al., 2014). It has become an effective method to study optimal estimation problems of non-linear and non-Gaussian dynamic system, and been widely used in the fields of machine vision, navigation, parameter estimation, target tracking, state monitoring and fault diagnosis etc. (Cheng and Zhang, 2008; Yang et al., 2006).

2.2. Variable frequency based mutation for particle filter algorithm

Artificial immune theory has been obtained from the study of natural phenomena such as biological genetics, biological immunity and natural selection. In recent years, the artificial immune theory has been widely applied to artificial intelligence including function optimization, process optimization, pattern recognition and other fields (Louati et al., 2018; Ulutas and Kulturel-Konak, 2011). The immune algorithm is an optimized algorithm for optimal solution search which simulates the main processes of biological immunity, including antibody production, cloning, mutation and the process of self-tolerance. The algorithm can make full use of the prior knowledge and characteristic information of the problem to be solved, which can effectively restrain the degradation phenomenon in the evolution process.

This work is inspired by the frequency conversion for energy-saving application in the industrial process. Taking the blower environment as an example, when smaller air volume is needed, the operating frequency of the motor can be reduced to decrease the motor speed and torque, which will lead to a sharp decline in energy consumption by the fan as it is proportional to the square of the motor speed. Similarly, when the particles' validity could meet the requirements, we can continue to use the existing particles or mutate a small number of particles for the estimation of the state. This will then reduce the operating costs of a system. When the particles' effectiveness cannot meet the requirements, offspring can be

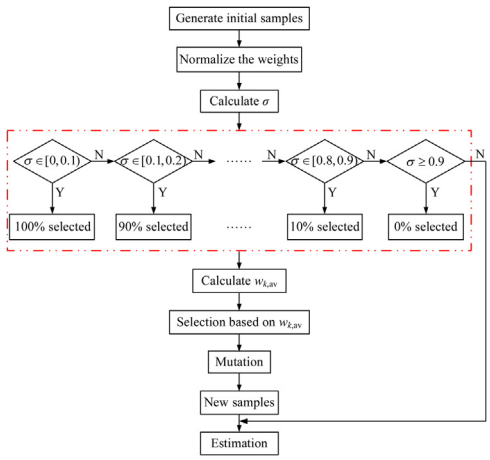

Fig. 1. Flow chart of the proposed VFM-based PF algorithm.

produced to maintain the particles' diversity and effectiveness via mutation of a large number of particles.

In this work, combining with the frequency conversion for energy-saving application in the industrial process, the number of particles for mutation are determined according to the distribution of particles' weights and an adaptive frequency conversion operator. That is, when the weights meet the set requirement, indicating that the particles' degradation degree is low at this point in time, a smaller number of, even no particles should undergo mutation operations; and when the weights distribution is not meeting the setting requirement, indicating that the particles' degradation degree is high at this point in time, more particles should be mutated to maintain the population size of effective particles to ensure the accuracy of the estimation. By doing this operation, the computational efficiency will be improved and the computational cost can be reduced. The main idea and steps of the new adaptive variable frequency-based mutation for particle filter (VFM-based PF) algorithm are detailed as follows and the flow chart of the new proposed VFM-based PF algorithm is shown in Fig. 1.

Firstly, Eqs. (3)–(5) are used to get a set of the normalized weights of the particles, $\{w_k(i)\}$, and then the frequency conversion operator σ, which is a ratio can be resulted from the number of the effective particles, is calculated.

$$\sigma = \frac{N_e}{N_{th}} \tag{7}$$

$$N_e = 1/\sum_{1}^{N}(w_k(i))^2 \tag{8}$$

Where, N_e is the number of the effective particles; N_{th} is a preset inspection threshold, which generally has a value of half of the total number of particles.

Using the effective particles ratio, σ as the frequency conversion operator, it has the advantage of a large number of particles mutation will only be taking place at the time when the particles are severely degraded; on the contrary, only a small number of particles would be mutated, or perhaps, not mutated at all. Hence, the efficiency of the proposed algorithm can be improved by avoiding large computational cost caused by the excessive mutation operation.

