A Novel Predictive Maintenance Method Based on Deep Adversarial Learning in the Intelligent Manufacturing System

CHANGCHUN LIU, DUNBING TANG, HAIHUA ZHU, AND QINGWEI NIE
College of Mechanical and Electrical Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, China

Corresponding author: Dunbing Tang (d.tang@nuaa.edu.cn)

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ABSTRACT Along with the number and the functional complexity of machines increase in the intelligent manufacturing system, the probability of faults will increase, which may lead to huge economic losses. Traditional passive or regular maintenance methods of solving the faults have the problems of low efficiency and huge resource consumption. Besides, traditional maintenance methods mostly contain single model, so all the prognostics and maintenance tasks of the intelligent manufacturing system can hardly be addressed at the same time. Therefore, this paper proposes a novel predictive maintenance (PDM) method based on the improved deep adversarial learning (LSTM-GAN). The long-short-term memory (LSTM) network can solve the disadvantage of vanishing gradients and the mode collapse from the generative adversarial network (GAN). The method can not only avoid the mode collapse of GAN but also realize the self-detection of abnormal data. Meanwhile, the predictive maintenance model includes two prediction models and a maintenance decision model. The prediction models can predict the state of the machine and the fault of the machine in advance. Then the maintenance decision model will arrange maintenance personnel and offer a plan of maintenance. Finally, a case study about predictive maintenance using LSTM-GAN in the intelligent manufacturing system is presented. The fault prediction accuracy of LSTM-GAN is as high as 99.68%. With the comparison between LSTM-GAN and other traditional methods, LSTM-GAN shows priority both in accuracy and efficiency. Moreover, the proposed PDM can reduce maintenance costs and downtime so that the life of machines in the intelligent manufacturing system will extend.

INDEX TERMS Predictive maintenance, deep adversarial learning, LSTM-GAN, intelligent manufacturing system.

I. INTRODUCTION
With the development of hardware, data analysis and intelligent algorithms, the traditional manufacturing system is transforming into a highly intelligent and autonomous manufacturing system. It can realize self-organizing operation and self-adaptive collaboration of complex and dynamic production activities [1]–[3]. However, the intelligent manufacturing system is composed of more intelligent and complex machines, which is prone to cause fault and downtime of the system. Too early interventions could represent a waste of resources by changing important components with remaining useful life. However, too late interventions could lead to catastrophic fault. Accordingly, predictive maintenance (PDM) can be presented as a maintenance strategy aiming at defining the accurate moment to trigger actual maintenance actions [4]–[6]. PDM is one of the key innovations of Industry 4.0 and it plays an important role in the intelligent manufacturing system. It can not only guarantee the reliability and safety of the machine but also effectively reduce the downtime and the cost of maintenance.

As shown in Figure 1, data-driven PDM has attracted many studies in recent years [7]–[12]. In most of these studies, machine learning techniques have already been applied in
the data-driven PDM [13], [14]. Although the existing models have achieved good performance, most of the data preprocessing methods are complicated in the existing studies. It highly relies on professional manual feature selection and construction. However, more and more types of data are increasing with the development of intelligent manufacturing systems, which brings new perspectives and challenges to the industry. Owing to this, it is difficult to predesign good handcrafted features. Besides, the supervised learning model is easy to fall into overfitting, which seriously reduces the generalization ability of the model. Therefore, it is essential to find a more effective data-driven PDM method.

Generative adversarial network (GAN) emerged as a new area in the machine learning field since 2014, which was proposed by Ian J. Goodfellow et al. [15]. GAN includes the generative model and the discriminative model. The mutual game learning between the generative model and the discriminative model makes GAN produce quite good output. The main purpose of GAN is to make the hidden problems in the intelligent manufacturing system explicit to avoid problems such as downtime. It can extract the hierarchical representation features of raw data automatically. With this advantage, GAN could avoid the effect of handcrafted features designed by engineers and it has a good prospect on PDM in the intelligent manufacturing system. However, GAN has the disadvantage of vanishing gradients and the mode collapse.

The long-short-term memory (LSTM) network is well-suited to learn from experience to classify, process and predict time series when there are very long-time lags of unknown size between important events. It can solve the disadvantage of vanishing gradients and the mode collapse from GAN. Accordingly, this paper proposes a novel network structure of autoencoder based on the LSTM network. Unsupervised learning is strengthened by a generative adversarial network (GAN), which realizes the self-detection of abnormal data.

With the development of technology and information, single-model approaches hardly address all the diagnostics and prognostics tasks of intelligent manufacturing systems [16], [17]. Most of the current PDM studies only have one fault model, which poses a challenge to extrapolate single-model approaches to real complex intelligent manufacturing system applications [18]–[21]. Therefore, this paper proposes a PDM method by using improved deep adversarial learning (LSTM-GAN) in intelligent manufacturing system. The PDM model of intelligent manufacturing system contains state prediction model, fault prediction model, reliability model, maintenance cost model and maintenance time model. Among them, the prediction model consists of state prediction model and fault prediction model. The maintenance decision model consists of reliability model, maintenance cost model and maintenance time model. The contributions of this paper are as follows:

(a) The proposed PDM can not only monitor the state of the machine in real-time but also predict the fault of the machine in advance. Therefore, it is possible to service and troubleshoot a hidden fault of the intelligent manufacturing system in advance. It will make predictive maintenance in the intelligent manufacturing system more intelligent and more reliable.

(b) The proposed PDM can make full use of the machine degradation information and real-time health state to arrange maintenance strategies. It can reduce maintenance cost and downtime so that the life of machines in the intelligent manufacturing system will extend.

(c) This paper designs a visual interface based on digital twin. Various indicators and the current operating state of the machine can be observed intuitively through this interface. In addition, it can also display the results of fault prediction in the intelligent manufacturing system.

(d) A case study of PDM in intelligent manufacturing system is presented to validate the performance of our proposed method. The proposed LSTM-GAN can avoid missing the global relationship and mode collapse. With the comparison between LSTM-GAN and other traditional methods, LSTM-GAN shows priority both in accuracy and efficiency.

