Condition Monitoring Based on An Improved Deep Learning Method

Chen Xiaoxiao, and Wang Maofeng*

Abstract—**The existing intelligent condition monitoring model needs a large number of historical data and corresponding tags under different health states to train the model. It is difficult to collect abnormal samples in some actual system. A new system anomaly detection method trained with no abnormal sample is proposed. The proposed method combines the reward function model with maximum entropy and generative adversarial networks (GAN). Firstly, the GAN is trained with expert samples to generate virtual expert samples. The non-expert samples are generated by using random strategy on this basis. The mixed sample set with expert and non-expert samples is constructed. Combined with the maximum entropy probability model, the reward function is computed, and the gradient descent method is used to solve the optimal reward function. Secondly, the proposed model is trained by the normal samples collected in the early stage, and then used to detect the unknown state. Finally, the system is monitored by observing the change of the difference index generated by GAN with maximum entropy. The experimental analysis results verify the effectiveness of the method. Compared with the traditional algorithm, the proposed method detects the system anomaly earlier, and the difference index increases more rapidly when the anomaly occurs.**

Index Terms—**deep learning, fault detection, maximum entropy, generative adversarial networks (GAN)**

I. INTRODUCTION

THE key system is sensitive to early fault warning to avoid serious failure. Once the fault occurs, the system may shut down and the economic loss may be large. If the condition monitoring technology can be used to monitor the data of the key system, the operation status with abnormal symptom of system can be found in advance. Condition monitoring can effectively reduce the failure time of the system, and improve the reliability of the system.

In literature [1], a fault monitoring method based on fuzzy association rule mining was proposed to monitor the operation status of distribution network. In literature [2], a dry-type air-core reactor turn fault model was set up to detect the hidden fault between turns of reactor. a method for evaluating the operating status and reliability of power transmission equipment in power systems was proposed in literature [3]. A method for the monitoring and warning of electric vehicle charging faults based on a battery model was proposed in literature [4], which is used in the fault monitoring and warning systems for the charging process of electric vehicles. In recent years, as a new method of big data analysis, deep learning gets rid of the uncertainty of human factors and the dependence of diagnosis technology experience, and directly extracts the feature relationship between parameters from a large amount of data. The deep learning methods have been used in condition monitoring in many fields [5-9]. At present, the research of deep learning mainly uses fault samples for training model to realize fault classification and identification. However, it is difficult to collect a large number of fault samples in practice, which brings some difficulties to the application of such algorithms. Therefore, the system anomaly detection in the case of missing fault samples is an urgent problem to be solved.

Generative adversarial networks (GAN) is a machine learning architecture proposed by Professor Goodfellow and his students at the University of Montreal in 2014 [10]. As a generative model, it has attracted wide attention of the academic community. GAN is mainly composed of generator model and discriminator model, which are trained by confrontation learning [11]. With the continuous improvement of the anti-learning idea, GAN has been widely used in image generation [12], image recognition [13], style transfer [14] and fault diagnosis [15,16]. In the existing research, GAN is effectively combined with reinforcement learning and inverse reinforcement learning [17,18]. However, the research on sparse expert samples at the initial stage of inverse reinforcement learning is relatively less. Considering the practical problems, the difficulty of expert data sampling will lead to the lack of expert samples, which makes the inverse reinforcement learning problem slow due to the lack of samples at the initial stage of training. In this paper, a maximum entropy-based GAN is proposed to solve the afore-mentioned problem. Then the improved GAN is used in condition monitoring model. The model only uses the samples of normal state for training, and uses the monitoring samples of unknown state for detecting. In the training process, the encoder is used to learn the potential features of normal samples and generated samples, and the difference between the potential features obtained by the two codes is minimized through the game between the generation network and the identification network[19]; in the detecting process, when the fault samples are input, the difference between the two potential features increases, so as to realize the anomaly detection under the training of fault free samples.

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This paper is organized as follows. In Section 2, the improved GAN is proposed based on GAN and maximum entropy. In Section 3, the condition monitoring model based on the proposed improved GAN is introduced. In Section 4, experiments are conducted to verify the effectiveness of the proposed monitoring model. Finally, in Section 5, discussions and conclusions are given.

