Stress Wave Analysis for Prognostic Health Management

CONDITION BASED MONITORING SOLUTIONS

ABSTRACT

Prognostic health management in industrial equipment plays an increasingly important role in the development of science and technology for instrument measurement and analysis, including in the Internet of Things, cloud computing, data mining, and artificial intelligence. This paper studies a prognostic health management technology based on StressWave Analysis. The ultrasonic signals of friction, mechanical shock, and dynamic load on equipment's moving parts (known as stress wave energy, or SWE) are detected and processed by stress wave sensors; the stress wave energy is then analyzed using the time and frequency domain feature extraction software, as well as data fusion technology based on neural networks. The equipment statuses are quantitatively analyzed, their faults accurately predicted, and their health diagnosis reports provided regularly. The operational test shows that, compared with the traditional vibration analysis technology, the StressWave system can monitor the operating condition of equipment better in real time and predicts faults earlier. Through use of these analyses, production safety is guaranteed, the equipment maintenance cost is reduced, and production efficiency is improved.

Keywords: Stress wave analysis, feature extraction software, neural network, data fusion.

INTRODUCTION

Modern society relies more and more on equipment, making it important to guarantee equipment quality, safety, and environmental protections to realize the goal of safe, reliable, efficient, and low energy consumption equipment. Therefore, it is of great significance to strengthen the modern equipment management.

The methods of equipment maintenance and repair can be classified into three categories: troubleshooting, preventive maintenance, and predictive maintenance. Troubleshooting is any passive repair done after a device has failed, often causing production losses and even accidents. Due to lack of historical data of the equipment's operation, this type of maintenance is blind and inaccurate. Preventive maintenance is done according to the provisions of a maintenance cycle and is the current main means to avoid obstacles and accidents; however, the equipment may be still in good condition when maintenance downtime occurs, resulting in excessive repairs, wasting manpower and material resources. By contrast to these other methods, predictive maintenance uses technology to calculate when a machine may fail or need repair, allowing for better repairs and resource management.

Based on the need for advanced equipment management development, it is necessary to adopt equipment prognostic health management technology as an important means of predictive maintenance. The ideal technology should show the vital information of running equipment by effectively analyzing the current working state, diagnosing and forecasting faults, and providing technical data for equipment maintenance, ensuring the equipment's normal and optimized operation[1].

Through the development of advanced instrumentation measurement and analysis technology, such as networking, cloud computing, data mining, and artificial intelligence, the digitization, automation, integration, and networking of instrument systems are continuously improving. In recent years, the effectiveness and reliability of equipment prognostic health management (PHM) technology has been continuously improved, being widely used in engineer-ing and playing more important roles in equipment health management and predictive maintenance in modern enterprises[2].

Most equipment condition monitoring and fault diagnosis technologies are currently based on a combination of vibration measurement/analysis, oil analysis, infrared thermal imagery, ultrasonic flaw detection, and temperature/pressure analysis techniques; because of their convenience, real time nature, and non-destructive methods, the use of vibration sensors and analysis instruments to measure mechanical equipment running status have become the most common method of equipment monitoring[3]. However, in the diagnosis of low-speed rotating equipment characteristic fault frequencies and device operating frequencies are covered by the

1 Yu Peng, Datong Liu, and Xiyuan Peng, "A review of Prognostics and health management," *Journal of Electronic Measurement and Instrument*, 24(1) (2010):1-9.
2 Hong Xia, Yong kuo Liu, and Chun-li Xie, *Equipment fault diagnosis technology*, (Harbin: Harbin Institute of Technology Press, 2010), 3.
3 National Key Laboratory of Vibration, Shock and Noise. *Mechanical equipment condition monitoring and fault diagnosis technology*, Shanghai: Shanghai Jiao Tong University, 2015.

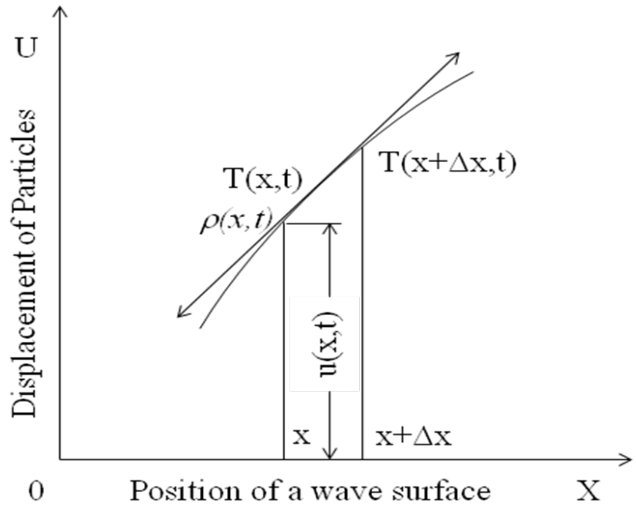

Figure 1: Transverse Vibration of One Dimensional Elastic Wave String

resonance and background noise of the equipment, meaning traditional methods can't detect the them. This means that when the components of low-speed rotating equipment begin to fail or fail entirely, the vibration technology does not detect the change[4].

Stress wave theory research is mainly concentrated on materials[5-6] and structures[7,8,9] for application in civil and transportation construction fields, although in recent years some studies have examined stress wave propagation in gears[10] but only on test technology and the results are used to verify the algorithm.

This paper studies StressWave, a prognostic health management technology based on stress wave analysis, which is designed to gauge the following: electronically signaled real-time measurements of equipment running friction, shock, and dynamic load; high frequency acoustic wave sensing techniques to filter out background vibration and noise; time and frequency domain extraction software features; and the use of data fusion technology based on neural network. This technology can carry out quantitative analysis and fault diagnosis of equipment to provide customers with regular analysis of equipment health, establishing a predictive maintenance system for enterprise.

STRESS WAVE PRINCIPLE

Stress waves are the propagation form of stress and strain disturbance. In a deformable solid medium, mechanical perturbations are represented by changes in particle velocity, as well as changes in corresponding stress and strain states. This change of the stress and strain state is transmitted by a wave called stress wave. The interface between the disturbed region and the undisturbed region is usually called the wave surface, and the velocity of wave front is called the wave velocity. Seismic waves, sound waves, and ultrasonic waves in solids are all common forms of stress waves[11].