The rest of this paper is organized as follows: In section II, predictive maintenance methods in the intelligent manufacturing system and deep adversarial learning are introduced. In section III, the framework of the PDM system and the proposed algorithm are discussed in detail. Experiments and results are studied in section IV, including data description, comparisons with traditional machine learning methods, and comparisons with other deep learning methods. These comparisons can verify the robustness of the proposed method. Finally, section V summarizes this paper.

II. RESEARCH BACKGROUND

In order to obtain high prediction precision for predictive maintenance, many approaches have been applied and constantly improved. In this section, research progress and present status about predictive maintenance methods in the intelligent manufacturing system, and deep adversarial learning are discussed in detail.

A. THE INTELLIGENT MANUFACTURING SYSTEM

The intelligent manufacturing system is widely defined as a fully integrated and collaborative manufacturing system that can respond to the changing needs and conditions of factories, supply chain networks, and customers in real-time [22]. It means that the manufacturing technology and system can respond to the complex and changeable situation of the manufacturing field in real-time.
In recent years, many scholars have proposed different intelligent manufacturing system architectures. Yingfeng et al. [23] proposed an intelligent manufacturing execution system architecture based on IoT technology. The system architecture is mainly composed of five parts: mutual inductance, object perception, information integration, application service, and data service center. The manufacturing data generated during the operation of the workshop in the IoT manufacturing environment is massive, multi-source, high-dimensional, and heterogeneous. Therefore, Jie et al. [24] proposed a new workshop operation mechanism by the big data-driven analysis and decision-making. Jihong et al. [25] proposed an integrated management framework of intelligent manufacturing for the aviation product workshop. Under this framework, the physical information of the aviation product in the production process can be automatically identified and obtained. Therefore, the management level, manufacturing capacity and product quality can be improved.

Based on the above-mentioned general intelligent manufacturing system architecture, this paper proposes a specific implementation method of PDM in the intelligent manufacturing system. Through the dynamic prediction of operation state and maintenance service, the optimal operation of the manufacturing system is realized. On this basis, product quality and production efficiency are improved.

**B. PREDICTIVE MAINTENANCE METHODS**

Aivaliotis et al. [26] used the technology of digital twins to propose a predictive maintenance method for the intelligent manufacturing process. They used physics-based simulation models and digital twin concepts to calculate the remaining useful life (RUL) of mechanical machines. They only studied the predictive maintenance of a single machine. However, the manufacturing system contains multiple types of machines. In order to achieve reliable predictive maintenance of CNC machine tools, Luo et al. [27] studied a hybrid method driven by digital twins. Under the proposed framework, a hybrid predictive maintenance algorithm based on the digital twin model and digital twin data was studied. But they only studied the tool fault and predictive maintenance methods of CNC machine tools. The type of fault is relatively single, and there is a lack of research on a potential fault that may exist in the overall manufacturing system. Stodola [28] proposed a mathematical model for predictive maintenance. This model can evaluate the actual maintenance of labor intensity and reduce human error. However, their maintenance strategy was to formulate monthly and annual plans. There is no designated predictive maintenance plan for the abnormal machines, which may increase maintenance costs. Sahal et al. [29] used a systematic method to review the advantages and disadvantages of the existing open-source technologies in terms of big data and stream processing in industry 4.0. They proposed two predictive maintenance cases in the railway transportation and wind energy sectors. Although the big data technology was adopted, the entire system was shut down during the maintenance period. This will cause the production progress to bog down. Liu et al. [30] proposed the method of implement routine diagnostic decisions based on empirical constant thresholds. In the proposed framework, the thresholds of monitoring parameters can be changed according to the real-time operating conditions and the reliability estimation results. Simulation results showed that compared with traditional methods, this framework could make more timely maintenance decisions. However, their proposed method couldn’t judge the fault type of the abnormal machines. Owing to this, the abnormal machines maintenance plan couldn’t be implemented correctly.

The development of the mentioned single-model approaches may face particular challenges. The lack of a systematic approach for designing the predictive maintenance model is an important challenge, which will make the potential risk exist. Combining different models may offer the opportunity for predictive maintenance of complex systems that include many fault modes. This can manage uncertainty and improve the accuracy of fault prognostics and maintenance plans.

**C. DEEP ADVERSARIAL LEARNING**

1) GENERATIVE ADVERSARIAL NETWORK

The basic idea of GAN is derived from game theory. It consists of a generator and a discriminator, and it is trained through adversarial learning. The purpose of GAN is to estimate the potential distribution of data samples and generate new data samples. GAN is being widely studied and has huge application prospects. Bo et al. [31] proposed an intelligent diagnosis method based on a generative adversarial network (GAN). A personalized intelligent diagnosis model was constructed for the individual machines. The results showed that this method didn’t require real fault samples and achieved a high diagnostic accuracy rate. Lin et al. [32] proposed a rolling bearing fault diagnosis method based on improved GAN. They used a semi-supervised generation adversarial network (SSGAN) including the function of processing and recognizing images. The results showed that the proposed fault diagnosis method could achieve higher accuracy compared with other mainstream diagnosis methods. Xiaorong et al. [33] proposed a heterogeneous wireless network fault detection and diagnosis algorithm based on a generative adversarial network (GAN). Through the GAN algorithm, a large number of reliable data sets were obtained on the basis of a small amount of network fault samples. Simulation results showed that the proposed algorithm could achieve more accurate and efficient fault detection and diagnosis for a heterogeneous wireless network.

However, the natural data distribution is highly complex and multi-modal. The existing methods are all tested in a limited set, which is easy to cause mode collapse and limits the diversity of generated samples. Therefore, it is essential to find an effective method to solve this question.
2) LONG-SHORT-TERM MEMORY DEEP LEARNING NETWORK

The long-short-term memory (LSTM) network includes memory units, gate structures, and attention mechanisms. Thus, it can effectively solve the above pain point. Xiang et al. [34] proposed an LSTM network based on weight amplification for gear life prediction. An attention mechanism was added in the method, which amplified the input weight and recursive weight of the hidden layer to varying degrees. The results showed that the prediction method had higher accuracy. Yang et al. [35] proposed an LSTM network for the prediction of the remaining useful life of rotating machinery. In order to verify the effectiveness of the LSTM method, it was compared with the BP neural network, gray prediction model, support vector machine, and other methods. The results showed that the LSTM method can predict the degradation trend of rotating machinery and significantly improve the prediction accuracy of the remaining useful life. Qun et al. [36] proposed a gearbox fault prediction method based on the LSTM network, which mainly included offline modeling and online monitoring. The results showed that this method not only had better predictive performance but also could predict the occurrence of fault earlier.