II. The improved generative adversarial networks (ImGAN)

In this paper, we combine GAN with the maximum entropy inverse reinforcement learning probability model to solve the problem of inverse reinforcement learning.

A. Generative adversarial networks (GAN)

The generative adversarial networks (GAN) model is a kind of unsupervised deep learning model. GAN includes two modules: generator and discriminator. The generator is responsible for generating data, and the discriminator is responsible for distinguishing data, as shown in Figure 1.

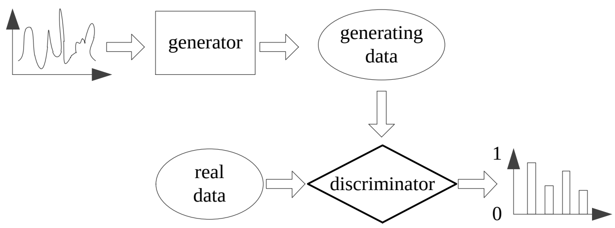


Fig. 1. The structure of GAN

The task of generator is to generate output classified by discriminator as from underlying data distribution. The task of discriminator is to classify its input as the output of generator or the actual sample from underlying data distribution $p(x)$. Generator and discriminator usually adopt neural network structure or convolution neural network structure. Convolution neural network structure is mostly used to process image data. Considering that the condition monitoring data is time series data, convolution neural network structure may bring a lot of inconvenience. Thus, neural network is used as the structure of generator and discriminator. Formally, the generator takes the noise as the input and outcomes the sample $x \sim G$. While the discriminator takes the sample x as the input and outputs the probability $D(x)$ of the sample from the data distribution. The loss of the discriminator is its average logarithmic probability assigned to the correct classification. The evaluation is conducted on a mixed set of actual samples and outputs from the generator.

$$L(D) = E_{x\sim P}[-\lg D(x)] + E_{x\sim G}[-\lg(1-D(x))] \tag{1}$$

The loss of generator is exactly opposite to the loss of discriminator. However, if it is easy to distinguish the output of the generator from the actual sample, it will provide very few training signals, which is not conducive to the training of the model. Therefore, the loss of the generator is defined as the sum of the two variables as follow.

$$L(G) = E_{x\sim G}[-\lg D(x)] + E_{x\sim G}[-\lg(1-D(x))] \tag{2}$$

By solving the two loss functions, the generator model and the discriminator model will eventually reach a Nash equilibrium. At this time, the generated samples have a high similarity with the real data. The basic idea behind GAN is to generate more experience samples from training and learn the probability distribution of these experience samples, so as to improve the speed of problem solving.

B. Reward function model based on maximum entropy

In order to solve the reward function effectively, a suitable objective function need to be found. The reward function is obtained by solving the objective function. There is no assuming of any unknown conditions except the constraint conditions for maximum entropy probability model. It avoids the ambiguity of the same expert strategy caused by different reward functions. Therefore, this model is selected as the basic model for solving inverse reinforcement learning.

The optimization problem is modeled as follows: supposing there is a potential probability distribution, under which expert trajectories are generated. On the premise that the trajectory of experts is known, the corresponding probability model is solved

$$\sum_{\xi_i} P(\tau_i) f_{\xi_i} = f_E \tag{3}$$

where ξ_i is the trajectory in the probability model, f is the feature expectation, and f_E is the expert feature expectation. Therefore, the objective function is defined as the optimal problem with maximum entropy, which is formalized as follow.

$$\begin{cases} \max - p\lg p \\ \text{s.t.} \sum_{\xi_i} P(\tau_i) f_{\xi_i} = f_E \\ \sum p = 1 \end{cases} \tag{4}$$

Using Lagrange multiplier method, the optimization problem can be transformed into

$$\min L = \sum_{\xi_i} p\lg p - \sum_j \alpha_j (pf_j - f_E) - \alpha_0 (\sum p - 1) \tag{5}$$

The probability p is differentiated and its derivative is set to 0. We have

$$\frac{\partial L}{\partial p} = \sum_{\xi_i} \lg p + 1 - \sum_j \alpha_j f_j - \alpha_0 = 0 \tag{6}$$

Finally, the probability of maximum entropy is obtained as follow

$$p = \frac{\exp(\sum_j \alpha_j f_j)}{\exp(1-\alpha_0)} = \frac{1}{Z}\exp(\sum_j \alpha_j f_j) \tag{7}$$

where α_i corresponds to the parameters in the reward function.