In the case of dynamic loads varying with time, each element in the medium is in a dynamic process with time. For all deformable media with inertia, the motion of a medium is always a process of stress wave propagation, reflection, and interaction when the stress wave passes through an object with significant changes in its internal and external loads. The characteristics of the process depend mainly on the characteristics of the material. Stress wave research mainly focuses on the unsteady motion of the medium, the local and early effects of the dynamic load on the medium, and the interaction of load and the medium[12].

4 Changzheng Chen et al., "Study on a new method for fault diagnosis of low speed rolling bearings based on stress wave," *Journal of Mechanical Strength*, 29 (6) (2007): 885-890.
5 A. Sadri, Pawel Gebski, and Ehsan Shameli, "Refractory wear and lining profile determination in operating electric furnaces using stress wave non-destructive testing," in *Proceedings of the 12th International Ferroalloys Congress,* ed. Asmo Vartiainen (Helsinki: Outotec Oyj, 2010), 881-890.
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8 H Xing, XY Sun, and MM Wang, "Sonic Frequency Stress Wave Propagation Characteristics Research of Anchor System Based on Wavelet Packet Analysis," *Journal of Guangxi Normal University*, 31(4) (2013): 13-17.
9 N. Yan. *Numerical modeling and condition assessment of timber utility poles using stress wave technique*, Sydney: University of Technology, 2015.
10 David Mohamed Elforjani, MBA, "Detecting AE Signals from Natural Degradation of Slow Speed Rolling Element Bearings," in *Proceedings of the Second International Conference "Condition Monitoring of Machinery in Non-Stationary Operations" CMMNO'2012*, ed. T. Fakhfakh, W. Bartelmus, F. Chaar, R. Zimroz, and M. Haddar (Berlin: Springer, 2012), 61-68.
11 Lili Wang, *Foundation of Stress waves*. (Beijing: National Defense Industry Press, 2005).
12 Herbert Kolsky, *Stress Waves in Solids* (London: Oxford University Press, 1953).

When the stress is linearly related to the strain, the elastic wave propagates in the medium; in a nonlinear relation, it is the plastic wave and the shock wave that propagate in the medium. As shown in Figure 1, the simplest string of transverse vibrations of a one dimensional elastic wave can be analyzed by analyzing its wave equation, which can demonstrate the common characteristics of many elastic dynamical problems[13].

In Figure 1, *U* represents displacement, *t* is time, *X* indicates the position of the wave surface along the direction of propagation in the physical coordinate, and *x* indicates the position of the wave surface along the direction of propagation in the spatial coordinate. *u(x,t)* represents the displacement of particles in x point at t time, *T(x,t)* represents the tension of the point, and $\rho(x,t)$ represents the density of this point. $C=dX/dt$ is called the material velocity or intrinsic wave velocity, and $C=dx/dt$ is the spatial velocity; these two wave velocities are different expressions of the same physical phenomenon. For a plane wave, the relationship between the two kinds of velocity is $c=v+(1+\varepsilon)K$. In this formula, *v* is the particle velocity and ε is the engineering strain.

For materials unconcerned with speed, assume the initial density is $\rho_{0.}$

There is a single function relationship between stress σ and strain σ under dynamic load: $\sigma=\sigma(\varepsilon)$. In Quasilinear Wave Equations with unknown displacements, *u(x,t)* can be obtained by the conservation of mass and momentum equations:

$$\frac{\partial^2 u}{\partial t^2} - C^2 \frac{\partial^2 u}{\partial X^2} = 0 \qquad (1)$$

Where:

$$C = \left(\frac{1}{\rho_0} \frac{d\sigma}{d\varepsilon} \right)^2$$

materials	$C_1(s/m)$	$C_t(s/m)$
aluminum	6100	3100
steel	5800	3100
lead	2200	700
Resin glass	2600	1200
polystyrene	2300	1200
magnesium	6400	3100

Table 1: The Elastic Wave Velocity of Several Common Materials

Equation (1) has two compatibility relations that represent the real characteristic line of the right and left traveling wave and the corresponding lines along characteristic lines respectively[14]:

$$dX = \pm C dt, \; d\sigma = \pm \rho_0 C dV \qquad (2)$$

In Equations (2), wave velocity *C* and wave impedance $\rho_0 C$ are completely determined by the material properties. This result is similar to one-dimensional stationary motion in gas dynamics. Thus, the problem of solving stress wave propagation is mathematically reduced to solving the wave equations in Equation (1) or equivalent characteristic line equations in Equations (2) under given initial and boundary conditions. The common numerical methods include the characteristic line method, finite difference method, and finite element method[15].

For isotropic linear elastic materials, $d\sigma/d\varepsilon$ is constant, so the linear elastic wave velocity (sonic speed) C_e is constant; for the one-dimensional strain longitudinal wave, $C_0=(E/\rho_0)^{1/2}$, where *E* is the Young modulus; for the one-dimensional strain longitudinal wave with lateral confinement, $C_1=(E^1/\rho_0)^{1/2}$, where E^1 is a lateral elastic modulus, as shown in Equation (3).

$$E^1 = \lambda + 2\mu = K + \frac{4}{3}\mu = E\left[(1-\nu)/(1+\nu)(1-2\nu)\right] \qquad (3)$$

λ is the first order of the lame constant, said material compression, equivalent volume elastic modulus, or the Young modulus. μ is the second order of the lame constant, that represents the shear modulus of materials. *K* is the volume of compression modulus, and ν is Poisson ratio. C_1 is also the longitudinal wave velocity in an infinite elastic medium. For the transverse wave, it is only necessary to understand μ, σ and ε as transverse particle displacement, shear stress, and shear strain, then the shear wave velocity $C_t=(G/\rho_0)^{1/2}$, with G for shear modulus[16].

The elastic wave velocity of some typical materials is shown in Table 1[17].

STRESS WAVE DETECTION AND ANALYSIS

When the equipment is subjected to an external force (load), it produces internal stress (internal change) or relative motion between surfaces. At the same time, the external force (load) generates a kind of elastic wave.

13 Qiantang Chen, *Dynamic stress analysis of gear based on stress wave propagation theory* (Xi'an: Northwestern Polytechnic University, 2006) 3.
14 David B. Board, "Stress Wave Analysis Provides Early Detection of Lubrication Problems", *Practicing Oil Analysis*, July 2003.
15 John S Rinehart. *Stress Transients in Solids* (Santa Fe: HyperDynamics, 1975).
16 W. K. Nowacki, *Stress Waves in Non-elastic Solids*. (London: Pergamon Press, 1978).
17 Weiguo Guo, Yulong Li, and Tao Suo, *Concise tutorial of stress wave foundations* (Xi'an: Northwestern Polytechnic University press, 2007) 4.