On the one hand, GAN generates a large volume of fault samples for the discriminant model to improve the accuracy of the model. On the other hand, the LSTM model includes memory units, gate structures, and attention mechanisms, which can ensure the correlation of feature memory between long sequence fragments. Thus, LSTM and GAN can be combined to avoid missing the global relationship and mode collapse.

III. RESEARCH METHODOLOGY

Most of methods mentioned above not only can’t manage uncertainty but also can’t improve the accuracy of fault prognostics and maintenance plans in the intelligent manufacturing system. In order to overcome these drawbacks, this section introduces the framework, implementation steps and improved algorithm used in the predictive maintenance.

A. FRAMEWORK OF PREDICTIVE MAINTENANCE IN THE INTELLIGENT MANUFACTURING SYSTEM

The framework of our proposed PDM method in an intelligent manufacturing system is shown in Figure 2. The procedure of our proposed PDM is generally divided into four layers and described as follows.

(a) The perception layer: It is responsible for sensing and capturing the real-time data of the registered sensors installed on the manufacturing resources during the production process. Basic operation data is acquired by various sensors in the intelligent manufacturing workshop.

(b) The information exchange layer: It is responsible for connecting and centrally managing the heterogeneous types of sensors for capturing the real-time data of manufacturing resources. The basic operation data from the perception layer is transmitted to the information processing layer by Bluetooth, 5G, Zigbee, industrial ethernet and so on.

(c) The information processing layer: It is responsible for processing the significant data captured by registered sensors to form useful and meaningful information. Although real-time data record the real-time status of manufacturing resources, they need to be processed to provide useful and meaningful information. The basic operation data is applied for training the LSTM-GAN network. Accordingly, the prediction models and the maintenance model are trained.

(d) The intelligent service layer: It is responsible for supplying the results of the state prediction and the fault prediction for the maintenance strategy. Finally, the maintenance strategy will arrange a corresponding maintenance plan based on the prediction result. If the prediction result is ‘Watching’ or ‘Warning’, maintenance personnel should adopt minor maintenance including repair of worn parts. The workload of minor maintenance is small, and the maintenance time of minor maintenance is short. If the prediction result is ‘Fault’, maintenance personnel should adopt major maintenance including replacement of important components. The workload of major maintenance is large, and the maintenance time of major maintenance is long.

For the convenience of programming, the code of the fault type is described minutely in Table 1. The proposed PDM will identify the fault type based on the fault code (1-24). At the same time, the maintenance decision model will identify the abnormal machine and make it offline in advance. Then the maintenance decision model will arrange maintenance personnel and offer the predictive plan of rescheduling.

The PDM in intelligent service layer feedback and control the perception layer in the intelligent manufacturing system, including monitoring, management, adjustment and optimization of the machines in the system.

B. STATE AND FAULT PREDICTION MODEL

1) THE STRUCTURE OF LSTM-GAN

As shown in Figure 3, a generative adversarial network (GAN) consists of encoder1 (Enc1), decoder (Dec), encoder2 (Enc2) and discriminator (Dis). The specific structure of encoder1 is shown in Figure 4. The number of hidden layers of LSTM is represented by \( h \). We use a 3-layer LSTM network to extract the temporal characteristics of the sample, followed by a 3-layer fully connected (FC) layer to extract potential feature vectors. The batch normalization (BN) layer and rectified linear unit (ReLU) activation function are used in the middle of the two FC layers to optimize the output distribution of the middle layer. Based on this, the training efficiency can be improved. The structure of the decoder is symmetrical to the encoder 1. At the same time, the structure of encoder 2 and discriminator is the same as the structure of encoder 1. However, their respective parameters learn independently during the training process. An autoencoder consists of the encoder1 and the decoder, which is generally called a generator.
The sample $X$ gets the reconstruction $\hat{X}$ of the sample through the generator. The latent vector $z = f_{Enc1}(X)$ is generated in the first encoding. The output of $Enc1$ is the latent vector $z$. At the same time, $z \in R^m$ and $m$ is the dimension of $z$. $\hat{X}$ is the reconstruction of the latent vector through the second encoding of encoder 2. During the process of training, the two reconstruction errors continuously reduce. Besides, the distribution of samples in the sample space $X$ and the latent vector space $z$ is learned by this model. The noise can

| State Code | State Type                          | State Code | State Type                                                      |
|------------|-------------------------------------|------------|----------------------------------------------------------------|
| 1          | Good                                | 15         | Motor fault of robot No.2                                       |
| 2          | Watching                            | 16         | Circuit board fault of robot No.2                               |
| 3          | Warning                             | 17         | Spindle fault of milling machine No.1                           |
| 4          | Fault                               | 18         | Transmitted chain fault of milling machine No.1                 |
| 5          | Communication fault of AGV No.1     | 19         | Automatic tool changer fault of milling machine No.1            |
| 6          | Motor fault of AGV No.1             | 20         | Spindle fault of milling machine No.2                           |
| 7          | Power fault of AGV No.1             | 21         | Transmitted chain fault of milling machine No.2                 |
| 8          | Communication fault of AGV No.2     | 22         | Automatic tool changer fault of milling machine No.2            |
| 9          | Motor fault of AGV No.2             | 23         | Spindle fault of turning machine No.1                           |
| 10         | Power fault of AGV No.2             | 24         | Transmitted chain fault of turning machine No.1                 |
| 11         | Communication fault of robot No.1   | 25         | Automatic tool changer fault of turning machine No.1            |
| 12         | Motor fault of robot No.1           | 26         | Spindle fault of turning machine No.2                           |
| 13         | Circuit board fault of robot No.1   | 27         | Transmitted chain fault of turning machine No.2                 |
| 14         | Communication fault of robot No.2   | 28         | Automatic tool changer fault of turning machine No.2            |
The loss function $L_2$ can be easily interfered with the reconstruction error of the sample layer, which can influence the effect of detection. Owing to this, the reconstruction error of the sample layer is no longer used as the standard for anomaly detection in the detection stage. Instead of it, the reconstruction error of the deeper latent vector is used as the anomaly detection. According to this, the anti-interference ability of the model can be greatly improved.

