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A New Implementation of Digital Twins for Fault Diagnosis of Large Industrial Equipment

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Abstract

Refurbishment and remanufacturing play a vital role in the sustainability of the large industrial field, which aims at restoring the equipment that is close to the end of their life. The EU-funded project RECLAIM proposes new approaches and techniques to support these two activities in order to achieve saving valuable materials and resources by renewing and recycling the mechanical equipment rather than scraping them when they exceed the end of the lifetime. As the most critical part of predictive maintenance in RECLAIM, the fault diagnosis technique could provide the necessary information about the identification of the failure type, thus making suitable maintenance strategies. In this paper, we propose a novel implementation method that can combine the digital twins with the fault diagnosis of large industrial equipment. Experiment result and analysis demonstrate that the proposed framework performs well for the fault diagnosis of rolling bearing.

Keywords: Digital Twins; Fault Diagnosis; Predictive Maintenance; Rolling Bearing.

Introduction

Sustainability is the most important research topic in the large industrial field of Europe [1]. Currently, we are facing the challenge that more and more large industrial equipment have been served over several decade years and closed to or even exceeded their design lifetime. The productivity and efficiency are highly related on these machines that need to be well-functioning and well-maintained. The weak maintenance strategies will significant reduce the overall performance of the industry between 5 and 20 percent [2]. Therefore, it is obvious that industrial companies should continuously improve their large equipment's effectiveness and efficiency to keep their highly competitive. This highlights the urgent need to improve the maintenance process, emphasizing the methods of refurbishment and remanufacturing. Refurbishment and remanufacturing are activities of the circular economy strategies for equipment lifetime extension, which aims at keeping the equipment operating at a highly effective and efficient state and recovering them when they get close to the end of life for making them work. Remanufacturing is a strategy that implies using parts of discarded products in a new product with the same function, and refurbishment means restoring an old product and bringing it up to date [3]. These activities will lead to the extension of equipment lifetime and reduce the unnecessary and wasteful use of resources. RECLAIM presents a new idea on refurbishment and remanufacturing based on big data analytics, machine learning, predictive analytics, and optimisation models using deep learning techniques and digital twin models with the aim of enabling the stakeholders to make informed decisions about whether to remanufacture, upgrade, or repair heavy machinery that is toward its end-of-life [4].

For supporting the refurbishment and remanufacturing of large industrial equipment, there are two main issue need

Reclaim Project: www.reclaim-project.eu

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to be considered, including "what is the fault attribution?" and "when does the failure happen?". Based on the detailed information of "what and when", the RECLAIM can decide the most suitable maintenance strategies for the specific machine and its components. Fault diagnosis [5] and remaining useful life prediction [6] are the most critical techniques in the predictive maintenance (PdM) field, which is directly used for solving these two problems about "what and when". Digital twins (DT) is one of the hottest topics in recent years due to the rapid development of the Internet of Things (IoT) and digitalization in the industrial field [7]. This technique is one of the very promising ways to transfer expert knowledge to valuable data. The data acquired from the digital model could support the AI approach relayed on the data to implement more advanced and efficient fault diagnosis and remaining useful life prediction applications.

In this paper, we design a novel general architecture of digital twins for the RECLAIM project, then propose the specific DT framework for the fault diagnosis of rolling bearing and provide the fault signal producing mechanism of rolling bearing. Finally, we conduct an experiment on the CWRU testbed to comparing the digital fault signal with the real-world fault signal and discuss what kind of the digital models should be built for intelligent maintenance.

Digital Twins for Fault Diagnosis and Predictive Maintenance

In order to achieve the more advanced remanufacturing and refurbishment activities, RECLAIM defined a new general digital twins architecture that aims at monitoring and predicting the health state, and performance of the large industrial equipment [8]. Based on this architecture, all the necessary data and information for the predictive maintenance activities can be collected in time, thus avoiding the shutdown of the machine caused by the unexpected failure. As shown in **Figure 1**, the architecture of RECLAIM's digital twins model has been split into three units, including the physical component, the simulation component, and the data and information interaction system to connect these two systems [4]. This technique is developed to support the RECLAIM project to reasonably recycle the waste of large industries situation. To be more specific, the AI environment is used to store and run the related algorithms, such as fault diagnosis and predictive maintenance. The AI engine is used to handle the interactions between different algorithms. The orchestrator is used to orchestrate all related missions, such as receiving, storing and processing the historical and real-time data. The simulation environment is used to run the different simulation models based on the real-time requires and each model is wrapped by a simulation manager.

