Development of an Effective Strategy for Prognostic Monitoring of a Large Centrifugal Air Compressor in an Automotive Plant

Hyunsu Kim[1], Jay H. Kim[2], Won Joon Song[3]

[1]*Ensemble Center for Automotive Research, Seoul, South Korea*
kim.2287@osu.edu

[2]*CEAS-Mech Eng & Materials Eng, University of Cincinnati, OH, USA*
kimj@ucmail.uc.edu

[3]*Dept. of Mechanical Systems Engineering for Energy Convergence, Dongshin University, Naju, South Korea*
wjsong@dsu.ac.kr

ABSTRACT

Prognostic monitoring of health condition of a large centrifugal air compressor that supplies compressed air in an automotive plant is crucial because its failure will seriously impair operation of the entire plant. It was desired to develop an effective prognostic maintenance methodology of air compressors after the failure of an air compressor in one of major automotive companies in US, which brought a highly undesirable situation to the manufacturing line of the plant. In this work, the shaft motion of the compressor measured at transient and steady-state conditions were used to develop techniques and a strategy for effective prognostic monitoring. The pseudo frequency response function (FRF) obtained from the Campbell diagram and directional Power Spectrum (dPS) were new techniques employed to develop the prognostic health monitoring strategy. The analytic wavelet transform (AWT) is adopted to monitor temporal change of the system characteristics during the start-up period. In addition, AWT was utilized to monitor the steady state condition.

1. INTRODUCTION

Large air compressors are widely utilized in industry area including automotive manufacturing plant. Due to its high speed and power for operating condition, normally journal bearings are applied to the compressors. Journal bearing could be efficient for the large compressor, but the dynamic characteristics can be challenge to understand. Such complication, therefore, sometimes brings an unpredictable failure.

Catastrophic failure in a manufacturing plant rarely happens, but, once it occurs, it can bring enormous cost. When such abrupt event is experienced, facility managers tend to replace (or check) the system more than normal replacement period even though it appears to be fine. An automotive manufacturer in US had reported an air compressor failure in their one of the plants. As shown in Fig. 1, the impeller blades were crushed and the shaft and bearing were rubbed. They also reported that the journal bearings are seriously damaged. Thus, to avoid the similar failure, a prognostic monitoring system is asked.

Enormous studies for diagnostic methodologies for rotating machinery including bearing failure can be found (Chen, Du, & Qu, 1995; Gómez-Mancilla, Sinou, Nosov, Thouverez, & Zambrano, 2004; Lee, Han, & Park, 1997; Qiu, Lee, Lin, & Yu, 2006; Singhal & Khonsari, 2005; Tiwari, Lees, & Friswell, 2002; Wan, Xu, & Li, 2004). Among them, Chen et al. (1995) suggested important frequencies for rotating machinery failures. Those frequencies are actually order components, and they illustrates that the combination of magnitude level changes with different frequencies can represent certain failures. Lee et al. (1997) demonstrates that the direction power spectra (dPS) to investigate the engine power fault. DPS can be efficient to track the system with orbit analysis information.

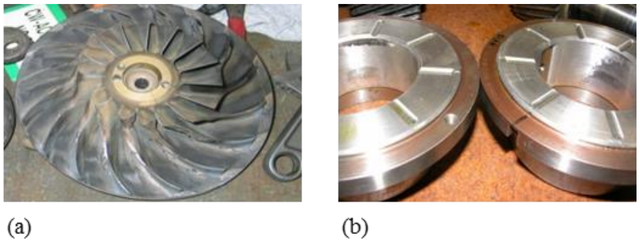


Figure 1. Failure of a large air compressor: (a) damaged centrifugal blade; (b) damaged thrust bearing.

Analytical wavelet transform (AWT) is effectively utilized to detect the fast short time variation in signals. Since the air compressor often operates start-up condition, the transient time-varying condition can be critical to the system. Thus, Kim (2006) developed a prognosis method for rotating machinery using damping ratio. They calculated the damping values from Pseudo-frequency response function using AWT.