If the operator is larger than 1, the mutation operation will not be executed and all the particles are directly used to estimate the state of the system. On the contrary, σ is divided into ten equal parts ranging from 0 to 1. 100, 90, 80, . . ., 20, 10 and 0% of the existing particles were randomly selected for preparing the mutation operation.

$$w_{k,av} = \frac{\sum_{j=1}^{\alpha} w_k(j)}{\alpha} \tag{9}$$

Where, $w_{k,av}$ is the average weight of the selected particles; α is an integral part of $(1\text{-}\sigma)N$.

When the particle's weight is larger than the average weight, Gaussian mutation will be operated according to Eqs. (10) and (11), and two times of the selected particles are generated after that.

$$x_k^{'}(j) = x_k(j) + \sigma(x_{best} - x_k(j))N(0, 1) \tag{10}$$

$$x_k^{''}(j) = x_k(j) + (1 - \sigma)(x_{best} - x_k(j))N(0, 1) \tag{11}$$

Where, x_{best} is the optimal particle; $N(0,1)$ represents a random number which obeys a standard normal distribution.

According to the weight function, the weights of the newly generated particles are calculated, and some of the particles with larger weights are selected to cover the particles with small weights in the original particles, and a new particle set is obtained.

Lastly, after normalizing the particles' weights, x_k was estimated by using Eq. (6).

3. Results and discussion

Section 3.1 presents the results of performance tests of state estimation and the application of the proposed methodology to the well-known benchmark BSM1 (benchmark simulation model no. 1) developed by International Water Association (IWA) in described in Section 3.2.

3.1. Performance tests of state estimation

Experimental model is shown in Eq. (12) (Zeng et al., 2016).

$$\begin{cases} x_{k+1} = \dfrac{x_k}{2} + \dfrac{25x_k}{1+x_k^2} + 8\cos 1.2k + n_k \\ y_k = \dfrac{x_k^2}{20} + v_k \end{cases} \tag{12}$$

Where, $n_k \sim \Gamma(2, 3)$ and $v_k \sim N(0, 1)$ are independent noises.

The above selected system is used by many researchers to verify the validity and feasibility of their proposed PF algorithms. It is highly non-linear, and its likelihood function curve appears double-peak characteristics. When traditional filtering algorithms are used, the system states estimation loses the accuracy.

Three comparison experiments were set up with the number of particles 20, 50 and 100, respectively. Figs. 2 and 3 show the comparison results with particle filer (PF), particle filter based on bat algorithm (BAPF) (Chen et al., 2017) and genetic resampling particle filter (GRPF) (Ye et al., 2007) algorithms when the number of particles is 20 and 100. Particle filer is apt to have particles' degeneracy with unstable filtering precision, and a large number of granules are required to estimate the nonlinear system accurately. So, it can be seen from Figs. 2 and 3, in the simulation, the estimation accuracy of PF algorithm is the worst because of the number of particles, no matter whether it is 20 or 100. Relatively, when the number of particles increases to 100, BAPF and GRPF perform better than when the number of particles is 20. The estimation performance of the newly proposed VFM-based PF algorithm in this paper is better than the other three algorithms with higher estimation accuracy, because the number of effective samples are increased. That is to say, the more effective samples, the better the accuracy of estimation.

To further verify the improvement of the proposed algorithm, particle distribution results when time step k equal to 25 and 50

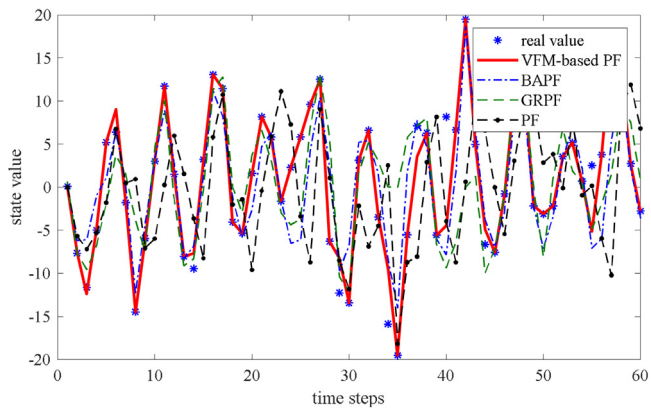

Fig. 2. Comparison estimation results when $N = 20$.