Digital Twins for Fault Diagnosis of Rolling Bearing

In this part, we customize the general digital twins' architecture in the specific mission of fault diagnosis for rolling bearing. As the most critical part of the large rotating machine, the health state of the rolling bearing should be real-time monitored because the malfunction of the bearing will result in the breakdown of their large equipment. Meanwhile, these unexpected failures will lead to an increase in the risk of failure, the cost of repair and

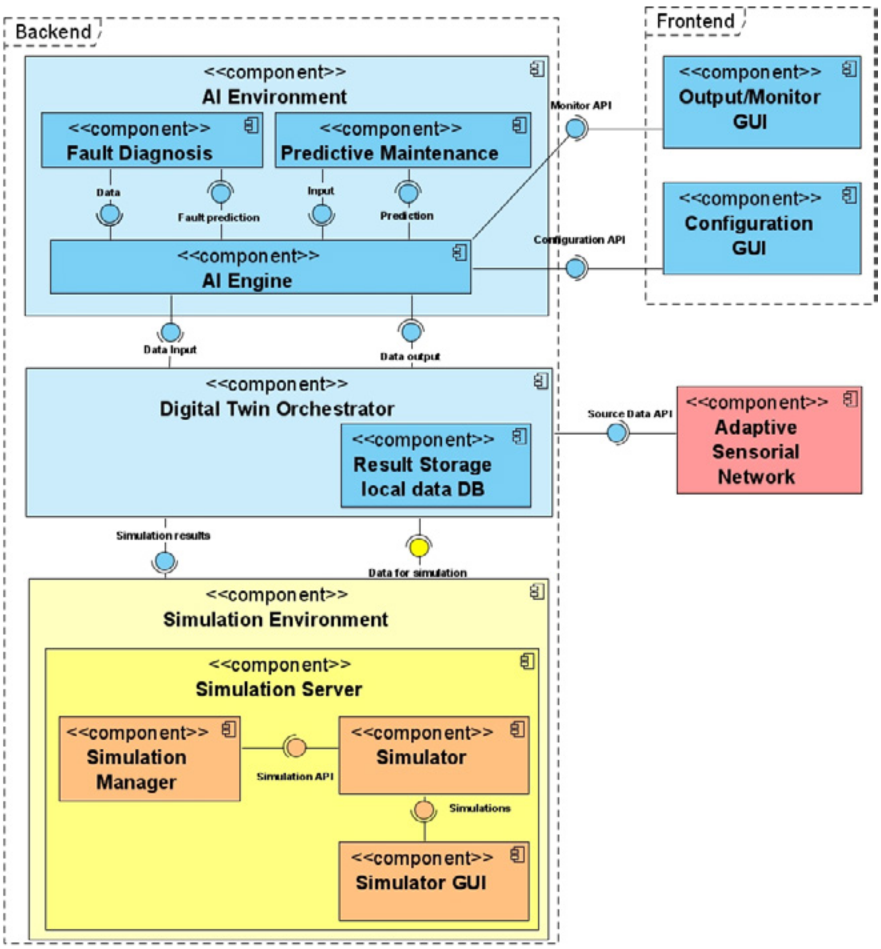

Figure 1: General architecture of digital twins.

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the time of maintenance. Therefore, it is very important to develop the fault diagnosis technique of rolling bearing for identifying the malfunction at the early stage. With the rapid development of the digitalization of the industrial system, more and more AI techniques have been widely used for fault diagnosis. However, these advanced methods are limited to the problem of collecting data. The reason is that it is difficult to acquire enough data for all kinds of machines and application scenarios from the complex and harsh industrial environment. The current studies are focus on dealing with this data challenge by using advanced deep learning methods, such as transfer learning [9,10], few-shot learning [11].