In this paper, therefore, an effective strategy for prognostic monitoring for a large centrifugal air compressor is illustrated using mostly AWT and dPS. Start-up condition is analyzed using AWT and dPS, and AWT is utilized to extract the damping ratios for 19 day data. For the steady state condition, AWT is also used to calculate the important frequencies, which is demonstrated by Chen et al. (1995). Lastly, the strategy is suggested for prognostics for the air compressor monitoring.

Following this introduction, Section 2 explains the experimental measurement briefly. Section 3 illustrates the prognostic methodologies, followed by the analysis results using the methods in Section 4. This study is then concluded with final remarks in Section 5.

2. EXPERIMENTAL MEASUREMENT

Fig. 2 illustrates the location of sensor installed to the rotating shaft. With 90 degree of angle, two proximity sensors are installed. These two signals can be utilized to formulate orbit analysis. One key phasor is also applied to calculate revolution per minutes (RPM). Fig. 3 (a) and (b) shows the measured signals in time for start-up condition. Note that it appears to have one resonance around 8 second during ramp-up. Fig. 3 (c) is the calculated RPM, which demonstrates ramp-up and steady state condition. Also note that the maximum rotating speed goes up over 20,000 rpm, and it takes approximately 13 seconds to reach the maximum speed.

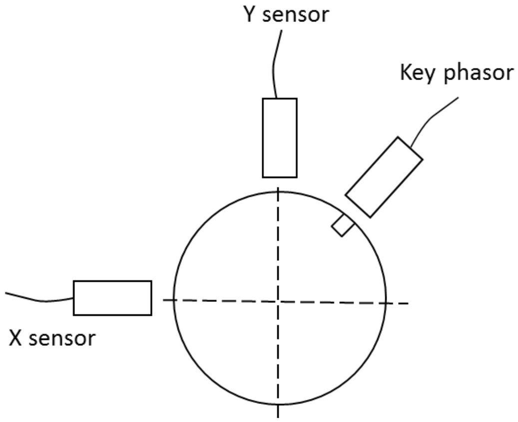


Figure 2. Sensor location for the air compressor.

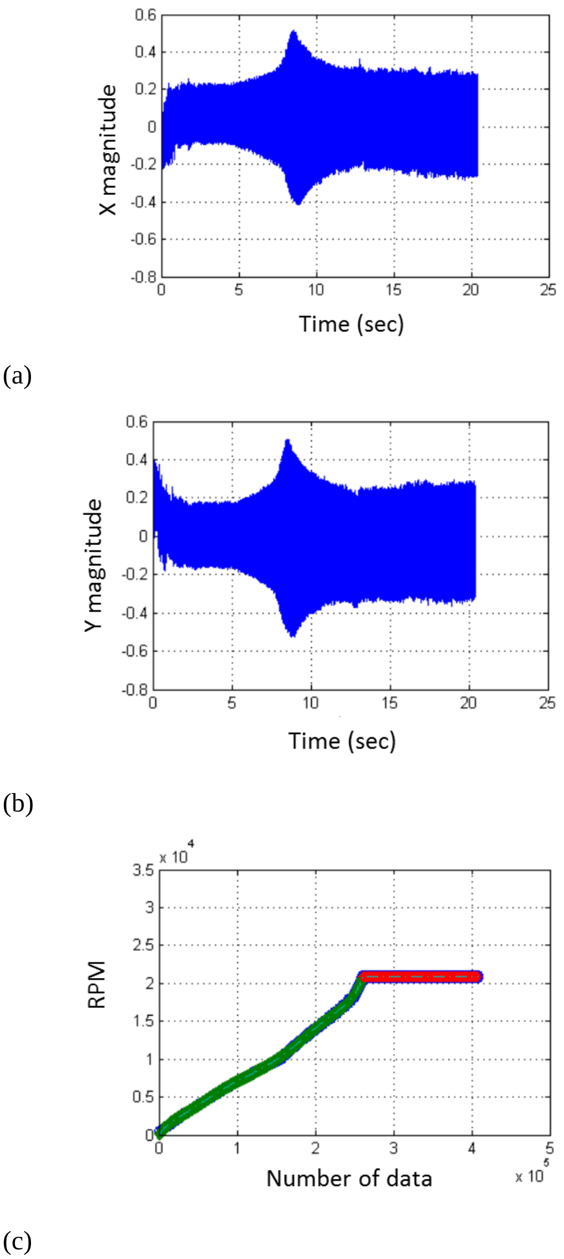


Figure 3. Measured data: (a) time series X; (b) time series Y; (c) RPM calculated Key phasor signal.