The probability model is modeled as a Boltzmann distribution. The expert trajectory $\{\tau_i\}$ is sampled from the following Boltzmann distribution

$$P_\theta(\tau) = \frac{1}{Z}\exp(-c_\theta(\tau)) \tag{8}$$

where $\tau = \{(s_0, a_0), (s_1, a_1), \cdots, (s_k, a_k)\}$ are trajectory samples, $c_\theta(\tau) = \sum_i c_\theta(s_i, a_i)$ is an unknown reward function parameterized by θ. s_i and a_i are the states and actions in time instance i. The partition function Z is the integral of $\exp(-c_\theta(\tau))$ on all trajectories. Experts are most likely to perform best in this model

In order to simplify the reward learning problem, formula (8) is derived based on the sample approximation. The corresponding negative log likelihood is shown in formula (9).

$$L=\frac{1}{N}\sum_{\tau_i}c_\theta(\tau_i)+\lg Z=\frac{1}{N}\sum_{\tau_i}c_\theta(\tau_i)+\frac{1}{M}\sum_{\tau_j}\frac{\exp(-c_\theta(\tau_j))}{q(\tau_j)} \tag{9}$$

To calculate the gradient of the target relative to the parameter θ of the reward function, let $w_j=\frac{\exp(-c_\theta(\tau_j))}{q(\tau_j)}$, $Z=\sum_j w_j$. The gradient is as follows.

$$\frac{\mathrm{d}L}{\mathrm{d}\theta}=\frac{1}{N}\sum_{\tau_i}\frac{\mathrm{d}c_\theta(\tau_i)}{\mathrm{d}\theta}-\frac{1}{Z}\sum_{\tau_j}w_j\frac{\mathrm{d}c_\theta(\tau_j)}{\mathrm{d}\theta} \tag{10}$$

The importance weight is evaluated by a fusion distribution. Suppose there are k distribution samples $q_1(\tau),q_2(\tau),\cdots,q_k(\tau)$, the correlation estimation of $f(\tau)$ expectation under uniform distribution is constructed as follow.

$$E[f(\tau)]=\frac{1}{M}\sum_{\tau_i}\frac{1}{\frac{1}{k}\sum_k q_k(\tau_i)}f(\tau_i) \tag{11}$$

Therefore, the importance weight is $z_i=[\frac{1}{k}\sum_k q_k(\tau_i)]^{-1}$, and the objective function is as follow.

$$L=\frac{1}{N}\sum_{\tau_i}c_\theta(\tau_i)+\lg\frac{1}{M}\sum_{\tau_j}z_j\exp(-c_\theta(\tau_j)) \tag{12}$$

C. GAN with maximum entropy

The algorithm updates the target by random gradient method. In each iteration, the generated expert sample pool D_d and non-expert sample pool D_s are partially sampled. When the number of samples in the batch is very small, it is necessary to add expert samples to the non-expert sample set to become a new mixed set. The specific algorithm is as follows.

step 1 Input: random noise n, $q_k(\tau)$ (let k = 1), reward function parameter θ;

step 2 Select a group of expert data as the real sample pool D_1; Use generator model G to generate virtual sample pool D_2;

step 3 Use GAN and real sample pool D_1 to train τ_i continuously to improve the quality of generated samples;

step 4 Mix the real sample pool D_1 and the trained virtual sample pool D_2 into a mixed sample pool D_d for inverse reinforcement learning; D_d' is obtained from D_d;

for each episode:

step 5 Execute the strategy $q_k(\tau)$ to get the non-expert sample set D_S; D_s' is sampled from D_s;

step 6 Merge D_d' and D_s' into D_s'';

step 7 Evaluate dL/dθ using D_d' and D_s''

step 8 Use gradient dL/dθ to update the parameter θ;

step 9 Use c_θ and D_s' to update $q_k(\tau)$ and obtain $q_{k+1}(\tau)$ by Sarsa algorithm;

end for;

step 10 Output: optimal reward parameter θ and corresponding strategy $q(\tau)$.