The digital twins' technique is a very promising method for this challenge because the missing data can be supplemented by the digital simulation model. According to this thought, the advanced AI approach can be implemented for the limited real data scenarios and even for the new application without real data. Therefore, we propose a digital twins framework for fault diagnosis of the rolling bearing in the RECLAIM project, which is shown in **Figure 2**. As one can see from the figure, all the industrial pilots, including welding, robotics and enamelling, woodworking, shoemaking and textiles, have numerous large rotating equipment with rolling bearing as the supporting. It is impossible to install the accelerometer sensor on each machine because these will cost too much. However, we still need the data to train the fault diagnosis model, thus the system can identify the fault. Therefore, we can simulate the fault signal based on the failure mechanism of the rolling bearing. Finally, the simulated data can promote the performance of the fault diagnosis system. The digital model of the rolling bearing fault will be presented in the next section.

Digital Model of Rolling Bearing Fault Signal

Digital model of rolling bearing fault signal x(t) is defined as follows [12]:

$$x(t) = \sum_{i=1}^{N} A_i \, . \, s(t - iT_0 - T_i) \tag{1}$$

where T_0 is the period of impulses, T_i is the minor random vibration around the average period T_0. N is the number of impulses and i is the sequence number of these impulse. A_i is the mixed dynamic force and load, which is defined as:

$$A(t) = \rho \, . (M(t) + T(t)) \tag{2}$$

where M(t) is related to gravity and T(t) is related to an unbalanced force. All the impulses are caused by the rolling element run over the defect and each of them can be considered as exponential decay oscillation and can be calculated as follows:

$$s(t) = e^{-Bt} \cos(2\pi f_n t) \tag{3}$$

where f_n denote the inherent frequency and B denotes the decay factor. Based on the above theoretical definition, the general fault signal of the outer race, inner race and ball, can be expressed as follows:

1. Simulation equation of Outer race fault signal:

$$x(t) = \sum_{i=1}^{N} \rho(mg\cos(\varphi_m) + me\omega^2 \cos(2\pi f_r t + \varphi_t)) \cdot s(t - iT_0 - T_i) \tag{4}$$

2. Simulation equation of Inner race fault signal:

$$x(t) = \sum_{i=1}^{N} \rho(mg\cos(2\pi f_r t + \varphi_m) + me\omega^2 \cos(\varphi_t)) \cdot s(t - iT_0 - T_i) \tag{5}$$

3. Simulation equation of Ball fault signal:

$$x(t) = \sum_{i=1}^{N} \rho(mg\cos(2\pi f_{cage} t + \varphi_m) + me\omega^2 \cos(2\pi (f_r - f_{cage}) t + \varphi_t)) \cdot s(t - iT_0 - T_i) \tag{6}$$