3. PROGNOSIS METHODS

This study suggests basically two signal processing methods which are AWT and dPS. AWT is utilized to monitor the compressor for both transient and steady state condition. AWT is first compared to a short time Fourier transform (STFT) for the transient analysis. Then, damping ratio is calculated from the first resonance of AWT, followed by dPS. Lastly, the important frequencies for failure phenomena, categorized by Chen et al. (1995), is recalled here and utilized for the steady state condition monitoring.

3.1. Analytic Wavelet Transform

Analytic wavelet transform (AWT) is originally suggested by Zhu & Kim (2006), but the brief explanation is provided for understanding. The Morlet wavelet (Mallat, 1998) can be defined as

$$\psi(t) = g(t)e^{j\eta t} \quad , \tag{1}$$

where j represents the complex number, η is a parameter related to the frequency, and $g(t)$ is a Gaussian function. With mother wavelet defined in Eq. (1), AWT of signal $f(t)$ can be defined as

$$\begin{aligned} W_s f(t) &= \langle f(t), \psi_s(t) \rangle = \int_{-\infty}^{\infty} f(u)\psi^*{}_s(u-t)dt \\ &= \int_{-\infty}^{\infty} \frac{1}{s} f(u) g(\frac{u-t}{s}) e^{-j\eta(\frac{u-t}{s})} dt, \end{aligned} \tag{2}$$

where s is the scale, $\psi_{t,s}(u) = g(\frac{u-t}{s})e^{j\eta(\frac{u-t}{s})}$ is the wavelet function. Fig. 4 illustrates the advantage of AWT compare to STFT as AWT can utilize flexible time-frequency component. It can pick up fast time varying high frequency component, and low frequency component with high resolution, as a result, resembling human ear sensitivity.

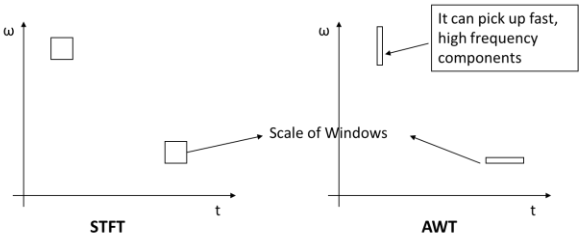


Figure 4. Comparison of time-frequency atom between STFT and AWT.

3.2. Directional Power Spectrum (dPS) Analysis

Orbit analysis can provide helpful information for monitoring rotating machineries, even though it requires two sensors. However, to monitor orbit as itself can be difficult to follow since it creates an orbit circle per every revolution. Thus, a complex expression for the orbit can be effectively utilized to transform the orbit information to numbers. Direction power spectrum (dPS) is one of the techniques to use the complex expression of orbits (Lee et al., 1997).

Fig. 5 illustrates the relationship between orbits and dPS. As the orbit shape is close to a perfect circle, dPS shows only one of the forward or backward components. Fig. 5(b) depicts how the direction of orbit can be represented in dPS. Note that if the dPS shows a similar level in magnitude between forward and backward components, then the orbit can be a straight line. The complex notation of the orbit can be defined as

$$p(t) = x(t) + jy(t)\,, \tag{3}$$

where $x(t)$ and $y(t)$ are the measured displacement signals. The frequency domain description of $x(t)$ and $y(t)$ can be expressed, respectively, as