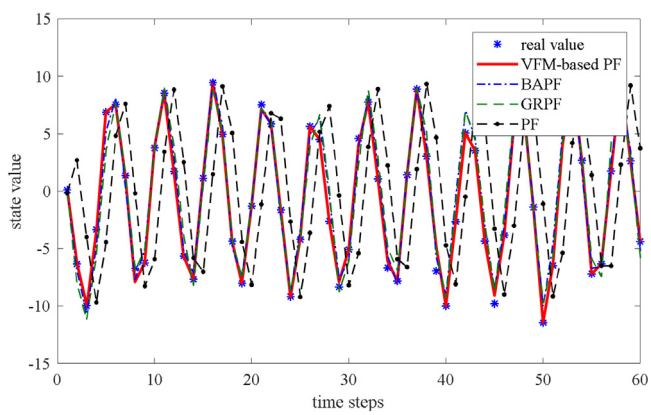

Fig. 3. Comparison estimation results when $N = 100$.

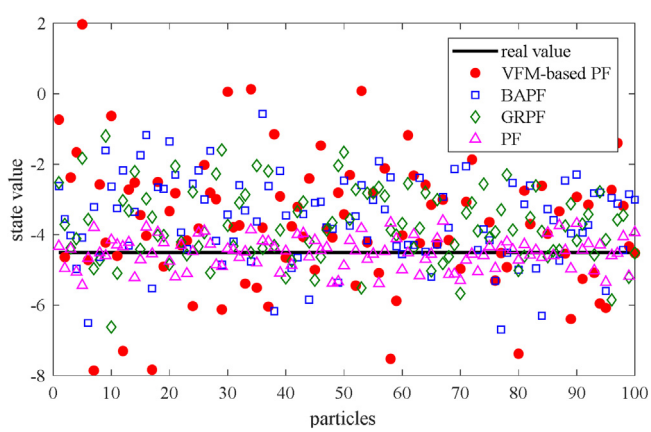

Fig. 4. Particle distribution when time step $k = 25$.

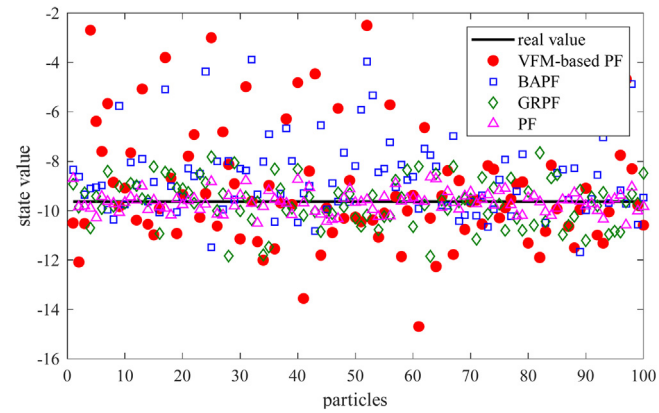

Fig. 5. Particle distribution when time step $k = 50$.

were compared (Figs. 4 and 5). As it can be seen from Figs. 4 and 5, the particles' diversity of the standard PF algorithm is the worst, especially in the later stages of the filter; the particles is basically concentrated on the state values, and the particles' diversity obviously weakens; the particles' diversity of BAPF is superior to GRPF, and the VFM-based PF algorithm is optimal among them. All the particles are widely distributed in the high likelihood region. Still, some particles are retained in the low likelihood region, ready to against the sudden change of system state for accurate estimation.

To verify the estimation accuracy and running time of the four algorithms, more simulation results were obtained based on different particle number (N) and different noise variance (Q) as shown in Tables 1 and 2. The estimation accuracy of the algorithm is evaluated by root mean squared error (RMSE) which is defined as shown in Eq. (13):

Table 1
RMSE error of the four algorithms.

Parameters	PF	GRPF	BAPF	VFM-based PF
$N = 20$, $Q = 1$	7.0753	1.5737	1.9332	0.9471
$N = 20$, $Q = 10$	8.2375	4.5786	6.1934	2.8418
$N = 50$, $Q = 1$	6.8964	1.1743	0.9793	0.3660
$N = 50$, $Q = 10$	7.4134	2.4289	2.9383	1.5912
$N = 100$, $Q = 1$	6.7143	1.1660	0.6598	0.2486
$N = 100$, $Q = 10$	7.2064	2.7255	1.9289	1.2533

Table 2
Run-time of the four algorithms in seconds unit.