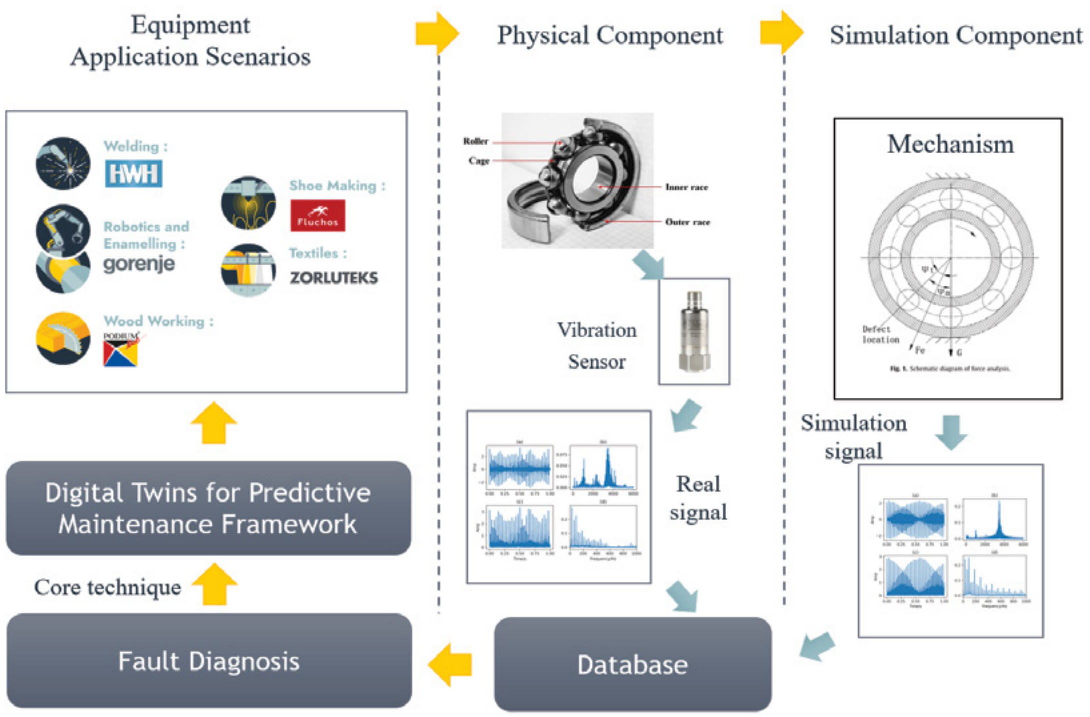

Figure 2: Digital twins' framework for fault diagnosis of the rolling bearing in the RECLAIM project.

where m denotes mass, g denotes gravity acceleration, e denotes eccentricity which used as a measure of its deviation from circularity, f_r denotes the rotating frequency, ω denotes the angular velocity, φ_m and φ_t denote the initial phase position between the failure position and the gravity and eccentricity, respectively, which is shown in **Figure 3**.

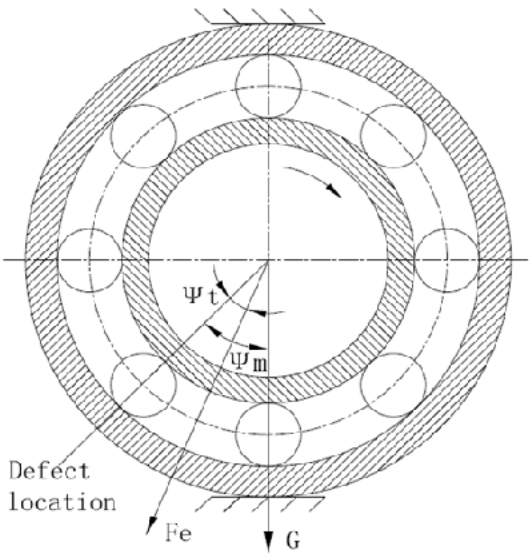

Figure 3: Force analysis.

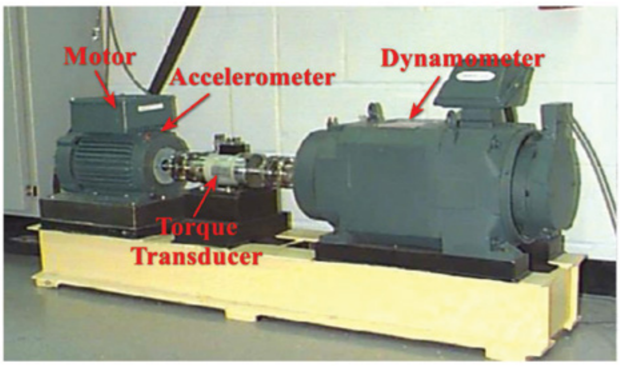

Figure 4: CWRU testbed.

Experiments

Real-world Bearing Fault Testbed Description

Figure 4 shows a real-world testbed which is built by the bearing centre of Case Western Reserve University (CWRU) [13]. This test stand is composed of a motor, a torque transducer, and a dynamometer. In the experiment, bearings have been installed on the two sides of the motor, SKF 6205-2RS and 6203-2RS have been installed on the driven end and fan end, respectively. The vibration signal is used as the analysis tool for identifying the failure type, which is collected by using accelerometers attached to the housing of the motor.

The data have been acquired by 16 channel DAT recorder and stored in the Matlab format. The sampling frequency is set to 12000 Hz and the test speed is around 1750 rpm. In this work, we choose the SKF 6203-2RS as the example to compare and analyse the digital simulation model of outer race fault and inner race fault. The detail structure parameter of the SKF 6203-2RS and the fault frequency are shown in **Table 1**.

Ball diameter d(mm)	Pitch diameter D(mm)	Ball number Z	Contact angle α
6.7462	28.4988	8	0
Test speed	**Outer fault frequency**	**Inner fault frequency**	
1750rpm	91.44Hz	148.08Hz	

Table 1: Detail parameter and fault frequency of SKF 6203-2RS.