III. Condition Monitoring Based on the Improved GAN

The health monitoring method based on the improved GAN is to realize the system early warning of abnormal state by analyzing the operation data in normal generation stage. The proposed method is shown in figure 2.

The whole condition monitoring contains three stages: data selection, model training and monitoring operation.

(1) Data selection

The historical data of system in healthy state is obtained from database. According to the monitoring position or subsystem and the experience of engineering personnel, the corresponding characteristics are selected as the model input.

(2) Model training

The monitoring model is trained with the real health data of the monitoring system. A group of random data with the same dimension as the real health data are input into the generator model to get the generated health data. Then the generated health data and real health data are input into the discriminator model together to get the discriminating results. Finally, the generator and discriminator model are trained alternately to update the generated health data and discriminating results until the training is completed.

(3) Monitoring operation

After the training, the discriminator has the ability to judge whether the input comes from the distribution of health data. When the health data is input into the discriminator model, its theoretical output should fluctuate around 0.5, and the closer to 1, the greater the probability that the input data is health, and the closer to 0, the greater the probability that the input is abnormal. To easily understand the monitoring result, the output is subtracted by 1. Then the criterion of judgment becomes the greater the probability that the input data is health, and the closer to 1, the greater the probability that the input is abnormal, the closer to 0.

It is a common method to determine the threshold value by using Weibull distribution. The distribution fits the output probability distribution of the discriminator for historical health data, and estimates the parameters through the maximum likelihood estimation method to obtain the optimal Weibull distribution parameters. The probability density function of Weibull distribution is as follows

$$f(x;\lambda,k)=\begin{cases}\frac{k}{\lambda}(\frac{x}{\lambda})e^{-(\frac{x}{\lambda})^k} & x\ge 0\\ 0 & x<0\end{cases} \tag{13}$$

The corresponding cumulative probability distribution function is

$$F(x)=\begin{cases}1-e^{-(\frac{x}{\lambda})^k} & x\ge 0\\ 0 & x<0\end{cases} \tag{14}$$

where $f()$ is the probability density function. $F()$ is the cumulative probability distribution function.

The thresholds used to distinguish the health and abnormal data in the Weibull distribution are set and converted into the thresholds corresponding to the output data of the discriminator model, so as to realize the health monitoring.

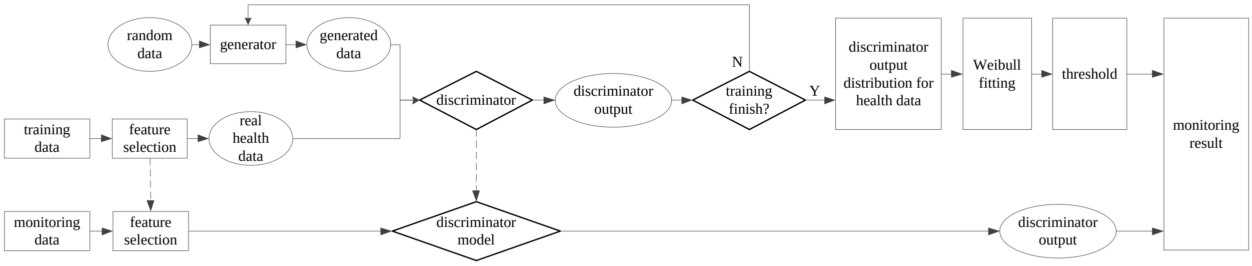


Fig. 2. The structure of condition monitoring method based on ImGAN

IV. Experimental Analysis

A. Three tank system

The effectiveness of the proposed condition monitoring method is verified by the three tank system, which is described below.