2) THE CONSTRUCTION OF THE PREDICTION MODEL

The loss function $L_G$ of the generator during the process of training is defined as follows:

$$L_G = \omega _1 l_x + \omega _2 l_z + \omega _3 l_{adv}$$  \hspace{1cm} (1)

In Equation (1), $l_x$ is the reconstruction loss function of $X$, $l_z$ is the reconstruction loss function of $z$, $l_{adv}$ is the counter loss function of the generator, and $\omega _i$ is the corresponding weight. $l_x$ uses loss function $L_1$ to acquire more robust and stronger anti-noise ability. $l_z$ is defined as follows:

$$l_z = \|X - f_G (X)\|_1$$  \hspace{1cm} (2)

$l_z$ uses loss function $L_2$ which is more sensitive to anomalies. In the phase of verification and testing, $l_z$ is also used to calculate the anomaly score $A(X)$. $l_{adv}$ is defined as follows:

$$l_{adv} = \|\hat{X} - f_G (X)\|_2$$  \hspace{1cm} (3)

$l_{adv}$ is the discriminative loss function of a generative adversarial network. Its purpose is to make the reconstructed sample $\hat{X}$ close to the real sample $X$ by updating the parameters of the generator. Based on this, the discriminator can treat $\hat{X}$ as a real sample. $l_{adv}$ can be expressed by binary cross-entropy loss function as follows:

$$l_{adv} = bce\_loss (f_D (f_G (X)), 1)$$  \hspace{1cm} (4)

In Equation (4), ‘1’ represents true.

In the phase of training, the loss function $L_D$ of the discriminator is also defined by the binary cross-entropy loss function. Its purpose is to update the parameters of the discriminator so that the discriminator can correctly distinguish the real sample $X$ and reconstruct the sample $\hat{X}$. Therefore, its usage is just the opposite of the generator. $L_D$ can be expressed as follows:

$$L_D = bce\_loss (f_D (X), 1) + bce\_loss (f_D (f_G (X)), 0)$$  \hspace{1cm} (5)

In Equation (5), ‘1’ represents true and ‘0’ represents false.

After the model is trained, the model will be evaluated based on the validation set. In the phase of verification, the generator and encoder 2 in the network are used to generate the latent vector $z$ of sample $X$ and its reconstruction $\hat{z}$. Then, the anomaly score $A(X)$ of $X$ is calculated based on the loss function $l_z$. $a(X)$ is used for zooming all samples $A(X)$. The range of zoomed $A(X)$ is controlled within the range of $[0, 1]$.

$$a(X) = \frac{A(X) - \min (A(X))}{\max (A(X)) - \min (A(X))}$$  \hspace{1cm} (6)

The corresponding recall rate $R$ and precision $P$ are calculated by taking different thresholds. The calculation equation of the equilibrium score $F_1$ is as follows:

$$F_1 = \frac{2RP}{R + P}$$  \hspace{1cm} (7)

In Equation (7), the value of the largest $F_1$ is selected as the threshold $\varphi$ for testing.

3) PROCEDURE OF STATE AND FAULT PREDICTION

In the phase of the output, the predicted state of the machine is determined by the relationship between $a(X)$ and $\varphi$. If $a(X) < \varphi_3$, the state of the machine is ‘Normal’. If $\varphi_3 = a(X) < \varphi_2$, the state of the machine is ‘Warning’. If $\varphi_2 = a(X) < \varphi_1$, the state of the machine is ‘Fault’. In Algorithm 1, the input is the data collected by the sensors in the intelligent manufacturing system, and the output is the state code (1-28). The parameters of the model and the specific algorithm flow are as follows.

C. MAINTENANCE DECISION MODEL

1) EVALUATION OF RELATED COSTS FOR THE PDM

If anyone of the machines in the system occurs downtime, the processing task cannot be performed. This will cause the entire system to downtime. Therefore, the reliability of the machines and the structure of the intelligent manufacturing
The total maintenance cost of the machine \( j \) during its previous \( i \) times is as follows:

\[
TC_{mj} = \sum_{i=1}^{N} C_{mj} \cdot n_{ij} = C_{mj} \cdot \sum_{i=1}^{N} \int_{t_{ij-1}}^{t_{ij}} \lambda_{ij} (t) \, dt \quad (10)
\]

The total maintenance time of the machine \( j \) during its previous \( i \) times is as follows:

\[
T_{t_{mj}} = \sum_{i=1}^{N} t_{mj} \cdot n_{ij} = t_{mj} \cdot \sum_{i=1}^{N} \int_{t_{ij-1}}^{t_{ij}} \lambda_{ij} (t) \, dt \quad (11)
\]

c: COST OF MAJOR MAINTENANCE

According to the actual situation, when the machine reaches the threshold of reliability, it will need major maintenance. The \( ith \) predictive maintenance cost of the machine \( j \) are as follows:

\[
C_{pmij} = C_{fj} + i \cdot C_{vj} \quad (12)
\]

The total predictive maintenance cost of the machine \( j \) during its previous \( i \) times are as follows:

\[
TC_{pmj} = \sum_{i=1}^{N} C_{pmij} = \sum_{i=1}^{N} (C_{fj} + i \cdot C_{vj}) \quad (13)
\]

The \( ith \) predictive maintenance time of the machine \( j \) is as follows:

\[
t_{pmij} = \tau \cdot i \cdot T_{i} \quad (14)
\]

The total maintenance time of the machine \( j \) during its previous \( i \) times is as follows:

\[
T_{t_{pmj}} = \sum_{i=1}^{N} t_{pmij} = \sum_{i=1}^{N} \tau \cdot i \cdot T_{i}, \quad j = 1, 2, \ldots, n \quad (15)
\]