Result and Analysis

Firstly, we analyse the real-world vibration signal of the outer fault and inner fault, which are shown in **Figure 5 (a)** and **Figure 6 (a)**. From these original signal, there are many impulses occurring in the period during the collection because of the defect on the outer and inner. The periodicity of these impulse signals represents the different feature of the fault signal, which is also the fault mechanism of rolling bearing. Based on the original signal **Figure 5 (a)** and **Figure 6 (a)** and it frequency spectrum **Figure 5 (b)** and **Figure 6 (b)**, it is difficult to find very distinguished feature, while the frequency spectrum of outer and inner fault is similar to each other. Therefore, we use the envelope detect technique [12] to process these periodic signal thus discover recognizable feature. The envelope waveform and its frequency spectrum are shown in **Figure 5 (c)(d)** and **Figure 6 (c)(d)**. After the processing, the fault frequency of the outer (91.44Hz) and inner (148.08Hz) and the rotation frequency (29.17Hz) are clearly displayed in the envelope spectrum.

Next, we use the digital model of rolling bearing fault mentioned in Section 2.2 to simulate the fault signal of outer and inner, the parameters are shown in **Table 2**. The simulation results are shown in **Figure 7** and **Figure 8**. The fault frequency and rotation frequency are clearly shown in the envelope spectrum, Which means that the simulation fault signal is very close to the real-world signal of outer and inner failure. In order to quantify the similarity of the real-world and simulation fault, we use the three different statistical correlation test methods including Pearson, Spearman, and Kendall [14]. The results are shown in **Table 3**, the p-value is less than 0.05 indicates that the correlation result is significant, and the correlation factors are high enough that verify the simulation signal is significantly matching the real signal.

f_r	m	g	e	f_n	B	φ_m	φ_t	ρ
29.17Hz	50kg	9.8m/s^2	0.05mm	3500Hz	350	0	0	0.002

Table 2: Detail parameters of simulation fault signal of SKF 6203-2RS.

	Outer race		Inner race	
	correlation	p value	correlation	p value
Pearson	0.7904	< 0.05	0.4419	< 0.05
Spearman	0.5788	< 0.05	0.4419	< 0.05
Kendall	0.4037	< 0.05	0.3018	< 0.05

Table 3: Quantitative results of signal similarity hypothesis testing SKF 6203.

Discussion and Conclusion

We have presented a novel digital twins' framework for supporting the refurbishment and remanufacturing of

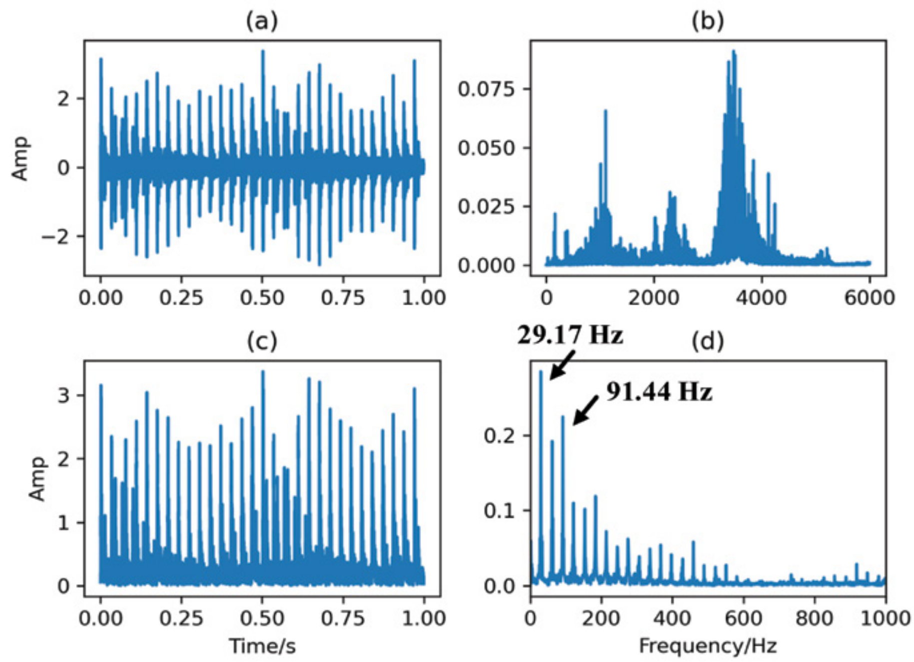

Figure 5: Real-world signal of outer race defect related waveform and spectrum. (a) The time domain waveform of simulation signal; (b) Frequency spectrum of (a); (c) Envelope waveform of (a); (d) Envelope spectrum of (a).