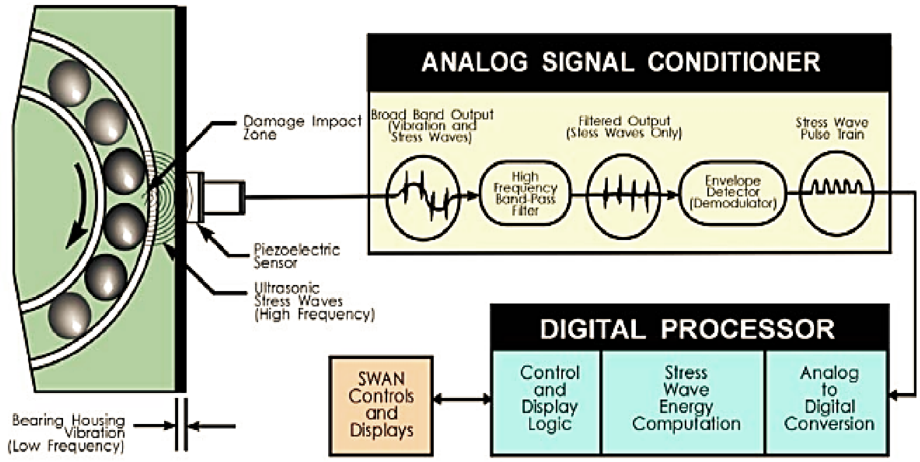

Figure 2: Stress Wave Detection and Analysis

This elastic wave propagates in all directions in solid, liquid, gas, and other mediums; this is the stress wave. Based on this characteristic, stress wave technology can evaluate and diagnosis the equipment at the earliest possible time for the equipment failure and operational issues.

The prognostic health management system based on Stress Wave Analysis (SWA) consists of three parts: the stress wave sensor, the signal processing unit, and the control display unit. The stress wave sensor is mounted on the surface of the equipment's moving parts (such as bearings, gear boxes, etc.). The stress wave signals transmitted by these equipment components, such as friction, mechanical shock, and dynamic load, are ultrasonic frequencies. The stress wave amplitude is converted to electrical signals in the piezoelectric sensors, then amplified and filtered through the high frequency band pass filter in the analog signal modulator to remove low frequency noise and vibration energy from normal equipment movement. After the signal is amplified by the data acquisition box, it is transformed into the data standard, which can be received by the system computer or DCS/PLC system used by factory. The data is then stored on the system server. The system collects this data and generates diagnostic reports after software analysis, as shown in Figure 2.

The main tools of stress wave analysis include Stress Wave Energy (SWE), Stress Wave Amplitude histograms, and the Stress Wave Spectrum.

The output of an analog signal modulator is a Stress Wave Pulse Train (SWPT) that represents the time history of the device's shock and mechanical friction events. The digital processor analyzes the SWPT to determine the peak levels and total energy produced by these friction and shock events. The calculated values of the Stress Wave Pulse Amplitude (SWPA) and SWE of the data are stored in the database as historical trends and compared with normal readings.

A vibration sensor works through a flat frequency response (e.g., 100mV/g) to detect a wide range of frequencies (e.g., 0~15000Hz), making it insensitive to minor changes in machine friction that occur in the early fault stages. Additionally, the vibration sensor can only detect abnormalities when the level of fault vibration is significantly higher than the background vibration, well after the deterioration of the fault. The stress wave sensor has a very narrow frequency range (36000Hz ~ 40000Hz) and very high frequency response (e.g., resonance), and therefore is very sensitive to small defects on the surfaces of the machine, even in the presence of background vibration. SWA can be employed to separate, detect, and analyze features like SWE, SWPA, and Stress Wave Peak Duration (SWPD) starting in the early stages of the failure process from a very low frequency range of working mechanical vibrations and audible noise, meaning SWA plays an incomparable role in monitoring gear and bearing damage in equipment.

The digital analysis of stress waves consists of computing both the amplitude and the energy content of detected stress waves. The amplitude (or peak level) of a stress wave is a function of the intensity of a single friction or shock event. The energy content is a computed value (the time domain integral) that considers the amplitude, shape, duration, and rates of all friction and shock events that occur during a reference time interval. The damage can be quantified by measuring the energy content of the friction event (shock amplitude and duration, i.e., the curve area produced by the pulse train)[18] as shown in Figure 3.

The SWE run history diagram (shown in Figure 4) is generated by collecting data from the system during routine operations, and shows the trend of SWE in relation to equipment failure. It shows the trend of SWE readings over time and graphically represents the health trends of the equipment in green, yellow, and red background areas.

18 Curtiss-Wright, "Proactive System Operation and Maintenance", *Stress Wave Technology,* 2011.

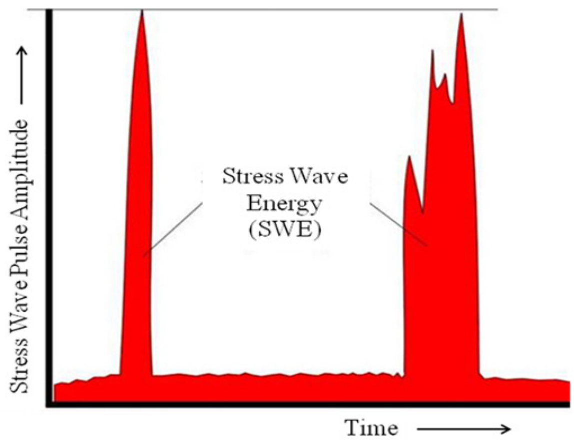

Figure 3: Stress Wave Energy (SWE)

The Stress Wave Amplitude histogram is shown in Figure 5; the Y axis represents the number of frictional events, and the X axis represents the peak amplitude of the individual friction pulses. The tool detects the peak amplitude of each pulse in the stress wave pulse and distributes it on a voltage scale corresponding to each reading value. In normal operation when the device is at its best performance, the histogram is distributed in a narrow bell shaped curve at the lower end of the voltage, as shown in Figure 5 (a). But in abnormal operations, friction and shock events (such as lubrication problems caused by fluid or particulate contamination, or slipping of the rolling element) will increase the high amplitude incidents, resulting is a more widespread distribution, as shown in Figure 5 (b), where the amplitude scale is skewed to the right.