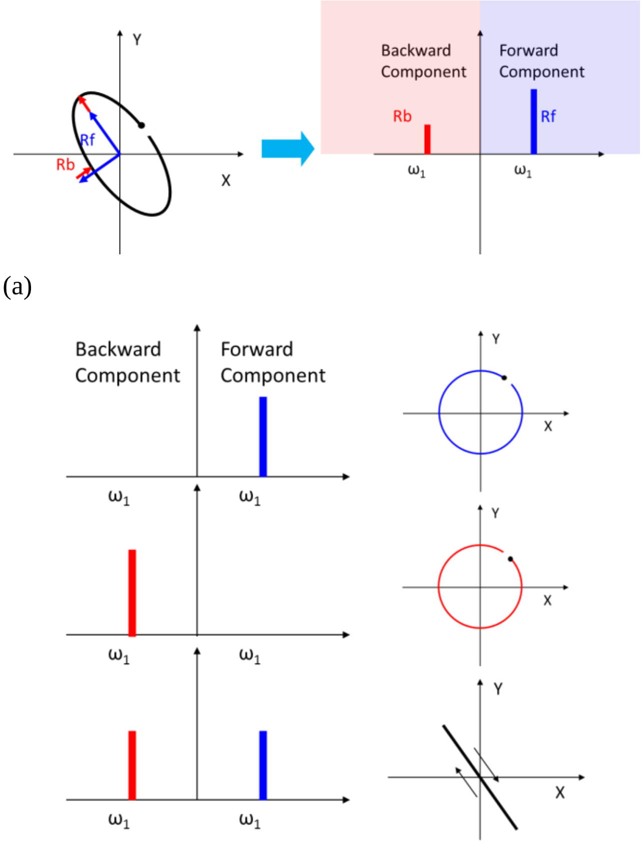
$$x(t) = \sum_{k=0}^{\infty}\left(X_k e^{j\omega t} + \bar{X}_k e^{-j\omega t}\right) \,, \tag{4}$$

$$y(t) = \sum_{k=0}^{\infty}\left(Y_k e^{j\omega t} + \bar{Y}_k e^{-j\omega t}\right) \,. \tag{5}$$

Then, the forward and backward components can be expressed, respectively, as

$$R_f(\omega_k) = X_k + jY_k \,, \tag{6}$$

$$R_b(\omega_k) = \bar{X}_k + j\bar{Y}_k \,. \tag{7}$$



(a)

(b)

Figure 5. Relationship between orbits and dPS: (a) orbit shape vs. dPS; (b) orbit direction vs. dPS.

3.3. Important Frequencies

For rotating machinery, it can be effective to monitor the orders. Chen et al. (1995) suggested that 11 different fault features can be captured with a combination of order components. The important orders, they called "important frequencies”, is shown in Table 1. Table 2 shows examples of fault features and diagnostic indices for imbalance, crack, misalignment, rub, and oil whirl.

Table 1. Important frequencies for rotating machinery (Chen et al., 1995).

Freq.	Freq. index	Mechanical interpretation
f_1	1	Rotating frequency of the machine
f_2	2	Second harmonic of the rotating frequency (2 f_1)
f_3	3	Third harmonic of the rotating frequency (3 f_1)
f_4	4	Fourth harmonic of the rotating frequency (4 f_1)
f_5	5	Fifth harmonic of the rotating frequency (5 f_1)
f_6	6	Sixth harmonic of the rotating frequency (6 f_1)
f_7	7	Surge frequency (peak frequency [0,0.4] f_1)
f_8	8	Oil whirl frequency (peak frequency [0.4,0.51] f_1)
f_9	9	Rotating stall frequency (peak frequency [0.7,0.9] f_1)
f_{10}	10	Loose cap bearing frequency (peak frequency [0,0.3] f_1)
f_{11}	11	Pipe excitation frequency (peak frequency [0.4,0.5] f_1)
f_{12}	12	Electrical power supply frequency (50 Hz)