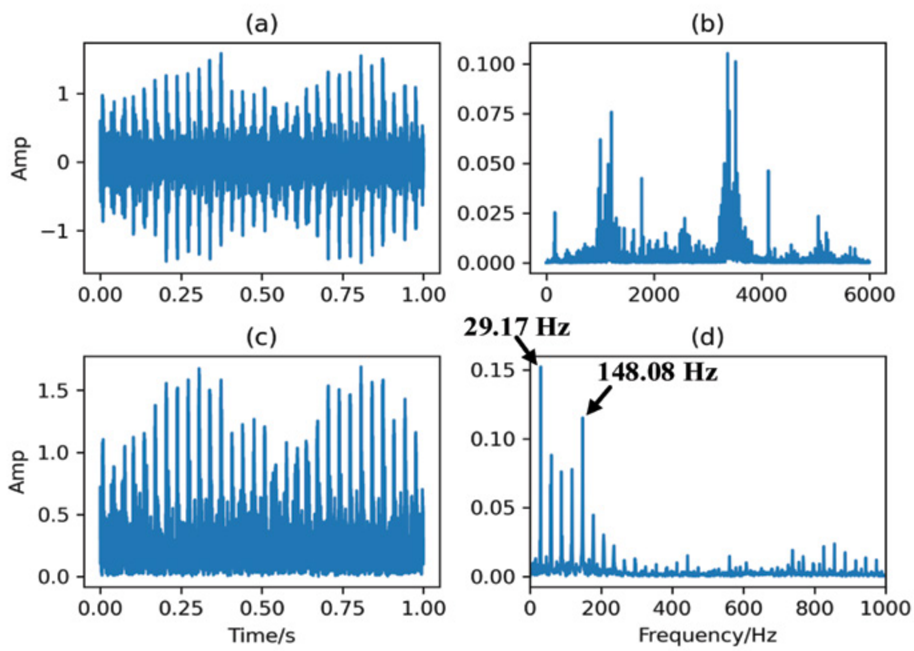

Figure 6: Real-world signal of inner race defect related waveform and spectrum. (a) The time domain waveform of simulation signal; (b) Frequency spectrum of (a); (c) Envelope waveform of (a); (d) Envelope spectrum of (a).

large manufacture machine in this work. The experiment results verify that the fault signal producing mechanism of rolling bearing perform well due to the high-level quantitive correlation factor and the envelope frequency spectrum. This simulated fault signal can be potentially used for training the fault diagnosis model in the limited real data situation or a totally new application without real data. However, the digital model certainly has some difference from the physical system. Therefore, we believe that it would need some new method to transfer the trained model to fit the practical environment.

Actually, there are many different types of digital model for equipment that can produce numerous data, such as the 3D designing model, performance estimation model, demand and market analysis model [7]. However, these digital models cannot reflect the operation state of a working machine in a practical situation.

Only the recorded data from the condition monitoring system can be used for equipment maintenance since these data represent the current and historical state of the specific machine. The vibration signal is the most effective way