The Stress Wave Spectrum is an algorithm for analyzing stress wave bursts to detect their spectral content (pulse amplitude as a function of the repetition frequency they occur), as shown in Figure 6. SWA only detects events that excite the sensor at ultrasonic frequencies, filtering out all low frequency vibrations associated with device dynamics and leaving only the time history of shock waves or frictional modulation events. Healthy equipment has the fewest shock events, so the stress wave spectrum for most healthy equipment is a relatively flat horizontal line, as shown in Figure 6 (a). In the case of a localized damage zone (such as a roller seat or the tooth of a gear), a repeated shock event occurs when the damage zone is in contact with its matching component. This repetitive shock event is shown in the spectrum in Figure 6 (b), in which frequency spikes exceed 10 dB above the background level. When these peaks occur, the geometry of the gear and the bearing element are analyzed at their rotational speed to determine the precise parts that could cause the shock events at this frequency, indicating the potential damaged parts and their positions.

These three tools (SWE, Stress Wave Amplitude histogram, and the Stress Wave Spectrum), are very successful in the diagnosis of various mechanical transmission gears and rolling bearing issues[19]. The operation history of SWE has the advantage of closely documenting trending fault symp-

19 Board, "Stress Wave Analysis Provides Early Detection of Lubrication Problems".

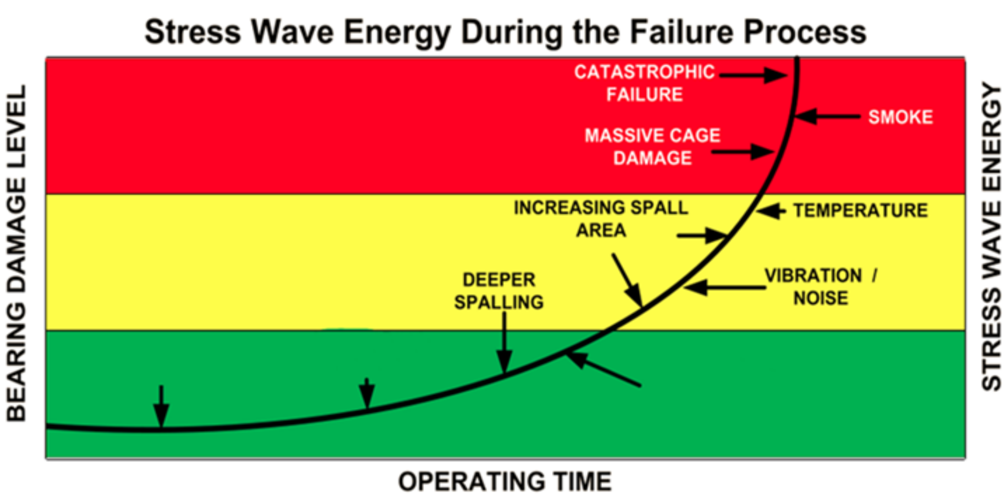

Figure 4: SWE during the Failure Process

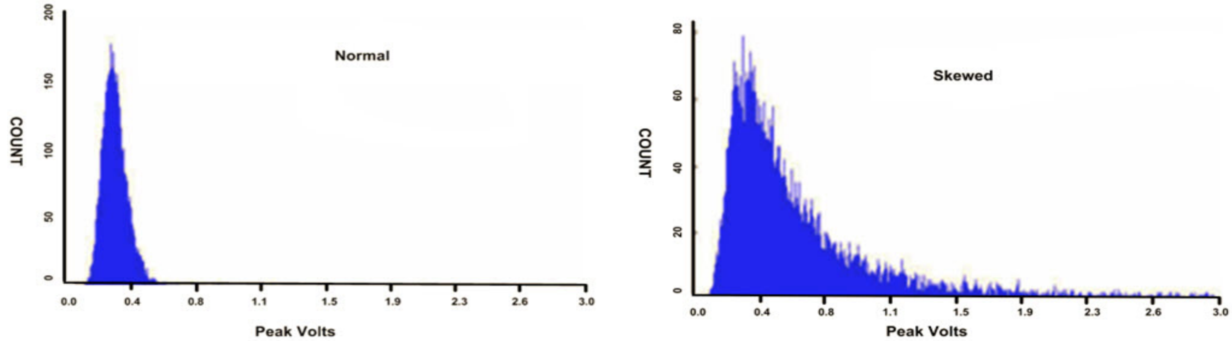

Figure 5: Stress Wave Amplitude Histogram

toms over time, and can be comprehensively used in the detection and quantification of a gear and bearing system's degree of damage. SWE is highly sensitive to the improper repair and lubrication degradation caused by oil pollution and abnormal pre-load, and SWE measurement provides accurate fault location data, down to even the internal mechanisms of a system. Stress Wave Amplitude histograms are extremely effective in early detection of non-periodic events (such as fluid or particle contamination, or slippage between rolling bearings and seat rings) that are often associated with lubrication problems. The Stress Wave Spectrum is very sensitive to abnormal dynamic loads and very small local fatigue damage in the early stage.

FEATURE EXTRACTION SOFTWARE

The main idea of the signal processing-based fault diagnosis method is that multiple feature vectors in the depth of the time domain and the frequency domain are obtained using signal analysis theory, then the location of the fault source is determined using the relation between these feature vectors and the system fault source[20].

Stress wave signal analysis and processing techniques can be done by time domain analysis, frequency domain analysis, time-frequency domain analysis, and time series modeling analysis. These analysis and processing techniques are used to observe and analyze the stress wave signals from different angles and provide different means for extracting feature information related to the device's running state.

The feature extraction software developed for stress wave analysis is used to accurately characterize SWPT and compressed SWPT digital recording files; Quantitative analysis of the SWPT of running equipment's friction and shock events can also be carried out by this software. The feature extraction software also analyzes SWA using various methods, including the time domain and frequency domain methods. The time domain method uses mean value, mean square deviation, peak value, pulse, and so on to analyze the waveform. The frequency domain method uses Fourier transform technique to analyze the waveform[21].

Time Domain Feature Extraction Method

The time domain method starts with the digital record file of SWPT. The mathematical transformation is then applied to the time series data to characterize a variety of waveform features such as pulse amplitude, duration, and energy content.

Figure 7 shows part of the SWPT time history digital record file. When the sampling rate of 10K is taken (10000 samples/s) for the duration of 2 seconds (i.e., 20000 data points), the size of the SWPT digital record file

20 Chen Guo, "Structure self-adaptive neural network model realizing structural risk minimization principle," *Chinese Journal of Scientific Instrument*, 28(10) (2007): 1874-1879.
21 Steve Scheeren, "Aircraft Engine Stress Wave Analysis Report [R]." Scientech, 2015.