In Equation(12), \( C_{fj} \) is used to represent the fixed cost of predictive maintenance for machine \( j \). Meanwhile, \( C_{vj} \) is the variable cost of predictive maintenance for machine \( j \). In Equation(14), \( \tau \) is the time adjustment coefficient of predictive maintenance. It means that the machine undergoes continuous wear and tear as the machine runs longer and longer, which makes the time for predictive maintenance of the machine longer and longer.
The total downtime of the machine during its previous i times is as follows:

\[
T_{park} = \text{Max} \left[ T_{pmj} \right] = \text{Max} \left[ \sum_{i=1}^{N} \tau \cdot i \cdot T_i \right] \tag{17}
\]

The total downtime cost of intelligent manufacturing system during its previous i times are as follows:

\[
TC_{park} = C_{park/h} \cdot T_{park} \tag{18}
\]

The total maintenance cost of intelligent manufacturing system based on the basic operation data in several constant parameters in the models. Performing the PDM strategy. The purpose is to estimate the relevant historical data of the machine and the experience of the machine during its life cycle can be obtained through the following calculation of Equation (22), an optimal combination of maintenance strategies can be found. It can choose the best maintenance time of the intelligent manufacturing system, so as to minimize the total maintenance cost of the system.

3) PDM STRATEGY

The PDM strategy is analyzed with mission reliability \( R_i \) as the optimization variable and minimum cumulative total cost \( C_i \) as the optimization objective. A PDM strategy procedure for intelligent service in the intelligent manufacturing system is developed, as shown in Figure 6. The optimal mission reliability threshold \( R_i \) can be obtained by minimizing \( C_i \) according to the PDM strategy optimization procedure illustrated in Figure 6, and the associated specific methods applied to each step are illustrated below.

Step 1. Basic operation data should be collected before performing the PDM strategy. The purpose is to estimate several constant parameters in the models.

Step 2. The state prediction model will predict the state of the intelligent system based on the basic operation data in step1.

Step 3. If the state of the intelligent system is ‘good’, it means that the system needs no maintenance.

Step 4. If the state of the intelligent system is ‘watching’ or ‘warning’, it means that the system needs minor maintenance. Then, the cost of minor maintenance and downtime \( TC_{park} \) will be calculated. Afterwards, the total maintenance cost \( C_i \) will be calculated. Finally, the mission reliability threshold \( R_i \) will be calculated. If \( R_i > 1 \), it means that the minor maintenance strategy can be implemented, and step6 should be performed accordingly. Otherwise, we will restart the procedure of step4.

Step 5. If the state of the intelligent system is ‘fault’, it means that the system needs major maintenance. The time point \( t_{pmj} \) and fault code will be calculated. Then, the cost of major maintenance and downtime \( TC_{park} \) will be calculated. Afterwards, the total maintenance cost \( C_i \) will be calculated. Finally, the mission reliability threshold \( R_i \) will be calculated. If \( R_i > 1 \), it means that the major maintenance...
strategy can be implemented, and step6 should be performed accordingly. Otherwise, we will restart the procedure of step5.

Step 6. The maintenance strategy will be implemented as follows. Firstly, the abnormal machine is offline in advance. Secondly, the type of the fault will be identified. Thirdly, the predictive plan of rescheduling will be implemented. The mission of the abnormal machine will be processed by the machine which has the same function. Afterwards, the maintenance personnel will be arranged to repair the abnormal machine. Finally, the abnormal machine is online after maintenance.

IV. EXPERIMENTAL DESIGN

In order to illustrate the effectiveness of our proposed method and algorithm, this section presents a case study about the proposed predictive maintenance method in the workshop of the intelligent manufacturing system.

A. DESCRIPTION OF THE PLATFORM

The experiment is performed in a typical intelligent workshop of a manufacturing enterprise located in Wuxi, China. In the perception layer, sensing devices have been deployed in the workshop over two years, as shown in Figure 7. The workshop consists of 8 stations, which are engaged in small structural parts processing. External data of machine tools is acquired by sensors such as AE sensors and so on. Internal data of machine tools is acquired by supervisory control and data acquisition (SCADA) and so on. In the information exchange layer, the data of AGV and robots is acquired by the industrial ethernet. Meanwhile, electronic terminals are equipped to store and display production data in real time. In the information processing layer, the algorithm is coded in Python3 to build the models. It is tested in a computer equipped with 16-GB RAM and an Intel Core i7 processor running at 3.6 GHz. In the intelligent service layer, the proposed PDM method is used to feedback and control the machines in the intelligent manufacturing system.

B. DESCRIPTION OF DATA SAMPLES

As shown in the Table 2, we take the first 15000h samples as the training set and the last 3334h samples as the prediction set. Each sample corresponds to a state of the machine within one hour. When a machine has multiple states within one hour, the most serious state shall prevail. For example, if state3 and state4 appear at the same time, we will select the most serious state4 as the state of the machine within one hour. Although the number of samples of machines with the same function is the same, the time when the samples occur is different. In terms of data preprocessing, we used the method of equal-width binning to avoid the effect of noise. Then, we divided each column into equal-width bins, and then used the bin mean smoothing.

| Parameters | \(\omega_1\) | \(\omega_2\) | \(\omega_3\) | \(h\) | dimension of \(z\) | Number of training rounds |
|------------|-------------|-------------|-------------|------|-------------------|--------------------------|
| Value      | 1           | 1           | 1           | 250  | 200               | 5000                     |

The machine code is explained as follows. M1 represents AGV No.1. M2 represents AGV No.2. M3 represents robot No.1. M4 represents robot No.2. M5 represents milling machine No.1. M6 represents milling machine No.2. M7 represents turning machine No.1. M8 represents turning machine No.2. The machine state code is explained as follows. State 1 represents the state of 'Good'. State 2 represents the state of 'Watching'. State 3 represents the state of 'Warning'. State 4 represents the state of 'Fault'. The data in the first 15000h includes good, watching, warning, and fault. The data in the last 3334h also includes good, watching, warning, and fault. Take the M1 device as an example in Table 2, the number of the first 15000h is 15000. The number of state 1 (good) is 13192. The number of state 2 (watching) is 1297. The number of state 3 (warning) is 402. The number of state 4 (fault) is 109. The total number of the data of these four states is 15000. All the data in the first 15000h is trained to generate the state prediction model. The data in the last 3334h is used to test the robustness of the state prediction model.
The types of faults are explained as follows. The faults of two AGV include communication fault, motor fault, power fault. The faults of the two robots include communication fault, motor fault, circuit board fault. The faults of two milling machines include spindle fault, transmitted chain fault, and automatic tool changer fault. The faults of two turning machines include spindle fault, transmitted chain fault, and automatic tool changer fault.