Parameters	PF	GRPF	BAPF	VFM-based PF
$N = 20$, $Q = 1$	0.0932	0.1259	0.1118	0.1013
$N = 20$, $Q = 10$	0.0953	0.1285	0.1165	0.1042
$N = 50$, $Q = 1$	0.1121	0.1508	0.1372	0.1295
$N = 50$, $Q = 10$	0.1155	0.1576	0.1436	0.1381
$N = 100$, $Q = 1$	0.1252	0.1986	0.1674	0.1552
$N = 100$, $Q = 10$	0.1236	0.2046	0.1743	0.1620

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_t - \hat{x}_t)^2} \tag{13}$$

Where, $T\,(=60)$ is the iterative step number.

As can be seen from Table 1, compared to PF, BAPF and GRPF, the VFM-based PF algorithm has better predictive precision for the state value with the same number of particles. Because VFM-based PF ensures a number of new particles with high weights by Gaussian mutation operation on the randomly selected small weight particles, while not destroying the superiority of the high weight particles. This makes the particles more efficient and the distribution more reasonable. When the number of particles is increased, all methods can improve the tracking accuracy effectively. VFM-based PF still has a higher estimation precision than the other three methods. However, the estimation accuracy of various algorithms is affected by the increase of noise variance, but VFM-based PF still maintains the superior tracking accuracy. From Table 2, VFM-based PF is slightly slower than PF, but obviously better than BAPF and GRPF. This phenomenon, compared to the standard PF, occurs because of the production of new particles doubles in the execution of the mutation operation of VFM-based PF. For selecting new high weights particles to replace the low weights particles, an additional calculation step will be applied to re-weight the newly generated particles. Furthermore, when the number of particles is 20, VFM-based PF with 20 particles has a better performance, both

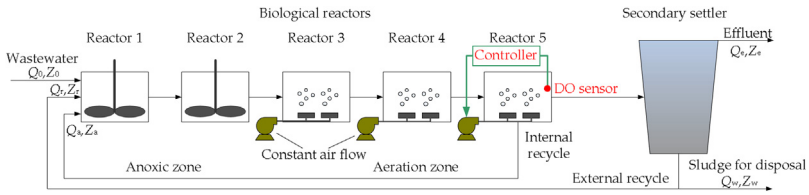

Fig. 6. Schematic representation of BSM1 model.

the estimation accuracy and the running time, than the standard PF algorithm with 100 particles. This shows that the VFM-based PF can perform estimation with high precision with fewer particles. In summary, from all the above results and analysis, the proposed method has a comprehensive cost performance with respect to higher filtering accuracy and faster running speed.

3.2. Fault diagnosis application in BSM1

The first BSM1 Layout which was based on the ASM1 is relatively a simple layout and is shown in Fig. 6. Similar to ASM1, the first part of BSM1 is also a biological (or biochemical) activated sludge reactor, which is comprised of five-compartments, two of them are anoxic tanks and the following three are aerobic tanks; the second part of BSM1 is a secondary settler. Reactor 1 and 2 are un-aerated in open-loop, but fully mixed; reactors 3, 4 and 5 are aerated. For the open-loop case, the oxygen transfer coefficients (K_La) are fixed; for reactors 3 and 4 the coefficient ($K_L a_3$ and $K_L a_4$) is set to a constant at 240 d^{-1} (10 h^{-1}), which means the air flow rate of the blower is constant; for reactor 5, the coefficient ($K_L a_5$) is selected as the control variable (or operational variable) in this study to manipulate for maintaining the DO concentration at 2 mg/L. Thus, the system can achieve biological nitrogen removal through nitrification in the aeration tanks and pre-denitrification in the anoxic tanks. The model equations to be implemented for the proposed layout, the procedure to test the implementation and the performance criteria to be used are described below along with the description of sensors and control handles. More information can be obtained elsewhere (Gernaey et al., 2014; Du et al., 2018).