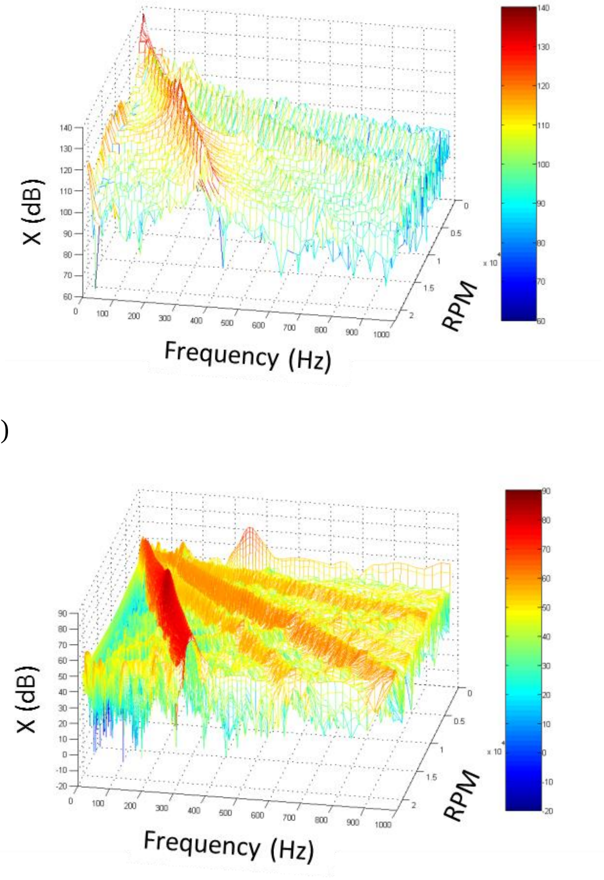
Table 2. Examples of fault features with diagnostic indices (Chen et al., 1995).

Defect	Fault features and diagnostic indices
Imbalance	f_1
Crack	f_1, f_2, f_3
Misalignment	f_2, f_4, f_1
Rub	f_1, f_2, f_3, f_5
Oil whirl	f_8

4. RESULTS AND DISCUSSION

4.1. Analytic Wavelet Transform

STFT and AWT results are compared in Fig. 6 for the same signal, and X data is analyzed for only ramp up condition. Both STFT and AWT can be effectively utilized to illustrate the transient phenomena where the acoustic/vibration source changes in both in time and frequency. STFT and AWT show the first order component well. However, the second and third orders are more clearly shown with AWT. As Fig. 5(b) shows, the low frequency component has more atom in the frequency axis than STFT does. In addition, AWT can detect the fast time varying high frequency component as well. Thus, it can be attractive to utilize for detecting a fast time varying transient signals.



(a)

(b)

Figure 6. Comparison of transient analysis with time-frequency domain: (a) STFT; (b) AWT.

In general, damping value can be calculated using a half power method. Here, Fig. 5(b) can be considered as a pseudo-frequency response function since the excitation force may be expressed as a function of frequency. The detail of the damping calculation is presented by Kim (2006). Table 3 shows the damping values calculated for 19 different data. The effect of damping may come mostly from the oil lubrication of the journal bearing. Note that the damping values are approximately around 0.1.

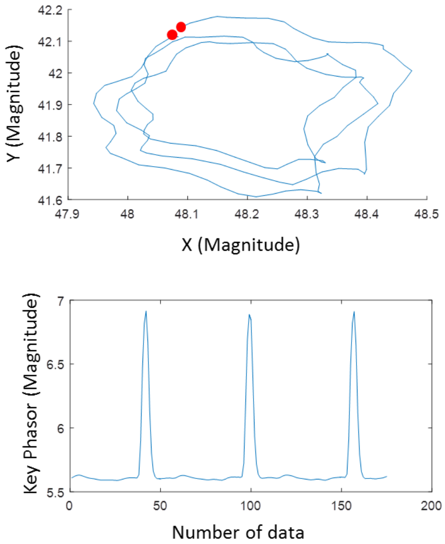
Table 3. Damping ratio ζ at each data collection.

Date and numbers	Zeta (ζ)	Date and numbers	Zeta (ζ)
09/06 startup	0.093	10/07 startup 001	0.085
09/19 startup 001	0.105	10/25 startup 001	0.086
09/19 startup 003	0.089	10/25 startup 003	0.093
09/20 startup 005	0.122	10/26 startup 002	0.113
09/21 startup 008	0.113	10/27 startup 001	0.128
09/21 startup 010	0.116	10/28 startup 001	0.119

09/22 startup 011	0.134	10/28 startup 004	0.083
09/29 startup 000	0.115	11/01 startup 007	0.083
09/30 startup 003	0.121	11/04 startup 003	0.084
10/04 startup 002	0.111		

4.2. Directional Power Spectrum

Fig. 7 shows the orbit analysis and the synchronized key phasor signals. It is illustrated for the example for three revolutions as the number of peak of key phasor signal is identical. Thus, the orbit has three “circles” even though it is not a perfect circle. The orbit is clearly distinguished here for only three revolution, but it can be difficult to obtain useful information where hundreds revolution occurs. Therefore, the complex expression for the orbit can provide useful information of the orbit.