V. EXPERIMENTAL RESULTS
A. RESULTS ANALYSIS OF STATE AND FAULT PREDICTION
Based on the data collected by the experimental platform in section IV, state prediction and fault prediction results are analyzed in this section. Firstly, the state prediction model is performed to evaluate the health state of the intelligent manufacturing system. If it is in a fault state, the fault type and time of occurrence are...
TABLE 4. The model parameters of CNN-LSTM.

| Network layer | Parameters | Input size | Output size |
|--------------|------------|------------|-------------|
| Convolutional layer | Size of cores: 64 | (1024,1) | (64,16) |
| | Number of cores: 16 | | |
| | Stride: 16 | | |
| | Activation function: ReLU | | |
| | Filling method: same | | |
| Pooling layer | Size of cores: 2 | (64,16) | (32,16) |
| | Stride: 2 | | |
| | Filling method: same | | |
| LSTM layer1 | Number of neurons: 128 | (64,16) | (64,128) |
| | Activation function: tanh | | |
| LSTM layer2 | Number of neurons: 128 | (32,128) | (128,1) |
| | Activation function: tanh | | |
| Softmax layer | Activation function: softmax | (128,1) | (4,1) |

specifically predicted according to the fault prediction model.

1) STATE PREDICTION OF THE INTELLIGENT MANUFACTURING SYSTEM

a: RESULTS OF STATE PREDICTION BASED ON LSTM-GAN

State prediction results of the intelligent manufacturing system are shown in Figure 8 (a-h). In order to fully verify the robustness of the system, the state of each machine in the system is predicted. The horizontal axis is the label corresponding to the predicted state and the vertical axis is the label corresponding to the actual state. Figure 8 (a-h) represents the confusion matrix from M1 to M8 based on LSTM-GAN. All the states in good are predicted properly. Almost all the watching, warning, and fault states are predicted correctly. The misclassification rates of them are merely 1.74%, 3.45%, and 3.77%, respectively. None of the unhealthy conditions are mistaken as a good state.

b: COMPARISON OF ACCURACY AMONG CNN-LSTM, WGAN, GAPCNN AND LSTM-GAN

In order to fully verify the robustness of the system, we selected Convolutional Neural Network-Long-Short-Term Memory (CNN-LSTM), Global Average Pooling Convolutional Neural Network (GAPCNN) and the Wasserstein Generative Adversarial Networks (WGAN) for performance comparison analysis. The model parameters of the three algorithms are as follows.

Table 7 shows the state prediction accuracy of the four algorithms in detail. In order to fully verify the robustness of the system, the state of each machine in the system is predicted. The average accuracies of state prediction of the four algorithms are 91.79%, 91.15%, 90.76%, and 98.87%, respectively. Meanwhile, Figure 9(a-h) shows the prediction accuracy of the four algorithms vividly. The horizontal axis is the label corresponding to the algorithm and the vertical axis is the label of prediction accuracy. The results of LSTM-GAN are better than the other three algorithms. It is notable that the potential risk could not be detected by the other three algorithms. Even when a breakdown occurs, the prediction models of the other three algorithms still estimate it as good. This is dangerous in the actual manufacturing process.

TABLE 5. The model parameters of WGAN.

| Parameters | Number of dimensions | Number of weight parameters |
|------------|----------------------|-----------------------------|
| Generator input dimensions | 100 | / |
| Generator hidden layer dimension | 128 | 100×128 |
| Generator output layer dimensions | 1024 | 128×1024 |
| Discriminator input dimension | 1024 | / |
| Discriminator hidden layer 1 dimension | 128 | 1024×128 |
| Discriminator hidden layer 2 dimensions | 256 | 128×256 |
| Discriminator output dimension | 1 | 256×1 |

TABLE 6. The model parameters of GAPCNN.

| Parameters | Size of cores | Number of cores | Stride | Number of parameters |
|------------|--------------|-----------------|--------|---------------------|
| Convolution kernel 1 | 5×5 | 32 | 1 | 25×32 |
| Pooling zone layer 1 | 2×2 | 32 | 2 | / |
| Convolution kernel 2 | 3×3 | 64 | 1 | 9×64 |
| Pooling zone layer 2 | 2×2 | 64 | 2 | / |
| Convolution kernel 3 | 3×3 | 10 | 1 | 9×10 |
| Average pooling layer | / | / | / | / |

TABLE 7. The state prediction accuracy of the four algorithms.

| Machine/Algorithm | CNN-LSTM | WGAN | GAPCNN | LSTM-GAN |
|-------------------|----------|------|--------|----------|
| M1 | 92.12% | 92.17% | 93.73% | 98.65% |
| M2 | 92.08% | 92.34% | 93.56% | 98.69% |
| M3 | 92.53% | 91.87% | 93.78% | 99.05% |
| M4 | 92.47% | 92.95% | 93.53% | 99.12% |
| M5 | 92.27% | 92.58% | 92.31% | 98.79% |
| M6 | 92.35% | 93.72% | 92.42% | 98.84% |
| M7 | 93.25% | 93.63% | 92.34% | 98.92% |
| M8 | 92.31% | 92.83% | 92.45% | 98.97% |
FIGURE 8. Confusion matrices of the state prediction results (a-h).
Table 7 shows the state prediction accuracy of the four algorithms in detail. In order to fully verify the robustness of the system, the state of each machine in the system is predicted. The average accuracies of state prediction of the four algorithms are 91.79%, 91.15%, 90.76%, and 98.87%, respectively. Meanwhile, Figure 9(a-h) shows the prediction accuracy of the four algorithms vividly. The horizontal axis is the label corresponding to the state and the vertical axis is the prediction accuracy. The results of LSTM-GAN are better than the other three algorithms. It is notable that the potential risk could not be detected by the other three algorithms. Even when a breakdown occurs, the prediction models of the other three algorithms still estimate it as good. This is dangerous in the actual manufacturing process.