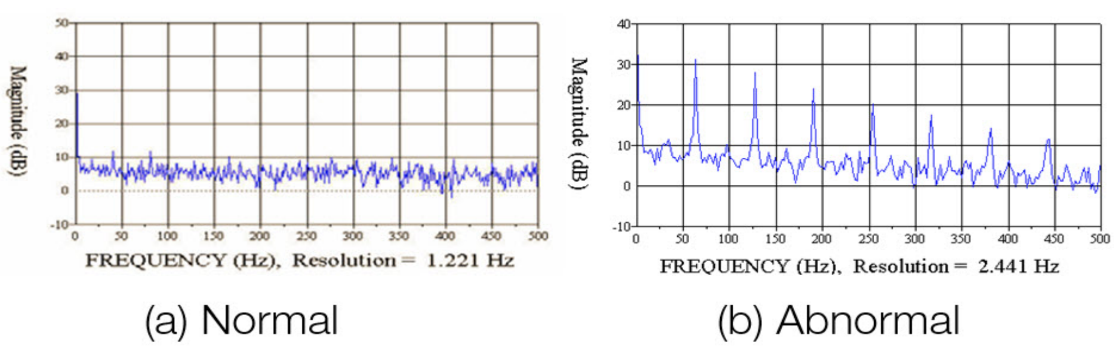

Figure 6: Stress Wave Spectrums

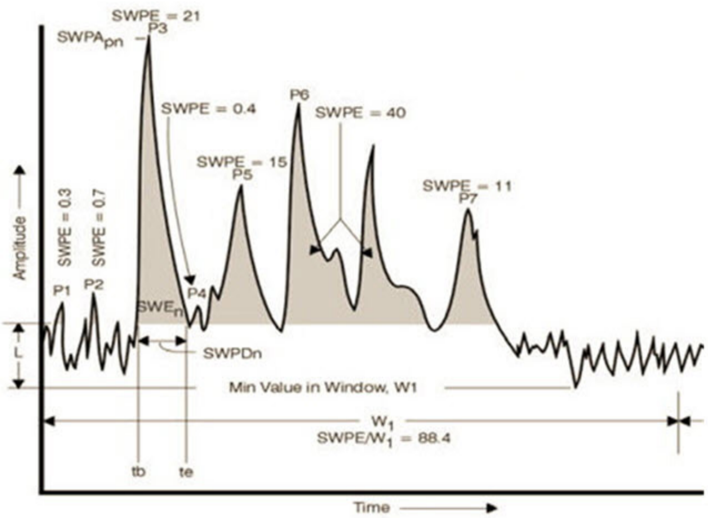

Figure 7: Time Domain Characteristics of Stress Wave

is about 40K (taken in binary format). The Time Domain Feature Extraction algorithms then compress this data into 32 waveform features in a file size of less than 1.3K. This converted information is then used by the AI algorithm to make decisions.

Figure 7 also illustrates how the extracted SWPT time domain features are computed. This diagram shows the duration of approximately 1 window; a window (W) is user-defined number of milliseconds, typically selected as the period corresponding to a characteristic machine frequency. The length of W is constant for the full data record, and is set by the analyst. A record (R) is the total time duration represented by the data file, which can be up to a maximum of 10 seconds of data (at a 10,000 sample/sec rate, this is 2,000,000 data points).

Both features extracted from the SWPT depend on exceeding the limit threshold (L). This limit is calculated for each window as a multiple of the mean of the lowest 10% of positive values of the instantaneous amplitude (Ai) of the SWPT during the window. The Limit Threshold Factor (LTF) used to calculate the L is a constant of the full record length, which can be set by the analyst.

In Figure 7:

- SWPD (Stress Wave Peak Duration): The period of time between an upward a breach of the threshold L and when the Ai next falls below L.
- SWPE (Stress Wave Peak Energy): The sum of each data point (Ai-L) during the SWPD. That is:

$$SWPE = \int_{t_b}^{t_e} (A_i - L)dt \qquad (4)$$

- Ai (Instantaneous Amplitude): The instantaneous amplitude of a stress wave pulse train (SWPT).
- SWPA (Stress Wave Pulse Amplitude): Maximum value of Ai during SWPD.
- SWPAp: Peak amplitude (SWPA) of SWPT in window Wn.
- L (Limit Threshold): User defined thresholds that are higher than the minimum A value during window W.
- W (Window): User defined window W1.
- R (Record): Record length.
- SWPE/W (Stress Wave Peak Energy at each Window): The sum of all individual SWPE in the window.
- SWE/W (Stress Wave Energy per Window): Values of all Ai values (greater than zero) in the data points occurring in the window.
- PEF/W (Peak Energy Factor per Window): The ratio of SWPE/W to SWE/W.
- SWE/R (Stress Wave Energy per Recording): The numeric sum of all the Ai values greater than zero for all data points that occur during all windows of a data record.
- SWPE/R (The Peak Energy of Each Stress Wave Recorded): The sum of all the individual SWPE values within a record.
- PEF/R (Peak Energy Factor per Recording): The ratio of SWPE/R to SWE/R.
- PEAKS/R (Peak Value per Record): The total number of SWPT peaks that occur during a record.
- SWPA/R (Stress Wave Peak Amplitude per Record): Maximum Ai value in records.

Four statistical parameters (S1, S2, S3 and S4) are also calculated for each of the 5 window length features for the full record duration. These 4 statistical parameters (describing the probability density distributions of the ex-tracted features) are calculated for all the individual SWPA values in the record – this yields multiple time domain statistical parameters of the SWPT. Statistical Parameters (S1, S2, S3 and S4) are defined as follows:

S1: 3rd Moment test for Normal Distribution.

S2: Maximum value of the population 10.
S3: The ratio of (Maximum - Mean) / (Maximum - Minimum).
S4: Ratio of the standard deviation of the population to the mean of the population.

Frequency Domain Feature Extraction Method

The time domain's statistical characteristic index can only reflect the general operational state of mechanical equipment, so it is best used in fault diagnosis system for fault monitoring and trend prediction. To know the location and type of the fault, further analysis via the frequency domain is necessary. Frequency spectrum analysis is an important and the most commonly used method of this analysis[22].