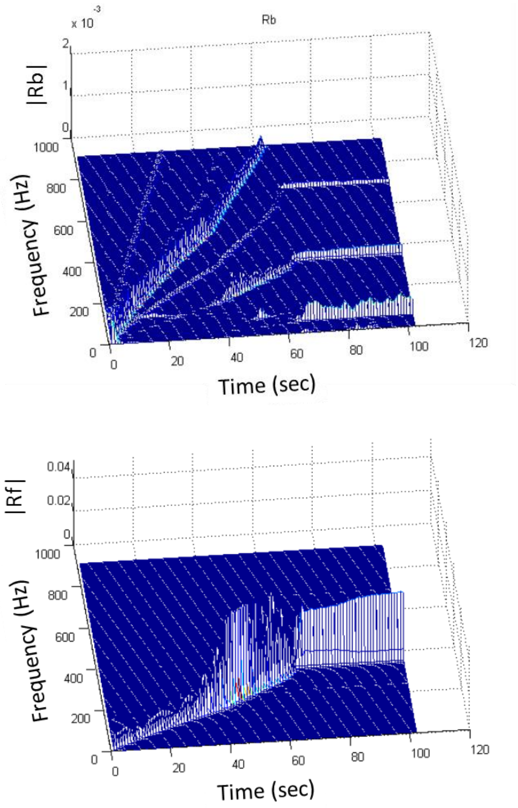


(a)

(b)

Figure 7. Orbit and key phasor signal.

Fig. 8 shows dPS for one of the 19 data shown in Table 3. It is apparently a slower ramp up compare to the data of Fig. 3. The forward component has at least more than 10 times bigger magnitude than the backward component. Thus, the orbit direction of the compressor can be considered as forward direction, and the shape of the orbit may be closed to circle. This may mean the compressor is under relatively good condition.



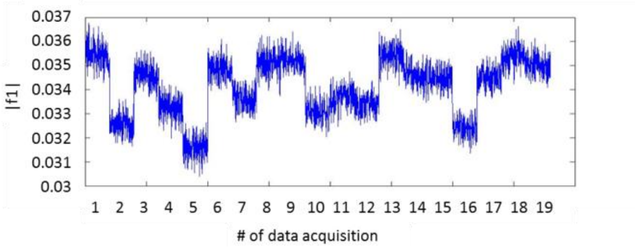
(a)

(b)

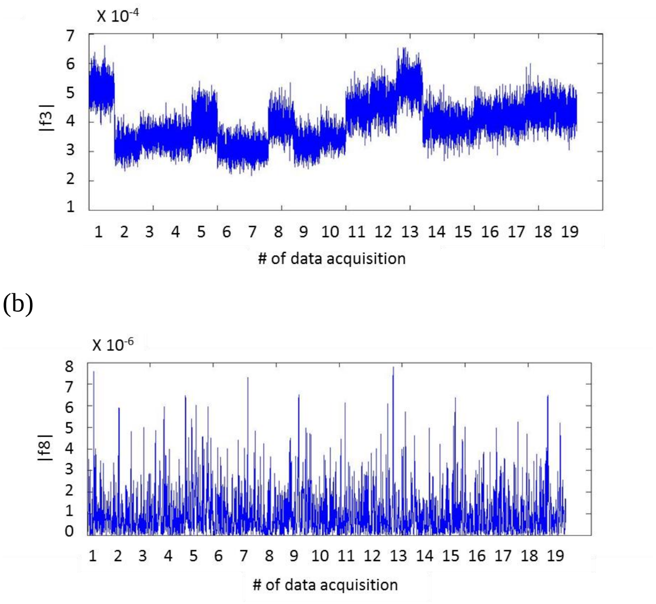
Figure 8. Direction power spectra: (a) backward; (b) forward.