$$\begin{cases} \dfrac{\mathrm{d}\boldsymbol{x}}{\mathrm{d}t} = \boldsymbol{Ax} + \boldsymbol{Bu} \\ \boldsymbol{z} = [x_1 \quad x_2 \quad x_3]^{\mathrm{T}} \end{cases} \tag{15}$$

The vector in equation (1) is defined as follows

$$\boldsymbol{Ax} = \frac{1}{A_s}\begin{bmatrix} -Q_{13} \\ Q_{32} - Q_{20} \\ Q_{13} - Q_{32} \end{bmatrix}, \quad \boldsymbol{B} = \frac{1}{A_s}\begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \tag{16}$$

where

$$\begin{cases} Q_{13} = az_1 S_n \,\mathrm{sgn}(h_1 - h_3)(2g\,|h_1 - h_3|)^{1/2} \\ Q_{32} = az_3 S_n \,\mathrm{sgn}(h_3 - h_2)(2g\,|h_3 - h_2|)^{1/2} \\ Q_{20} = az_2 S_n (2gh_2)^{1/2} \end{cases} \tag{17}$$

In equation (16), sgn(·) is a sign function. The parameters are as A_s=0.0154 m^2, S_n=5×10^{-5}m^2, Q_1=4.5×10^{-5}m^3/s, Q_2=4.5×10^{-5} m^3/s, g=9.81m/s, az_1=0.5, az_2=0.6, az_3=0.5. For the differential function in (14), it can be transformed into a discrete model by Euler algorithm.

$$\begin{cases} \boldsymbol{x}_k = \boldsymbol{x}_{k-1} + \Delta t \cdot \boldsymbol{Ax}_{k-1} + \Delta t \cdot \boldsymbol{B} \cdot \boldsymbol{u}_{k-1} + \boldsymbol{w}_{k-1} \\ \boldsymbol{z}_k = \boldsymbol{x}_k + \boldsymbol{v}_k = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \boldsymbol{v}_k \end{cases} \tag{18}$$

The whole simulation step is 500Δt, the initial liquid level is h_1^0=1m, h_2^0=0.9m, h_3^0=0.95m.

B. az_2 failure

Suppose az_2 fails and increases from k=200, as shown below, seen in figure 3.

$$az_{2,k} = \begin{cases} 0.6 & k \le 200 \\ az_{2,k-1} + 0.0003 & k > 200 \end{cases} \tag{19}$$

The liquid level of h_1, h_2 and h_3 with az_2 failure is shown in figure 4. As shown in figure 4, the liquid level of h_2 descends since k=200. It indicates that az_2 failure is related to h_2. Thus, liquid level of h_2 is selected as the condition monitoring parameter.

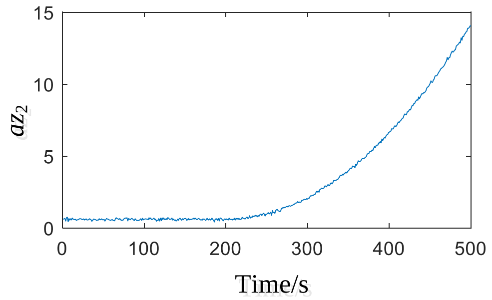
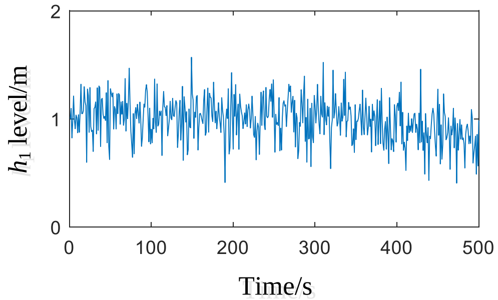
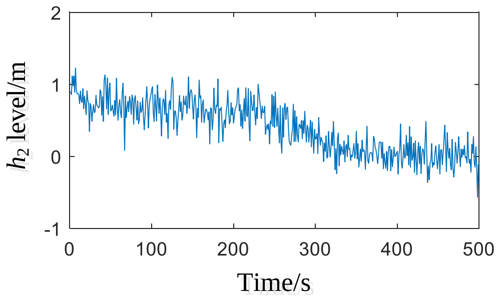


