Development of Data Analytics Tools for Acoustic Measurement of Positive Displacement Machines

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ABSTRACT

Noise control is an important factor in evaluating the design of positive displacement machines. This research aims to develop new tools in MATLAB, with emphasis on visual approaches, to comprehensively characterize the noise generated by positive displacement machines in spatial, temporal and frequency domains. Sound pressure level (SPL), sound intensity level (SIL) and loudness were calculated and plotted on a measurement surface surrounding the pump, which illustrates the spatial characteristics of the sound field. In order to highlight the phenomenon within specific frequency bands, Butterworth filters were used to isolate desired frequencies, such that specific harmonic content or 1/3 Octave Bands content can be analyzed. In addition to static visualization methods, videos were created by compressing a series of sphere plots in time to illustrate the dynamic characteristics of the measured sound. Corresponding phase plots were generated at the same time to statically demonstrate these dynamic characteristics shown on videos. The successful generation of the various methods of characterizing and visualizing pumps generated noise was evaluated on a large sample set of more than 150 measure grids with nearly 30000 individual microphone measurements. The creation of these analytics has already changed the conversation and challenged the state of the art in hydraulic Noise Vibration and Harshness (NVH).

KEYWORDS: acoustics, noise, fluid power, hydraulic pumps, positive displacement machines, data analytics

1 Introduction

Positive displacement machines are widely used in many areas, and are known for not only their high power density but also the high level of noise. Noise control has become one of the main metrics of evaluating the performance of a hydraulic pump or motor.

The noise research for hydraulic pumps or motors can be traced to the 1970s; researchers in the UK successfully defined two main sources of noise generated by displacement machines: Structure Borne Noise (SBN) and Fluid Borne Noise (FBN). The oscillating forces generated by varying pressure of the displacement chambers energizing the vibration of the
machine structure is named structure borne noise source (SBN). Due to the finite number of displacement elements like pistons in piston machines the pump kinematics introduce a pulsating flow at the pump ports. This kinematic basic flow ripple is amplified with effects caused by fluid compressibility and other design related effects like internal and external leakages. The pulsating pump delivery flow causes pressure ripple in the connected pipes, which are transmitted through the system. The resulting periodically varying pump delivery flow (flow ripple) is referred to as the fluid borne noise (FBN) source, see Edge (1999).

The earliest work on the reduction of noise was focusing on the SBN, and then the spotlight switched to FBN, because it is easier to simulate the fluid flow ripple. As the understanding of pump dynamics progressed, several mathematical models were created, and many simulation tools were developed. These tools are used to predict the noise sources and therefore help design quieter fluid power system. Edge (1999) conducted one of the earliest measurement of sound intensity to quantify noise generated by pumps and promoted new ISO standards for fluid power positive displacement machines.

Even though great accomplishments of modeling noise sources have been achieved, there is still a great need for further research to predict and reduce audible sound. A general solution for the noise reduction necessitates a comprehensive understanding of the phenomenon of noise generation, and it’s essential to understand what design elements influence the sound.

Research in Maha Fluid Power Research Center recently developed a new approach for the accurate sound field measurement named Automated Sound Intensity Measurement (ASIM). The nearly quarter spherical sound field around a pump is evenly sampled with a certain number of points (usually 199). Three microphones held by a robot with two joint arms automatically traverse all measurement locations with an optimized shortest route and capture the sound signal. At each point, the data acquisition system is programmed to collect 4 seconds of measurement data, see Kalbfleish et al. (2016). This paper introduces the analytical tools to utilize the data gathered by this new measurement approach.

2 Noise Data Analytics Toolbox

2.1 Overview

The structure of the toolbox shows on Figure 2. Based on the frequency we are interested in, there are three types of analysis; they are all-frequency analysis, harmonic analysis, 1/3 Octave Bands analysis. Several sound quantity metrics are used to describe the audible noise, including sound pressure, sound intensity, and sound power. Sound pressure is defined as the change of pressure, caused by a sound, at a single spatial location where a sound wave propagates across. Sound intensity is an energy-related concept representing the
surface power per unit area. Sound power is the integration of the sound intensity normal to a surface enclosing a sound source. Sound pressure, sound intensity, and sound power are usually quantitatively described in decibels as the logarithm of a ratio of their absolute values to respective references. These logarithms are referred to as sound pressure level (SPL), sound intensity level (SIL), and sound power level (SWL), see Kinsler et al. (2000). Besides these three metrics, a psychoacoustic concept loudness is applied; it is defined as that “attributes of auditory sensation in terms of which sounds can be ordered on a scale extending from quiet to loud” (Moore, 1997).