Vibration signals generated by operating machinery are periodic signals related to speed. They are represented with the following sine signal:

$$x(t) = A\sin(\omega t + \theta) = A\sin(2\pi ft + \theta) \tag{5}$$

If the period of the sinusoidal signal is T, then:

$$f = \frac{1}{T} = \frac{\omega}{2\pi} \tag{6}$$

Periodic signals satisfy the Dirichlet condition, and can be expressed by a sine function in the form of Fourier series:

$$x(t) = a_0 + \sum_{n=1}^{\infty} A_n \sin(n\omega_0 t + \theta_n) \tag{7}$$

(n=1,2,3,......)

The physical meaning of Equation (7) shows that periodic signals can be expressed as the sum of a constant component α_0 and a series of sinusoidal components.

The sinusoidal component of $n=1$ is called the fundamental frequency; the corresponding ω_0 is called the fundamental frequency of the periodic signal. The other sinusoidal components are called the N sub-harmonic, according to the values of n. Assume that the highest frequency components contained in $x(t)$ is f_x, the highest analysis frequency of the fast Fourier transform (FFT) $f_c=(1.5\sim2)f_x$, and the suitable sampling frequency is $f_s=2f_c=(3\sim4)f_x$.

Frequency refining analysis can improve the resolution of the key spectral regions and the analysis accuracy. The basic idea of frequency refining analysis is to use the frequency shift theorem to modulate the analyzed signal, and then resample it into the Fourier transform to obtain higher frequency resolution. If the frequency is refined in the frequency band ($f_1\sim f_2$), the center frequency of this band is $f_0=(f_1+f_2)/2$. The analyzed signal $x(k)$ is modulated repeatedly to obtain the frequency shift signal:

$$y(k) = x(k)e^{-f\,2\pi KL/N} \tag{8}$$

Among Them: $$L = \frac{f_0}{\Delta f}$$

In Equation (8), Δf is the frequency interval before the refining analysis.

According to the frequency shift theorem, $Y(n)=X(n+L)$. It is equivalent to moving the line L of $X(n)$ to the zero spectral line position of $Y(n)$ to reduce the sampling frequency $(2N\Delta f/D)$. After resampling the frequency shifted signal (or after selecting sampled data after frequency shift processing), the frequency resolution can be increased by D times, and the spectrum near the $Y(n)$ zero spectrum line (the spectrum near the line L of $X(n)$) is analyzed.

D is a scale factor, also called a select ratio or a refining factor.

$$D = N\frac{\Delta f}{(f2 - f1)} \tag{9}$$

In order to ensure that the selection does not cause frequency mixing, anti-aliasing filtering should be performed before selection, and the cutoff frequency of the filter should be ½ of the sampling frequency.

The Zoom Spectrum Analysis refining (or Fast Fourier Transform, FFT) includes both amplitude refining and phase refining. Because of the additional phase shift caused by the digital filter in the Zoom/FFT process, the real refined phase spectrum can be obtained by modifying the phase characteristic of the filter[23].

In an application example, a frequency analysis subroutine is used to generate an output signal with amplitude range from 0 to 5000Hz in 2000 frequency bands. Each power spectrum density file is then further processed into 68 frequency domain features.

The frequency domain feature extraction process begins with the SWPT digital record file being processed by a 2000-line FFT spectrum analysis module. All of the Stress Wave Spectral Density spectra are obtained by Root Mean Square (RMS), averaging 10 individual time records with a 60% overlap of the data. This gives a frequency resolution of 2.5 Hz/line, over a 0 to 5000Hz range, from a 2 seconds TH (time history) file.

Each stress spectrum density is then converted into a table, listing each signal amplitude in the first 1300 frequency lines (The 1300 lines x 2.5

22 Jian Zhang, *Mechanical fault diagnosis technology* (Beijing: China Machine Press, 2014) 5.
23 Wenxiang Lu and Runsheng Du, *Measurement Information signal analysis in Mechanical engineering* (Wuhan: Huazhong University of Science and Technology press, 2014) 4.

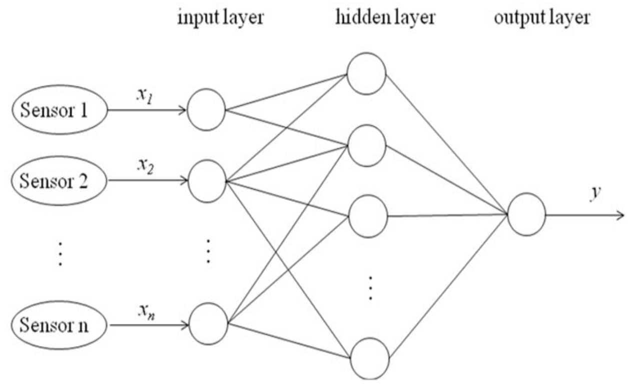

Figure 8: Multiple Input Three Layer Polynomial Neural Network

Hz/line = 3250 Hz). Then, the software divides the first 1300 lines of the spectrum into 65 segments (20 lines (50Hz)), calculates the average amplitude of all 1300 lines, and calculates the maximum amplitude in the 65 50Hz band. Next, the ratio of the maximum in each band to the 1300 line average is calculated and tabulated as 65 "peak to average" ratios (in dB) for each of the 65 bands of the 1300 line spectrum. The frequency domain feature extraction software then computes the ratio of the maximum amplitude in all 1300 lines to the average of all 1300 lines. Finally, the standard deviation is calculated for the "peak to average" ratios in the 65 bands of the 1300 line spectrum. The 65 "peak to average" ratios, the 1300 line average amplitude, the max to average ratio, and the standard deviation of the "peak to average" ratios are then tabulated as 68 features that characterize the SWPT in the frequency domain.

DATA FUSION BASED ON POLYNEURAL NETWORK

Neural network technology, an information processing technology that simulates the human brain, has developed rapidly and been widely used in recent years. A neural network uses a large number of simple processing units (neurons) to process information according to their organizational form of hierarchy; each layer of neurons is connected in a weighted manner with the other layers using parallel architecture and parallel processing mechanism. Thus, the network has strong fault tolerance, self-learning and self-organizing abilities, and the adaptive ability to simulate the complex nonlinear mapping of a human brain.

Since neural networks can effectively approximate various mappings, neural networks have been widely used in diagnostic reasoning, which can be understood as the solution of the nonlinear mapping relation of the fault modes. The neural network diagnosis method of stress wave analysis takes the time domain and frequency domain charac-teristics of the stress wave signal as the input of the neural network, then, through neural network learning and training, the nonlinear mapping relation between the fault type and the fault symptom can be automatically formed, realizing the fault diagnosis[24].