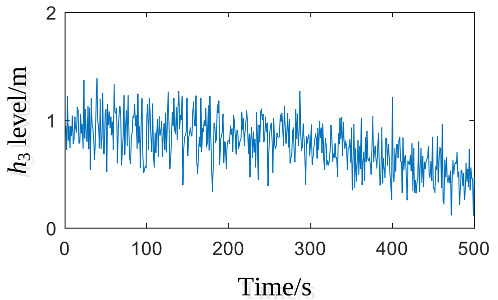
Fig. 3. az_2 failure trend



(a) h_1 liquid level



(b) h_2 liquid level

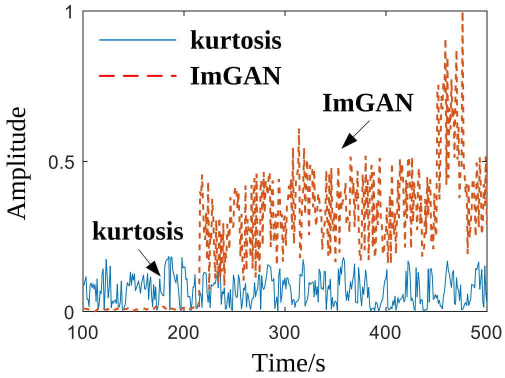


(c) h_3 liquid level

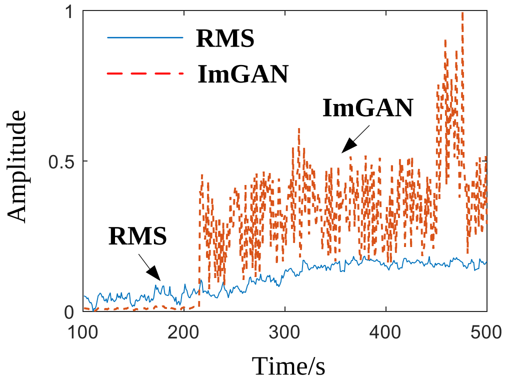
Fig. 4. Liquid level of three tanks with az_2 fault

Firstly, the condition monitoring method proposed in this paper is used to analyze the data. The first 100 groups of liquid level of h_2 (i.e., signals under normal state) are used as training data. After completing the training, the rest 400 h_2 signals are taken into the model in turn. The potential characteristic difference values of each group of signals are calculated. Then the curve of characteristic difference values with time is obtained. The sliding average calculation with window length of 10 is carried out, and finally normalized to the range of [0, 1]. The results are shown in Figure 5.

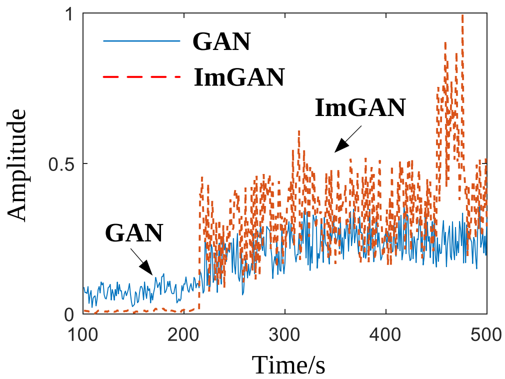
In order to prove the superiority of the proposed improved GAN (ImGAN), two commonly used time-domain statistical characteristics of system monitoring: kurtosis and root mean square (RMS), are used to analyze the same data set. In addition, the traditional GAN model is used as the comparison method.