As part of the developed data analysis toolbox the authors proposed and developed the following four data visualization methods: spectrum plot, magnitude sphere plot, sound field video, and phase plot. By applying Fast Fourier Transform (FFT) or power spectral density (PSD) estimate, which is derived from Fourier Transform, are used to create spectrums.

2.2 Spectrum Plot

Frequency content is constitutional information for characterizing sound signals, and the most intuitive way to present the frequency composition of a sound signal is spectrum. Theoretically, any arbitrary periodic signal can be decomposed to a certain number of simple cosine signals with different frequencies; the process of converting a time domain signal to frequency domain is called Fourier Transform. In this toolbox, Fast Fourier Transform (FFT) and power spectral density (PSD) estimate, which is derived from Fourier Transform, are used to create spectrums.

2.2.1 All-frequency & Harmonic Spectrum

A harmonic is a signal or wave whose frequency is a positive integral multiple of a referral frequency, and the referral frequency is called fundamental frequency. Take the measurement for a pump with 9 pistons rotating with speed of 3000 rpm for example, the shaft frequency is 50 Hz, and thus the fundamental frequency of the pump is 50 Hz multiplied by 9, which is 450 Hz. Therefore, the harmonic frequencies in this case are 450 Hz, 900 Hz, 1350 Hz, and etc.

FFT was applied to convert the signal from time domain to frequency domain, and the mean values and max values of the measured 199 locations at each frequency were plotted on the spectrum. In the example case, the spectrum tells most energy of the measured sound is in harmonic frequencies and 1st and 2nd harmonics are most active.

2.2.2 1/3 Octave Bands Spectrum

For a sound that is not harmonic, the audible frequency range is divided into several bands to simplify the frequency analysis. An Octave is a band whose upper frequency is twice the lower frequency. In order to achieve a higher frequency resolution, an Octave is divided into 3 1/3 Octave bands by inserting two points between an Octave and making the upper band frequency is the lower band frequency multiplied by \(\sqrt[3]{2}\), see Kinsler et al. (2000).

2.3 Magnitude Sphere Plot

In order to characterize the measured sound field in spatial domain, the tool that generates the magnitude sphere plots has been developed. SPL, SIL,
or Loudness is firstly computed at each measured location by conventional methods. Subsequently, a function in MATLAB called “scatteredInterpolant” is applied to generate a function estimating the values on the whole measured spherical surface. At the end, the function “surf” is called to plot the surface, on which the colors represent the magnitudes of a specific metric.

2.3.1 Magnitude Sphere Plot of Weighted SPL

For all-frequency analysis, the weighted SPL are applied. Weighted sound pressure levels are designed to correlate SPL with loudness. Sounds with the same SPL may have different loudness, and this feature is usually expressed on the equal-loudness contours. It’s clearly shown on the Figure 5 that: 1) the lower the frequency is, the higher the SPL is required to maintain equal perceived loudness, when the frequency is lower than 1000 Hz; 2) extra required SPL decreases while loudness increases. Weighted sound pressure levels were designed to describe the sound pressure at different loudness.

A, B and C weighting SPL were originally designed as the mirror of 40 phon, 70 phon and 90 phon Equal-loudness level contour, respectively, and written as dBA, dBB and dBC. In this toolbox, approximate equations below (ANSI S1.42-2001) are used to weight the original signals:

$$\text{Ra}(f) = \frac{12200^2 \cdot f^4}{(f^2 + 20.6^2)(f^2 + 12200^2)(f^2 + 158.5^2)^{0.5}}$$  

$$A(f) = 2.0 + 20 \cdot \log(Ra(f))$$  

$$\text{Rb}(f) = \frac{12200^2 \cdot f^2}{(f^2 + 20.6^2)(f^2 + 12200^2)}$$  

$$B(f) = 0.17 + 20 \cdot \log(Rb(f))$$  

$$\text{Rc}(f) = \frac{12200^2 \cdot f^2}{(f^2 + 20.6^2)(f^2 + 12200^2)}$$  

$$C(f) = 0.06 + 20 \cdot \log(Rc(f))$$

where $f$ is frequency; $A$, $B$, $C$ are the attenuation in dB of corresponding frequency for A, B and C weighting sound pressure level respectively. Response curves of these weighting functions are shown in Figure 6. A weighting filters most energy in low frequency among these three methods; and C weighting is almost the same as no weighting.
Weighting functions were applied after decomposing the original sound pressure signals into frequency domain. Figure 7 and Figure 8 are SPL sphere plot for the same measurement using A weighting and C weighting respectively. As 1st harmonic is filtered out a lot, A weighting sphere plot looks much quieter than C weighting.