This study focuses on the dissolved oxygen (DO) process in ASP-based wastewater treatment. The concentration of dissolved oxygen (DO) in the aeration tank(s) in an activated sludge process is an important process control parameter which has a great effect on the treatment efficiency, operating cost and system stability. As the dissolved oxygen drops, the quantity of filamentous microorganisms increases, adversely affecting the settle-ability of the activated sludge. It is important to recognize these early warning signs and make corrections to dissolved-oxygen levels before the quality of the effluent deteriorates. If dissolved oxygen continues to drop, treatment efficiencies will be further affected. At this point, effluent turbidity will increase. Higher dissolved oxygen is often a target, but in reality, this is for the assurance of mixing. But if the dissolved oxygen is excessive then there could be problems in the settling of activated sludge due to shearing of flocs and re-suspension of inert materials. A high DO concentration also makes the denitrification less efficient. On the other hand, a low DO level cannot supply enough oxygen to the microorganisms in the activated sludge and thus reducing the efficiency of degradation of organic matter (Bo and Zhang, 2018; Holenda et al., 2008). Therefore, the premise of how the wastewater treatment process can perform stably will depend on how effectively the concentration of DO is maintained within an acceptable range (Zhang et al., 2007). But if unexpected faults happen to the DO sensors, operators will get wrong signals to execute incorrect actions, which will lead the effluent quality to become worse and move away from meeting the effluent standards.

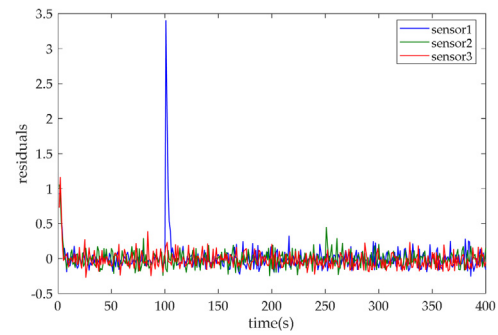

Fig. 7. Gain fault with sensor 1 at time = 100 s.

In BSM1, model for dissolved oxygen ($S_{O,k}$) can be surmised as below,

$$\frac{dS_{O,k}}{dt} = \frac{1}{V_k}(Q_k - 1S_{O,k} - 1 + r_k V_k + (K_L a)_k V_k (S^* - S_{O,k}) - Q_k S_{O,k}) \tag{14}$$

Where, Q is the flow rate, V is the volume of the reactor, r is the reaction rate, K_La is the oxygen transfer coefficient, S_O is the dissolved oxygen concentration. S^* is the saturation concentration for oxygen (S^* =8 g/m^3 at 15 °C); also $Q_1 = Q_a + Q_r + Q_0$; $Q_k = Q_{k\text{-}1}$.

To detect abnormal situations (faults), the residuals can be used as an indicator. These residuals are close to zero when the behavior of the monitored system is normal. However, when an abnormal situation or fault occurs, the residuals deviate significantly from zero, indicating the presence of a new situation that is distinguishable from the normal one. Three kinds of faults namely the gain fault, bias fault, and stuck fault are considered.

The performance of the proposed monitoring methodology is validated by the most common index, the miss-alarms rate (MAR), for evaluating process monitoring performance (Bakdi et al., 2017; Sanchez-Fernandez et al., 2018; Tong et al., 2017). The MAR is the number of normal data samples classified as faulty data over the total number of faultless data and is defined as:

$$MAR = 100\frac{N_{N,M}}{N_N}\% \tag{15}$$

where $N_{N,M}$ is the number of normal samples identified as faults and N_N is the number of normal samples.

Three man-made faults of sudden change of the system states are set up at 100, 200, 300 s to verify whether this method can accurately detect them during the simulation process. As can be seen from Fig. 7 through 9, the proposed fault diagnosis methodology can perform this requirement based on the residuals that are calculated in real-time. As mentioned above, if the system has no faults and runs steadily, the system state residuals will change within a small range around zero. However, when a fault occurs, the residuals of the system state will be deviating significantly from zero within a short time since the estimation error would have exceeded the acceptable range. When the system state is tracked again, the residual will return to the vicinity of zero. Therefore, the method presented in this study is effective (Figs. 8 and 9).