Multi-sensor data fusion is a new developing technology involving signal processing, probability statistics, information theory, pattern recognition, artificial intelligence, fuzzy mathematics, and other fields. It is a practical application technology dealing with the data processing of the problem of using a variety of sensors in a system. The neural network's signal processing and automatic reasoning functions paired with its powerful nonlinear processing ability meet the requirements of the multi-sensor information fusion technology.

Abnormal measured data will reduce the quality of data fusion in the fusion process, so a multi-sensor data fusion method based on the Bayesian method is used; the abnormal data is therefore eliminated before fusion by identifying the inconsistencies between the measured data, improving the accuracy of the data fusion. A probability factor can also be added to the Bayesian method to characterize the probability that the measured data is non-abnormal. When a sensor's output data is inconsistent with other sensors, the added factor has the effect of increasing the posterior distribution variance. This method can effectively identify the inconsistencies between sensor data so that the fusion accuracy can be further improved[25].

By using a direct analytic solution of multi-sensor data fusion to avoid multiple iterative calculations of nonlinear differential equations, the amount of required calculation is reduced, raising the solution efficiency of multi-sensor data fusion. The performance control technique of the sensors can ensure the confidence and safety of multi-sensor data fusion.

24 Wuke Liang et al., "Research on artificial neural network selection of vibrated faulty diagnosis of hydraulic generating set," *Chinese Journal of Scientific Instrument*, 27(12), 2006: 1711-1714.

25 H. Y. Jia and Y. Y. Su, "Multi-sensor fusion method based on Bayesian in singular conditions," *Electronic Measurement Technology*, 36(8), 2013: 104-107.

The multi-sensor adaptive detection fusion technique can be used to raise the detection capabil-ity of multi-sensor networks for the less noticeable objects or objects in a jamming environment[26].

The neural networks identify the normal and abnormal feature patterns extracted from SWPT through training – feature extraction software is used to compress data intelligently into a small amount of information, then the neural network uses these features to make accurate equipment state monitoring decisions. Because of the SWPT's high signal-to-noise ratio, the classification is easy, and the neural network can be implemented with only a small amount of software code.

The neural network of polynomial equations (PNN) can automatically classify stress wave data to represent the health status of equipment components. The numerical modeling software uses a set of features extracted from SWPT as input to comprehensively evaluate the PNN.

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The numerical modeling software is based on statistical modeling, neural networks, and artificial intelligence re-search, and is a supervised inductive learning tool. It combines network concepts from neural networks and ad-vanced regression techniques to automatically synthesize polynomial network models from input and output value databases.

Many studies show that PNN has stronger generalization abilities and classification accuracy than the more widely used BP (Back Propagation) algorithm. Due to adopting the full training set to construct the network without any redundancy operations, the PNN's recognition speed is slower; the space and time complexity is O(nm) (n is the number of samples, M is the characteristic dimension). This has been studied using various clustering techniques, including Learning Vector Quantization (LVQ), K-Means, and Fuzzy C-Means algorithms to reduce the network size. Using the class center as the model layer of the PNN, the clustering technique divides each class into several categories; this reduces the number of neurons needed and improves the computing speed at the expense of a small amount of accuracy, and is a two stage algorithm of first clustering and then classification. A new optimization algorithm from the data theory field, the Gaussian-PNN (G-PNN), has been proposed based on Gauss potential. The dense region of the intra-class sample is found through Gauss potential and then the G-PNN of iterative feedback error correction increment density is constructed. In order to further improve the generalization accuracy, a G3-PNN algorithm, which integrates 3 classifiers, is proposed based on the resample technique[27].

26 Xing Liu, "Realization Techniques in Multisensor Data Fusion," *Chinese Journal of Electronics*, 29(9), 2001: 1240-1242.
27 Chun-fang Li, Lian-zhong Liu, and Zhen Lu, "Probabilistic Neural Network Based on Data Field," *Chinese Journal of Electronics*, 39(8), 2011: 1739-1745.

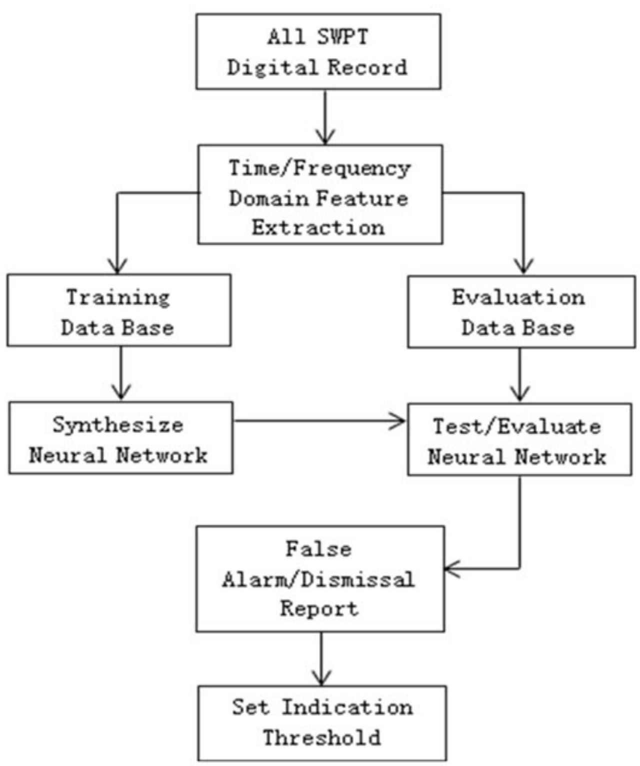

Figure 9: PNN Training and Evaluation

False Alarm/Dismissal Report

Model:A Decision Threshold: 0.5

Categary	Event	Correct	Correct Alarms	Correct Dismissals	False Alarm	False Dismissal
Decision Threshold: 0.05	10	80%	70%	10%	20%	20%
Decision Threshold: 0.10	10	80%	70%	10%	20%	20%
Decision Threshold: 0.15	10	90%	70%	20%	10%	10%
Decision Threshold: 0.20	10	90%	70%	20%	10%	10%
Decision Threshold: 0.25	10	90%	70%	20%	10%	10%
Decision Threshold: 0.30	10	90%	70%	20%	10%	10%
Decision Threshold: 0.35	10	90%	70%	20%	10%	10%
Decision Threshold: 0.40	10	100%	70%	30%	0%	0%
Decision Threshold: 0.45	10	100%	70%	30%	0%	0%
Decision Threshold: 0.50	10	100%	70%	30%	0%	0%
Decision Threshold: 0.55	10	100%	70%	30%	0%	0%
Decision Threshold: 0.60	10	90%	80%	30%	10%	10%
Decision Threshold: 0.65	10	90%	60%	30%	10%	30%
Decision Threshold: 0.70	10	70%	40%	30%	30%	30%
Decision Threshold: 0.75	10	70%	40%	30%	30%	30%
Decision Threshold: 0.80	10	70%	40%	30%	30%	30%
Decision Threshold: 0.85	10	60%	30%	30%	40%	40%
Decision Threshold: 0.90	10	60%	30%	30%	40%	40%
Decision Threshold: 0.95	10	60%	30%	30%	40%	40%

Table 2: Decision Threshold Optimization

Figure 8 shows a data fusion model describing the three layers of neural networks: The first layer neuron is fused with the original data layer; the second layer completes the feature layer fusion, and makes the decision according to the features extracted from the previous layer; the output layer is corresponds to the decision fusion. For target recognition, the output is the target recognition conclusion and its confidence. The input and output of the decision layer should be the confidence of the soft decision and the corresponding decision.