2) FAULT PREDICTION OF THE INTELLIGENT MANUFACTURING SYSTEM

a: RESULTS OF FAULT PREDICTION

The fault prediction curve diagram in the next 3334 hours is shown in Figure 10(a)-(f). The horizontal axis is the label corresponding to the time and the vertical axis is the label of the fault code. Figure 10 shows that the fault prediction results of the eight machines in the intelligent manufacturing system in the next 3334 hours. The code of fault type that will occur at a certain time in the future can be clearly seen through the figure. For example, as shown in Figure 10(b), the proposed PDM system predicts that the fault code 20 will occur in the 947th hour in the future. From Table 1, we can find that the fault code 20 represents the transmitted chain fault of M7(turning machine 1). That means the transmitted chain fault of turning machine 1 will occur in the 947th hour in the future. Then, the proposed PDM system will provide a reasonable maintenance plan before the transmitted chain fault of M7 occurring.

b: COMPARISON OF FAULT PREDICTION ACCURACY WITH OTHER METHODS

Table 8 shows the fault prediction accuracy of the four algorithms in detail. In order to fully verify the robustness of the system, the state of each machine in the system is predicted. Almost all faults of the eight machines in the intelligent manufacturing system are predicted correctly and the average misclassification rate of LSTM-GAN is 1.16%. However, the average misclassification rates of the other three algorithms are 8.12%, 8.94%, 9.12%, respectively. Meanwhile, Figure 11 shows the prediction accuracy of the four algorithms vividly. The horizontal axis is the label corresponding to the algorithm and the vertical axis is the label of prediction accuracy. The results of LSTM-GAN are better than the other three algorithms. Notably, the fault could not be correctly detected by the other three algorithms. Even when a fault occurs, the prediction models of the other three algorithms will predict it as the other fault. This will mislead the maintenance plan, which will make the potential risk still exist.

| Machine | CNN-LSTM | WGAN | GAPCNN | LSTM-GAN |
|---------|----------|------|--------|----------|
| M1      | 93.25%   | 92.28% | 92.87% | 98.79%   |
| M2      | 92.55%   | 92.29% | 93.68% | 98.87%   |
| M3      | 91.61%   | 91.57% | 93.54% | 98.89%   |
| M4      | 92.54%   | 91.86% | 93.48% | 99.68%   |
| M5      | 92.36%   | 92.49% | 92.57% | 98.85%   |
| M6      | 93.29%   | 92.67% | 91.58% | 98.72%   |
| M7      | 92.87%   | 91.68% | 93.25% | 98.86%   |
| M8      | 92.62%   | 92.33% | 92.52% | 98.71%   |

B. RESULTS ANALYSIS OF MAINTENANCE DECISION

According to the state and fault prediction results mentioned above, the maintenance decision model will offer corresponding maintenance strategies to avoid the fault of the intelligent manufacturing system. The results and analysis of the maintenance decision are as follows.

1) PDM VISUAL INTERFACE

In order to visually observe the real-time status and prediction results of the intelligent manufacturing system, this paper develops a monitoring interface based on the digital twin as shown in Figure 12. It can make maintenance personnel master the state information of the intelligent manufacturing system, so as to facilitate maintenance. The specific functions of the visual interface based on digital twin are as follows.

① The list of information overview: it contains the number of machines, the number of sensors, the number of faults, the downtime, and the utilization rate of the past month.
② The list of machine state: it contains the current state, the possibility of the fault, the predictive time of the fault.
③ The list of sensors trends: it contains the numerical trend of each sensor, which is convenient for clear observation of abnormal conditions by using the LSTM-GAN method.
④ The list of machine state prediction: it contains the predictive probability of each machine in the future. The color of red represents ‘fault’, the color of green represents ‘normal’, the color of yellow represents ‘watching’ and the color of orange represents ‘warning’.
⑤ Monitoring and prediction based on digital twin: each machine has a corresponding digital twin for monitoring and predicting state. In Figure 12 (a), the digital twin of the turning machine is presented. In Figure 12(b), the prediction results of fault and maintenance time are presented.

2) RESULTS ANALYSIS OF PDM STRATEGY

In order to verify the function of the predictive maintenance decision, a set of orders are submitted in sequence as follows. As shown in Table 9 and Table 10, these orders include the processing of board, axis, and flange, which needs the machines of the intelligent manufacturing system to work together. If a machine becomes faulty, the entire intelligent manufacturing system will be severely affected.

The parameters of the eight devices are shown in Table 11. It can be seen from Figure 13 that when the reliability...
FIGURE 9. Comparison of state prediction accuracy between CNN-LSTM, WGAN, GAPCNN, and LSTM-GAN (a-h).
threshold $R_0$ of the system is different, the preventive maintenance plan obtained is also different. The solution of the model can also calculate the corresponding minimum maintenance cost. As the requirements for the reliability threshold $R_0$ of the intelligent manufacturing system increase, the maintenance interval of the device will gradually become shorter, and the maintenance cost will continue to increase.

Gantt chart of the original work plan is shown in Figure 14. It takes 70 minutes for the entire intelligent manufacturing system to complete ten orders. Meanwhile, the fault prediction model in our proposed PDM method predicts that the machine M8 will become faulty due to the fault of the automatic tool changer at 22:42 on December 17th. Therefore, the maintenance decision model offers a predictive rescheduling plan as Figure 15 shown. It makes the faulty machine M8 offline in advance. Because M7 has the same

FIGURE 10. Fault prediction curve diagram in the next 3334 hours (a-h).

FIGURE 11. Comparison of fault prediction accuracy between CNN-LSTM, WGAN, GAPCNN and LSTM-GAN.
function as M8. Then, the predictive rescheduling plan transfers the job of M8 to M7. At the same time, the maintenance decision model in our proposed PDM method informs the maintenance staff that the tool changer of M8 is faulty and it should be repaired as soon as possible. At 23:45 on December 17th, M7 begins to process the task of O5 which belongs to M8.