(a) Contrast with kurtosis



(b) Contrast with RMS



(c) Contrast with GAN

Fig. 5. Condition monitoring result comparison for different methods with az_2 fault

In figure 5 (a), kurtosis index is fluctuating without growth, which means kurtosis fails to find system abnormal under minor fault. In figure 5 (b), RMS index begins to increase at about 230s. The increase trend of RMS is not obvious, so system anomaly is detected later than the proposed method. In figure 5 (c), the time of detecting system anomalies using GAN models is similar to that of the method proposed in this paper, which is 220s for GAN method, 215s for ImGAN method. The increase range of the index value of GAN is small when the anomaly occurs, that is, the slope of the curve rise of GAN is smaller than that of ImGAN method. The results indicate that the reliability of anomaly detection of the comparison methods is not as good as that of the method proposed in this paper. Therefore, the method proposed in this paper can improve the time and reliability of system anomaly detection.

The corresponding threshold T is calculated by using the cumulative probability density distribution function of Weibull distribution, so that the data proportion contained in the interval [0, T] is x, here x= 0.3%, and t= 0.05 is obtained, as shown in figure 6. Seen from figure 6, the index is always higher than the threshold value since the system has failed. The result shows that the proposed condition monitoring method always indicating system in abnormal state. It demonstrates the proposed method is stable for condition monitoring.

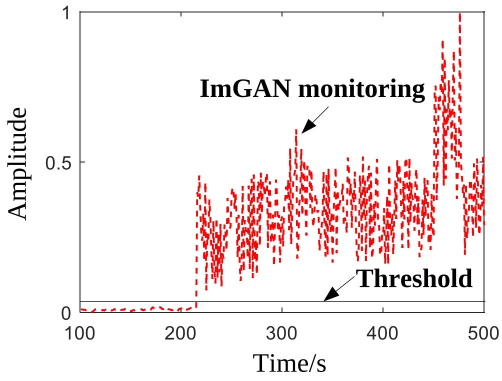


Fig. 6. Condition monitoring of ImGAN with monitoring threshold

C. az_3 failure

In order to further verify the effectiveness and superiority of the proposed method in system anomaly detection, suppose az_3 fails and starts to decline from k=200, shown in figure 7.

$$az_{3,k} = \begin{cases} 0.5 & k \le 200 \\ az_{3,k-1}\text{-}0.00001 & k > 200 \end{cases} \tag{20}$$

The liquid levels of h_1, h_2 and h_3 in case of az_3 failure are shown in figure 8. Seen from figure 8, the liquid level of h_3 increases from k = 200. It shows that the failure of az_3 is related to h_3. Therefore, the liquid level of h_3 is selected as the condition monitoring parameter.

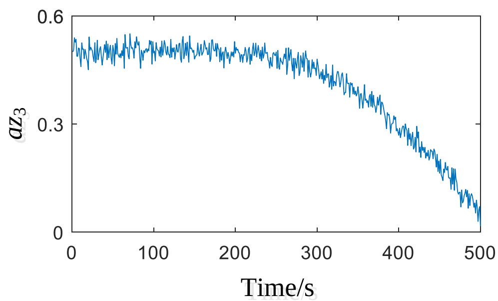
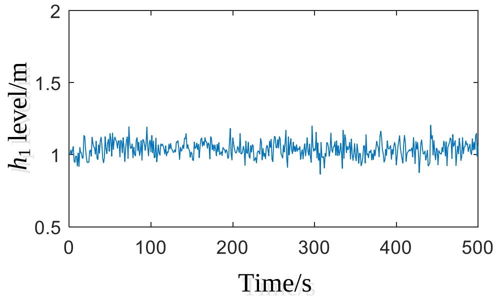
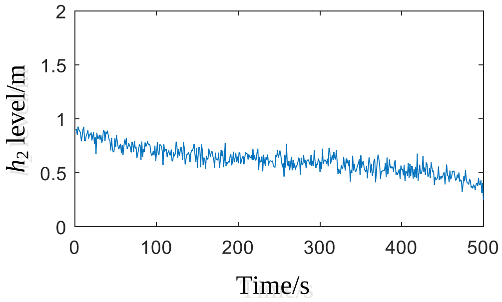