4.3. Important Frequencies

Fig. 9 shows examples of the important frequencies for the first, third, and eighth order of 19 data set. The important frequencies are extracted using AWT at the steady state condition. As expected, the first order (f1) has the biggest magnitude, and the eighth order (f8) is the smallest one.



(a)



(b)

(c)

Figure 9. Important frequencies at steady state condition using AWT; (a) f1: (b) f3: (c) f8.

The first and third frequency shows the different mean value for each data but having a certain range of the magnitude. For example, magnitude of f1 has the range between 0.03 – 0.037. However, f8 shows no difference for the mean value per each data, and the magnitude is very small. It may be the magnitude of f8 is not critical or rather should be considered as a background noise for the “good” condition in the current situation.

4.4. Strategy for prognosis of the compressor

Since the current situation can be considered as a good condition, the collected data may be assumed as a baseline for the criteria. Using AWT, damping value for the transient (ramp up) condition and the important frequencies at the steady state condition can be extracted. In addition, dPS can provide the orbit information. Thus, the strategy for the prognosis of the compressor can be set as follows:

(1) Collect data periodically (once a week, for example)

(2) Check the damping if the value in the initial range (for example, 0.07 – 0.14)

(3) Check the magnitude of important frequency in the certain range.

(4) Check the forward and backward component. Investigate if the orbit shape or direction has been changed.

Further development can be remained in the combination of checking AWT and dPS or automatic alarm algorithm for abnormal changed in AWT and dPS values.

5. CONCLUSION

A large centrifugal air compressor is investigated for the rotor condition by measuring vibration at the shaft. AWT and dPS is extensively utilized to extract the damping value for the ramp up condition, the important frequency component at the steady state condition, and the information of orbit shape and direction, respectively. Using these analyses, a strategy of monitoring the air compressor condition is suggested. Future work would be the data collection and the validation of the suggested prognosis stategy.

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BIOGRAPHIES

Hyunsu Kim, Ph.D. received his doctor degree at the Ohio State University in 2011 after achieving B.S. from Kookmin University in 2001 and M.S. from University of Cincinnati in 2006. His research area is acoustics of intake/exhaust system especially focusing on nonlinear characteristics in silencers in the presence of flow. Also, he focuses on the prognostics and health management. From 2011 to 2016, he worked at Hyundai-Kia Motor Company as a senior researcher in the power-train NVH team expanding his area of interest to (hybrid) electrical vehicle motor noise. He is currently CEO of Ensemble Center for Automotive Research.

Dr. Jay Kim has been a faculty in Mechanical Engineering program of the University of Cincinnati (UC) since 1990. He is currently Professor and Head of the Department of Mechanical and Materials Engineering. He received his B.S., M.S. and Ph.D. degrees respectively from the Seoul National University (1977), KAIST (1979) and Purdue University (1988), all in Mechanical Engineering. He also has 6 years of experience in industry in the U.S. and Korea, working in the area of noise and vibration control, before joining the University of Cincinnati. Dr. Kim's research activities have been in acoustics, structural vibration and rotordynamics, which were funded by both federal agencies and industry. He graduated 14 Ph.D. students and 27 M.S. students as the major advisor, published more than 160 papers in journals and conferences. He is an elected fellow of ASME, and a member of INCE, SAE and ASSE.

Won Joon Song is currently a professor of the Department of Mechanical Systems Engineering for Energy Convergence (MSEEC) of Dongshin University, Naju, Korea. He received his B.S. and M.S. degrees from Hanyang University, Seoul, Korea, in 1995 and 1997, respectively. He received his Ph.D. degree from University of Cincinnati (UC), OH, USA in 2010. He worked at BOSCH, Sejong, Korea from 1997 to 2003 as an R&D engineer. He served as a researcher at KIMM, Daejeon, Korea from 2010 to 2011. He also worked as a research scholar at IFTP in Hanbat National University, Daejeon, Korea from 2011 to 2016. His research interests include auditory system modeling, signal processing for artificial cochlea, hearing loss assessment, online monitoring of combustion stability, and image processing of combustion flame.