At 23:59 on December 17th, M8 is repaired well and online. Then, M8 will continue completing the rest task (O10). It takes 97 minutes for the entire intelligent manufacturing system to complete ten orders by using the proposed PDM method. However, it will take several hours or one more day to repair the abnormal machine without the PDM method. Meanwhile, the intelligent manufacturing system will be in a state of downtime. Even if the operation time of the PDM method is a little more than the operation time of the original work plan, but we can prevent the entire system from downtime due to the fault of M8.

C. DISCUSSION

In the case study, two levels of experiments including prediction results and maintenance decision results are conducted. In the first experiment, there are three comparisons on LSTM-GAN. The accuracy of LSTM-GAN is as high as 99.12%, which outperforms other deep learning methods and traditional algorithms, showing the good potential of the proposed LSTM-GAN. The second experiment contains the results and analysis of maintenance decision. A set of orders are submitted in sequence to verify the function of the maintenance decision model. The results show that the maintenance decision model can arrange a reasonable maintenance plan to avoid the downtime of the intelligent manufacturing system. It shows that our proposed PDM method can not only predict fault in advance but also provide a reasonable maintenance.
VI. CONCLUSION AND FUTURE WORK

This paper presents a novel predictive maintenance method based on LSTM-GAN in the intelligent manufacturing system. On the one hand, GAN generates a large volume of fault samples for the discriminant model to improve the accuracy of the model. On the other hand, the LSTM model includes memory units, gate structures, and attention mechanisms, which can ensure the correlation of feature memory between long sequence fragments. Thus, the improved deep adversarial learning method can not only avoid the mode collapse of GAN but also realize the self-detection of abnormal data.

The main contribution of this paper is developing a novel PDM method that can not only monitor the state of the machine in real-time but also predict the fault of the machine in advance. Besides, the method can also provide a predictive maintenance plan for maintenance staff to service and troubleshoot hidden faults in advance. The experiment is performed in a typical intelligent workshop of a manufacturing enterprise located in Wuxi, China. During the experiment, the PDM method is investigated to be helpful to the process of prediction and maintenance, since it can extract more robust latent feature from the data set. After four comparisons with other algorithms, the results show that the proposed method can avoid occurring the mode collapse and missing the global relationship. What is more, the results also show that the proposed PDM method can accurately predict fault and provide a reasonable maintenance plan for maintenance staff rather than the crash in the intelligent manufacturing system. On this basis, the proposed PDM method can make predictive maintenance in the intelligent manufacturing system more intelligent and reliable. It can improve the production efficiency of intelligent manufacturing system and ensure the safety of workers and machines.

Further, there are more challenges to be considered in future research, such as the ability to predict unknown faults needs to be optimized. Future research can be extended in the following ways. Firstly, other feature representation methods can be attempted in the latent feature extract process. Secondly, this method can be extended to other related fields, such as predictive maintenance for intelligent machines in other manufacturing areas by using deep transfer learning. We hope this work will help catalyze more in-depth investigations and multi-disciplinary research efforts to advance the predictive maintenance for the intelligent manufacturing system.

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NOTATIONS

X the sample
\( \hat{X} \) the reconstruction of the sample
z the latent vector
\( \hat{z} \) the reconstruction of the latent vector
L_G the loss function of the generator
l_x the reconstruction loss function of X
A(\( X \)) the anomaly score
l_{adv} the discriminative loss function
L_D the loss function of the discriminator
F_1 the equilibrium score
\( R_i(t) \) the reliability of the system
C_{mj} the cost of the minor maintenance
TC_{mj} the total maintenance cost of the machine j during its previous i times
T_{mj} the total maintenance time of the machine j during its previous i times
C_{pmij} the ith predictive maintenance cost of the machine j
TC_{pmij} the total predictive maintenance cost of the machine j during its previous i times
T_{ipmj} the total maintenance time of the machine j during its previous i times
T_{iparkj} the total downtime of the machine j during its previous i times
T_{ipark} the total downtime of the intelligent manufacturing system for predictive maintenance
C the total downtime cost
\( A_j \) the effectiveness of machine j
F_1 the equilibrium score
\( \varphi_1 \) the maximum threshold of \( F_1 \)
\( \varphi_2 \) the middle threshold of \( F_1 \)
\( \varphi_3 \) the minimum threshold of \( F_1 \)

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CHANGCHUN LIU was born in Yangzhou, Jiangsu, China, in 1995. He received the B.S. degree in electric engineering from the Yancheng Institute of Technology, Yancheng, China, in 2017, and the M.S. degree in mechanical engineering from Shanghai Polytechnic University, Shanghai, in 2020. He is currently pursuing the Ph.D. degree in mechanical and electrical engineering with the Nanjing University of Aeronautics and Astronautics, Nanjing, Jiangsu. His research interests include deep learning, the Internet of Things, and fault diagnosis of the intelligent manufacturing systems.

DUNBING TANG was born in Xiantao, Hubei, China, in 1972. He received the Ph.D. degree in mechanical engineering and automation from the Nanjing University of Science and Technology, Nanjing, Jiangsu, China, in 2000. From 2000 to 2002, he did his Postdoctoral Research at Tsinghua University, Beijing, China. From 2002 to 2004, he was a Humboldt Research Fellow with RWTH Aachen University, Aachen, Germany. In 2005, he was a Research Fellow with Cranfield University, Bedford, U.K. Since 2005, he has been a Professor with the College of Mechanical and Electrical Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing. His research interests include smart manufacturing systems, complex system modeling, and open design.

HAIHUA ZHU was born in Ningbo, Zhejiang, China, in 1985. He received the Ph.D. degree in mechanical engineering and automation from the Nanjing University of Science and Technology, Nanjing, Jiangsu, China, in 2013. From 2009 to 2011, he was a Research Scholar with the University of Greenwich, London, U.K. He is currently an Associate Professor with the College of Mechanical and Electrical Engineering, Nanjing University of Aeronautics and Astronautics, Nanjing. His research interests include smart manufacturing systems, digital twin, and the Internet of Things.

QINGWEI NIE received the B.S. degree in mechanical engineering from the Nanjing Institute of Technology, Nanjing, China, in 2015, and the M.S. degree in mechanical engineering from Yangzhou University, Yangzhou, in 2018. He is currently pursuing the Ph.D. degree with the Nanjing University of Aeronautics and Astronautics.