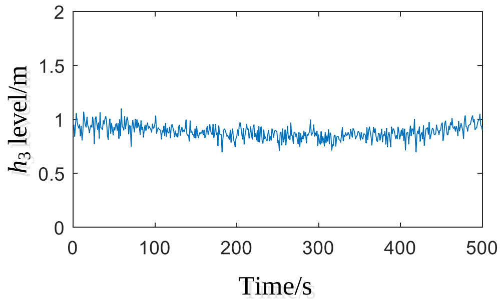
Fig. 7. az_3 failure trend



(a) h_1 liquid level



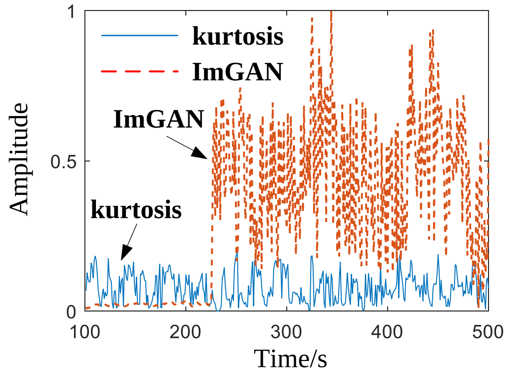
(b) h_2 liquid level



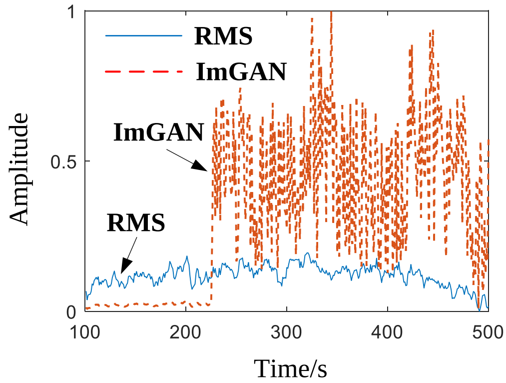
(c) h_3 liquid level

Fig. 8. Liquid level of three tanks with az_3 fault

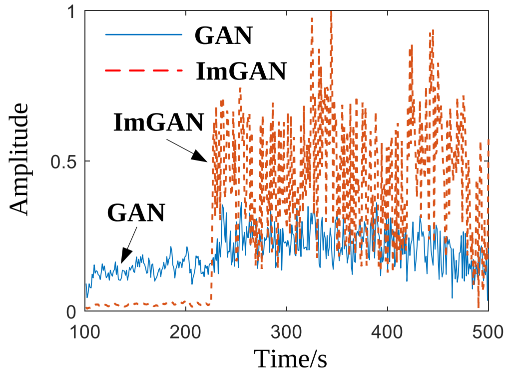
The proposed method and three comparison methods are used to analyze the monitoring data, and the results are shown in figure 9. In this paper, the method detects that the system is abnormal when it runs for about 226s, and the index increases greatly since this time instance, which indicates that the reliability of abnormal detection is very high. In figure 9 (a), the kurtosis index almost fails. In figure 9 (b), the RMS index can get the same result as the proposed method during 230s to 390s, but the RMS index fails to detect abnormal since 391s. The reliability of RMS is not as good as the proposed method. In figure 9 (c), the difference index of GAN model rises when the fault occurs, but the amplitude is lower than that of ImGAN. The experiment proves that the method can detect the system abnormality in time, and the reliability and stability are high.



(a) Contrast with kurtosis



(b) Contrast with RMS



(c) Contrast with GAN

Fig. 9. Condition monitoring result comparison for different methods with az_3 fault

V. Conclusion

The existing condition monitoring methods are mainly based on the failure physical model and abnormal data analysis. However, it is difficult to build the failure physical model, and the sample size of abnormal data is relatively small in practice. Therefore, based on the generative adversarial networks with maximum entropy model, a health condition monitoring method using normal operation state data is proposed. Then, the improved GAN based condition monitoring method is verified and analyzed by using the fault data from three tank system. The results show that the proposed method can detect the abnormal condition of the fault earlier, and has better performance than kurtosis, RMS and traditional GAN methods in the abnormal detection. The proposed method is in line with the actual situation for health monitoring results.

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