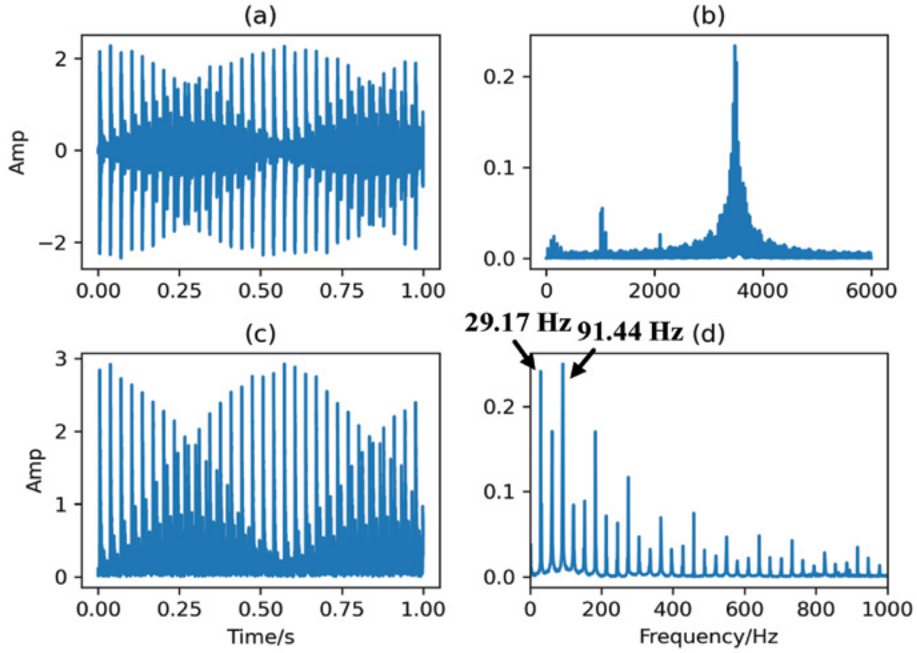

Figure 7: Simulation signal of outer race fault related waveform and spectrum. (a) The time domain waveform of simulation signal; (b) Frequency spectrum of (a); (c) Envelope waveform of (a); (d) Envelope spectrum of (a).

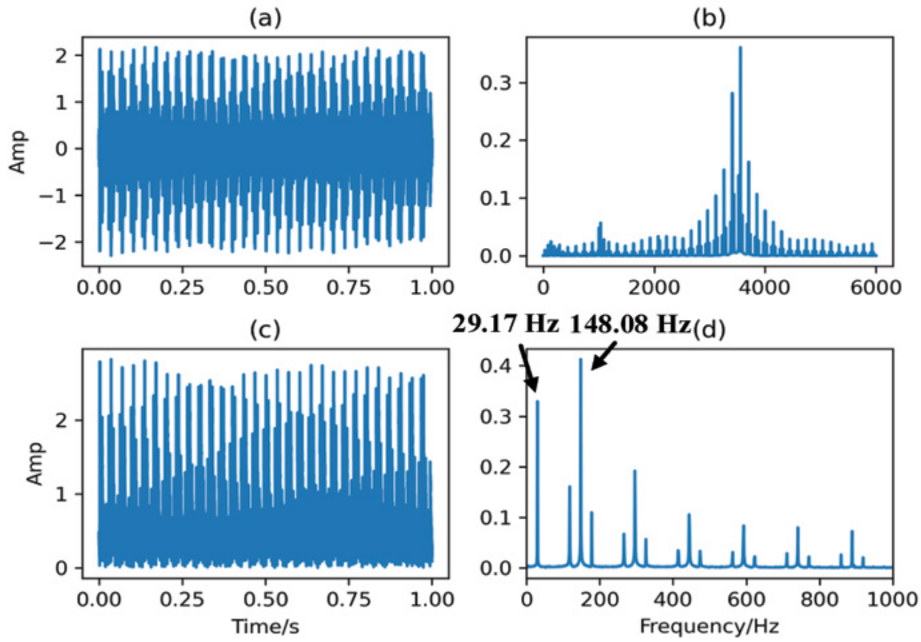

Figure 8: Simulation signal of Inner race fault related waveform and spectrum. (a) The time domain waveform of simulation signal; (b) Frequency spectrum of (a); (c) Envelope waveform of (a); (d) Envelope spectrum of (a).

to monitoring the mechanical failure of the large rotation equipment. Due to the wide application of rolling bearing, we take it as an example to analyse. Although many different kinds of digital models and data of the bearing can be obtained from the manufacturing company, e.g. the detail parameter, designed working condition, and estimated lifetime, etc., it is still impossible to build a digital model for maintenance of the bearing working in the real world scenarios. The reason is that the practical situation is significantly different from the designed test situation, and the manufacturer cannot 100% assure that all the bearing could run close to the designed lifetime which is only the statistical results tested in the ideal environment. Once the unexpected failure appears on any bearing of the user's machine, it will lead to immeasurable losses. Therefore, the user needs the condition monitoring system to collect the vibration data of the bearing, thus get know the current condition of their machine and make a suitable maintenance schedule to replace the bearing. In a word, for predictive maintenance, we need to build the digital twins model that can produce the monitoring data, these data can really support the advanced maintenance method to work on the practical industrial system.

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