2.3.2 Magnitude Sphere Plot of Isolated frequency

In order to highlight the characteristics within specific frequency bands, the magnitude sphere plots are also created for each single harmonic or 1/3 Octave Band. The harmonic SPL or SIL is determined by finding the corresponding SPL or SIL at the harmonic frequencies on all-frequency spectrum; and the SPL and SIL for each 1/3 Octave Band is computed through trapezoidal numerical integration.

2.4 Sound Field Video

Knowing how the spatial distribution changes with time is essential for researchers to understand the phenomenon of noise generation; hence an approach to create the sound field videos has been developed to achieve this goal. Hundreds to thousands of sphere are plotted with time series, and written into the video frame by frame.

2.4.1 Shaft Trigger

The biggest challenge of creating a sound field video was how to use a group of single location measurements taken at different time to present a simultaneous phenomenon on a surface. In order to solve this problem, the sound signals generated in every single revolution of the shaft were assumed very similar when a pump is working steadily. Then, a shaft trigger generating a square wave designed for helping find the starting points of every revolution. When the laser was on the shaft, the high level of square wave would be generated; when the laser was on the tape that absorbs light, the low level of square wave would be generated. By finding the falling edge of the square wave, the starting point of every revolution can be determined.

The triggering error is ±1 time steps due to the imperfect square wave. At the same time, the varying shaft speed makes the length of one revolution change. In order to achieve higher reliability, an average method was applied to generate a more representative sound signal than a single measured revolution.
2.4.2 All-frequency Video

![Image: Frame 1 of the All-frequency Sound Field Video]

Fig. 12: Frame 1 of the All-frequency Sound Field Video

After the data gathered at different locations was synchronized, a series of sphere plots were generated as frames of the video. For every revolution of the shaft, the microphone with sampling frequency of 51.2 kHz captured 1024 sound pressure values at every single measured location. Therefore, the maximum number of frames can be drawn for one revolution is 1024. In the purpose of achieving high credibility and smooth motion of the video, all the 1024 frames were plotted and the frame rate was set up as 51. As a result, a video with a duration of 20 seconds demonstrated the dynamic characteristics of the sound field generated by the working hydraulic pumps within 0.02 second with a speed 1000 times slower than the actual phenomenon. In order to present the phase at the same time, signs were put in front of the decibels. Positive means the measured gauge pressure is higher than atmospheric pressure, and negative is opposite. The color map was also modified to coordinate the distribution of the SPL values.

2.4.2 Harmonic Video

![Image: Magnitude Response Curves of Designed Filters]

Fig. 13: Magnitude Response Curves of Designed Filters

The all-frequency sound field video illustrates the time varying feature of a complicated sound field composed by several simple sound waves. Examining one of these compositions can help researchers to interpret the phenomenon of pumps’ noise generation further. Therefore, digital filters were designed to isolate desired frequency bands out so that the time varying features of a specific harmonic can be analyzed.

![Image: Frame 1 of the 1st Harmonic Sound Field Video]

Fig. 14: Frame 1 of the 1st Harmonic Sound Field Video

The filters used were Butterworth passband filters generated by function ‘fdesign.bandpass’ in MATLAB. The central frequencies of the passbands were determined by the frequencies of each harmonic. Both the passbands and stopbands’ width were designated with 90 Hz, and the stopband attenuation is -60 dB, which means that at the corner of the stop band, the filtered signal drops down to at least 1000 times weaker than the original signal.