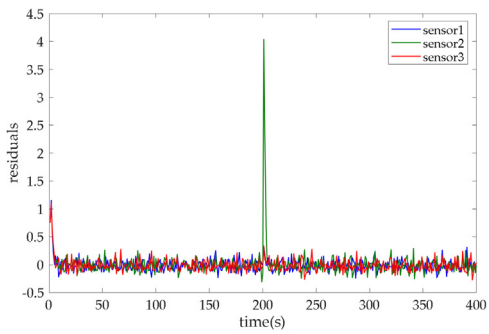

Fig. 8. Bias fault with sensor 2 at time = 200 s.

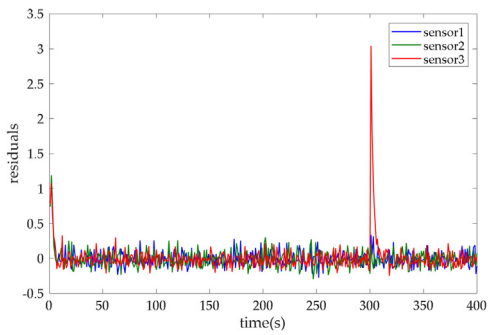

Fig. 9. Stuck fault with sensor 3 at time = 300 s.

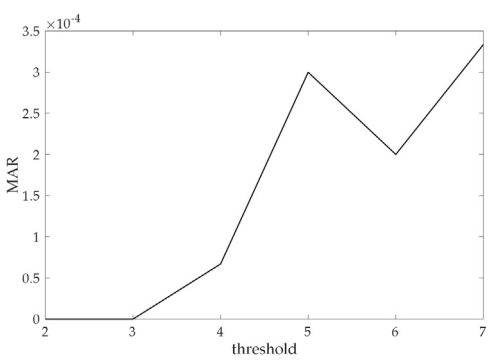

Fig. 10. Miss-alarms rate (MAR) with different thresholds (average of 50 experimental results).

Fig. 10 shows the MAR results with different thresholds (average of 50 experimental results). The results can be summarized as follows: (i) With the increase of threshold value, MAR generally shows an upward trend; (ii) When the threshold continues to increase, the MAR finally tends to reach 1. Actually, the reasonable setting of threshold is an important factor to improve the accuracy of fault diagnosis. However, for practical non-linear systems, due to unavoidable uncertainties such as modeling errors, noise and disturbances, residual errors will fluctuate within a certain range. This means that if the threshold is set too small, the false alarms rate of system faults will increase. On the contrary, if the threshold is set too high, the miss-alarms rate of system faults will increase. Both the issues will affect the accuracy of the diagnosis. So, it is necessary to adopt adaptive threshold method in fault diagnosis, which should also be the focus of future research.

All methods used in fault diagnosis have limitations in real time applications. Wastewater treatment process is a complex and large-scale system and therefore it is difficult to know the exact reaction mechanisms involved in the process. Thus, the accuracy of the model will be limited in many cases. All the uncertainty will affect the effectiveness of the algorithm in practical applications. In order to ensure the accuracy of fault diagnosis, in the follow-up studies, we will combine artificial intelligence method with the method proposed in this study to achieve efficient and reliable fault diagnostic strategy during their applications in WWTPs.

4. Conclusions

The reliability of sensors with respect to important qualities is often poor, mainly due to the hostile environment in wastewater plants (WWTPs). For sensor fault diagnosis application in ASP, we have developed a VFM-based PF algorithm, which is inspired by the mutation thought of the immune theory and the adaptive frequency conversion strategy used in the industrial process.

(1) By considering the prior information of the system states, which can ensure the diversity of particles, reduce the degradation degree of particles and effectively improve the estimation accuracy.
(2) Computational efficiency can be improved and the computational cost can be reduced by finding the effectiveness of existing particles (conversion operator) by determining the amount of the particles which will mutate.
(3) The proposed fault diagnosis method based on residual values can detect faults of multiple sensors quickly and accurately, and reduce the rate of miss-alarms based on a fixed threshold.

In order to apply particle filter algorithm to fault diagnosis of non-linear systems, such as activated sludge processes, first the ability and accuracy of the system state estimation of particle filter algorithm should be improved which in turn will improve the generalized performance of the algorithm. The main contribution of this paper, compared to some other monitoring methods applied in this field, is that the improved PF algorithm has higher estimation accuracy than others in both non-linear Gauss system and non-linear non-Gauss system. The proposed fault diagnosis method based on VFM-based PF can detect faults rapidly and isolate them accurately.

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