The output of any given element can be entered into the subsequent layer with the original input variable. The net-work is synthesized from one layer to the next until the network model stops improving. Each layer's qualified in-puts and network synthesis policies are defined in a set of rules and heuristics that are inherent in the synthesis algorithm.

All the data in the network modeling database is the feature data record extracted from the stress wave sensor sig-nals, such as SWPA (Stress Wave Pulse Amplitude), SWE (Stress Wave Energy), and SWPD (Stress Wave Peak Du-ration). Irrelevant variables must be ignored while retaining useful information; if the scale is not good enough, it will cause the model to be too sensitive to irrelevant variables or it won't extract practical features. A model can understand the correspondence between the data information and its status tag.

By using a random number generator, the network modeling database is divided into two sets of data sets for train-ing and testing. The training data set is 75% of the modeling database, and the test data set is 25% of the modeling database. The training data set is used to estimate the parameters of all the candidate models and to establish clas-sifiers. The test data set is used to test the classification ability of the trained models and evaluate the synthetic network. The mean square error is calculated for each model, and then compared. The least square error model is then chosen as the selection model. Modeling parameters are used to adjust the network structure or to control the complexity of the model.

Figure 9 shows the development process of the PNN.

Table 2 shows a typical false alarm/dismissal report, which is applied to polynomial neural network outputs (ranging from 0 to 1) to optimize the decision threshold. By optimizing the PNN, the evaluation data set is iterated, and the false alarms and false dismissals are tabulated as the decision threshold function to generate the reports.

To achieve comprehensive and accurate state monitoring, feature extraction and polynomial neural network (PNN) software modules can classify input data in many different ways. For example, a PNN can determine if the data from one sensor is not normal, while another network utilizes data from multiple sensors to confirm the difference detected by the PNN. Tests show that within 1 hours of equipment failure, the probability of detecting gear or bear-ing damage is greater than 99.9%, and the false alarm probability of running 1000 hours under the condition of equipment health is less than 1/1000. The data fusion architecture software not only can detect the fault accurately, but also can find the fault, separate the fault source into its part, show the deterioration rate, and estimate the part's remaining service life. In addition, in order to guarantee the high probability of fault detection and low false positive rate of early fault detection, the confidence test is usually needed. The data fusion framework combines all of these capabilities in the rules of the expert system.

The adjustable data fusion architecture of stress wave analysis has demonstrated high levels of accuracy in making diagnostic decisions. The key to simultaneously achieving both a high probability of problem detection and a low probability of false alarm is to define quantitative accuracy requirements, and to have an easily adjustable data fusion architecture.

The development of system accuracy requirements for diagnostic indications is based upon the way each individu-al indication is used, and the differing consequences an error can impose on operational safety, mission reliability, availability, and life cycle costs. Only three adjustment parameters are required to tailor the accuracy of this data fusion architecture to system requirements: the decision threshold for the per-measurement decision making net-work, and the *X* & *N* parameters in the *iX* of *Nî* Confidence Test.

Each polynomial equation network is implemented as a separate software object. As more data can be used for training, individual networks can be updated and replaced to improve their diagnostic accuracy. Each updated polynomial network will adjust its threshold according to the performance results of the training and evaluation data. Then, the confidence checking parameters (*X* and *N*) are adjusted to meet the decision accuracy requirements of the system. In this way, the software objects in the data fusion architecture can be easily updated and adjusted without the need to modify the software code that defines the entire data fusion architecture.

CONCLUSION

Prognostic health management technology based on stress wave analysis can diagnose and evaluate equipment status and failure at the earliest point in time. The operational tests show that it has the following advantages when compared with other monitoring methods at present mainstream application:

1) Stress wave analysis can provide equipment trend parameters so that operators can understand the extent of equipment damage and deterioration rate, and better predict when damage will cause production shutdown. Based on this data, the planned outage can be carried out ahead of schedule, or parts can be delayed until the next outage, avoiding huge economic losses caused by unexpected shutdown.
2) Compared with the current mainstream adoption of vibration and lubrication analysis technology, stress wave technology has more advantages in the detection of bearing and gear damage, axial unbalance, decreased lubricating effect, sealing damage, and other failure mechanisms, providing a better solution for predictive equipment status monitoring solution.
3) The stress wave technique is based on ultrasonic waves, which can detect even slight damage signs in their earliest stages. At this point in the damage process, the temperature or vibration signal has not yet risen and thus cannot be detected by other techniques.
4) Stress wave technology can detect not only equipment failure, but also determine whether the failure is related to the production process, and whether it is affected by the operation process. Therefore, it can provide effective basic equipment operation data for high quality and high efficiency production control processes, and provide data analysis for optimizing production operation.

Prognostic health management technology based on stress wave analysis has incomparable advantages. It adopts advanced instrument measurement and analysis technology to detect and analyze the friction, mechanical shock, and dynamic load of running equipment in real time. Combined with neural networking, cloud computing, data mining, and artificial intelligence technology, it provides real-time remote equipment monitoring, predicts faults early, provides customers with regular equipment health diagnosis analysis reports, helps enterprises to improve production safety, reduces costs, and achieves better production efficiency.

The system has an adjustable data fusion architecture; therefore, it can be easily combined with other inputs from continuous variable diagnostic parameters (vibration, temperature, pressure, etc.) to form a distributed sensing and monitoring system, centralizing the diagnosis and management for entire plant equipment systems. It can also be combined with the further research of equipment maintenance planning models and system scheduling optimization strategies to realize whole lifecycle health management of modern enterprise intelligent manufacturing systems.

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