![Image: Frame 1 of the 2nd Harmonic Sound Field Video]

Fig. 15: Frame 1 of the 2nd Harmonic Sound Field Video

The same process as creating the all-frequency video was applied for the filtered data. As results, the harmonic videos looked much more simple and intuitive than all-frequency videos. The patterns of the first and second harmonic were pretty distinguishable; the rest harmonics’ videos looked chaotic but still periodic, which means they were generated by the pumps instead of random noise.
2.5 Phase Plot

Fig. 16: 2nd Harmonic Phase Plot

The sound field videos enable researchers to build greater insight of the phenomenon of pumps' noise generation; however, one of the biggest drawbacks is they cannot be presented on papers. Therefore, the phase plots are generated to illustrate the dynamic characteristics of a measured sound field in a static way. Phase here means the relative position in a sinewave with a range from $-\pi$ to $\pi$. $\pi$ indicates the point is on the peak of a sinewave, and $-\pi/2$ is on the valley. At every measured location, Fourier Transform is applied for an averaged single-revolution signal. The phase plot accompanied with a direction can clearly explain how the sound wave propagates in space.

3 Discussion

3.1 Similarity of Sound Signals

One of the most important foundations of the sound field video is the assumption that the sound signals generated in different revolutions are very similar when the measured pump is working steadily. Therefore, finding supports for the assumption is essential to prove the credibility of the sound field video.

Pearson’s linear correlation coefficient are used to describe linear correlation between two variables, where 1 indicates total positive linear correlation and -1 indicate total negative linear correlation. An arbitrary measured location were taken for computation. During the 4-second measurement, 200 revolutions signal are captured. Pearson’s linear correlation coefficients between every two revolutions sound signal are computed on MATLAB. As results, the Pearson’s linear correlation coefficients vary from 0.9619 to 0.9904 with a mean of 0.9834 and a standard deviation of 0.0035. Based on these results, the assumption can be still considered as reliable. Qualitatively, the simultaneous sphere plots and video were created for 4 random different revolutions. 4 videos look almost the same; but differences can be seen if studying a single frame.

Fig. 17: Simultaneous Sphere Plots of the 4 Random Revolution

It's safe to conclude that the video itself is much more reliable than a single frame in the video.

3.2 Averaging Method

Even though the sound signals generated in every revolution are very similar, there is still variance. Meanwhile, the imperfect square wave and the varying shaft speed cause the error. Thus, an averaging method was developed to moderate the variance and error.

There were 3 averaging methods that had been studied. First one is average in time domain; second one is average the FFT of every single revolution, and invert the averaged FFT back to time domain; the last approach is inverting the down-sampled 200-revolution FFT to time domain. First and second approaches are mathematically equivalent and the results turned out to be exactly the same. The last approach is a filter in nature; thus the results are less authentic. In this toolbox, the sound signals generated in different revolutions are averaged in time domain directly. Signals whose length are not 1024 are not taken into computation.

For the same example measured location in 3.1, the Pearson’s linear correlation coefficients between the averaged data and all the measured revolutions vary from 0.9888 to 0.9944 with a mean of 0.9855 and a standard deviation of 0.0805. In general, the averaged revolution is much more representative than an arbitrarily picked single measured revolution.
3.3 Triggering Error Tolerance Study

As mentioned, the triggering error is $\pm 1$ time steps due to the imperfect square wave. It’s also important to know how much impact the error has for the sound field video.

![Current Synchronization](image1)

**Fig. 18: Current Synchronization**

Current synchronization was used as the baseline, and then artificial random triggering error of $\pm 3$ time steps and $\pm 10$ time steps are added respectively. Videos were generated for all the cases for comparison. The videos of the baseline and $\pm 3$ time steps have almost the same phenomenon, even though the frames differ a lot. $\pm 10$ time-step error made every single frame looks even more different, but the motion of the sound field still looked the same as the other two.

![Synchronization with +/- 3 Artificial Error](image2)

**Fig. 19: Synchronization with +/- 3 Artificial Error**

Another safe conclusion can be drawn: the triggering error does effect the simultaneous sphere plots; however, the sound field video is tolerant at least for an error of $\pm 3$ time steps.

4 Conclusion

This paper introduces the noise data analytics toolbox for a new measurement approach called ASIM. These tools describe characteristics of the measured sound field in space, time and frequency.

Spectrum plots created by FFT and PSD demonstrates the frequency content of the measured sound. Magnitude sphere plots can characterize the spatial distribution of a specific acoustic metric. In addition to the static analytics tools, sound field video tool are designed illustrate the dynamic characteristics. Due to the limit of the video, phase plot is designed as an assistive tool of sound field video.

References


