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| DEEC_medium.jpg | **Big Data Measuring Systems**  **LAB 3 Short Report** |

**Digital Acquisition and Processing**

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| **Week day** | **Date** | **Hour** | **Group** | **Students Numbers** | |
| Friday | 24/4/2020 |  |  | Paolo Frazzetto | 94942 |

**Step 1**

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| **Signal** | | | **Acquisition** | | **Apparent frequency** |
| **Waveform** | **Frequency**  **[kHz]** | **Amplitude**  **[V]** | **Points** | **Rate**  **[kHz]** |
| Sinusoidal | 1 kHz | 1 V | 100 000 | 100 kHz | **1 KHz** |
| Sinusoidal | 1 kHz | 4 V | 100 000 | 100 kHz | **1 KHz** |
| **Observations:**  As expected, when the acquisition rate matches the signal frequency, the FFT outputs a sharp value in the corresponding frequency. | | | | | |
| Sinusoidal | 1 kHz | 1 V | 100 000 | 100 kHz | **1 KHz** |
| Sinusoidal | 1 kHz | 1 V | 999 950 | 100 kHz | **≈1 kHz** |
| **Observations:**  In the second measurement, spectral leakage is observed since the overall acquisition duration does not match an integer number of signal periods. | | | | | |
| Sinusoidal | 20 kHz | 1 V | 100 000 | 100 kHz | **20 kHz** |
| Sinusoidal | 40 kHz | 1 V | 100 000 | 100 kHz | **40 kHz** |
| Sinusoidal | 50 kHz | 1 V | 100 000 | 100 kHz | **50 kHz** |
| Sinusoidal | 60 kHz | 1 V | 100 000 | 100 kHz | **40 kHz** |
| Sinusoidal | 100 kHz | 1 V | 100 000 | 100 kHz | **0 kHz** |
| **Observations:**  Now we sample below the Nyquist frequency, resulting in an inaccurate signal acquisition and hence its spectrum shows apparent frequencies. About the signal, an extra phase was added to avoid to sample at the same output () for rising and falling sine wave. For we notice the mirrored fundamental at . Finally, since the 100 kHz signal matches the sampling frequency, the acquired signal is ideally at the same point () resulting in a reconstructed constant signal. | | | | | |
| Triangle | 1 kHz | 1 V | 100 000 | 100 kHz | **1 (+3+5+...) kHz** |
| Square | 1 kHz | 1 V | 100 000 | 100 kHz | **1 (+3+5+7+…) kHz** |
| Square | 15 kHz | 1 V | 100 000 | 100 kHz | **15 (+ 45) kHz** |
| **Observations:**  Non-sinusoidal signals as triangle and square waves are approximated by summing odd harmonics of the fundamental with power-decreasing amplitudes. This is indeed noticed in this simulation where the fundamental frequency is clearly observed (at 1 kHz and 15 kHz) plus minor frequencies at its odd multiples.  In the last case frequencies of the higher harmonics () are folded and start being mirrored at . The power decrease is also slower than a triangular wave ( versus ). | | | | | |

**Step 2**

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| **Mean value formula, MEAX(x)** |  |
| **MEAN(X)** |  |
| **MEAN(Y)** |  |
| **MEAN(Z)** |  |
| **Observations:**  The signal is generated with Motor Power Supply since the generator does not accept (and unbalancing , health ).  Y and Z axes are neglected since this is a simulated scenario. | |

**Step 3**

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| **Root mean square formula, RMS(x)** |  |
| **RMS(X)** |  |
| **RMS(X – MEAN(X))** |  |
| **Observations:**  In the second RMS the DC component is subtracted. It captures only on the AC component, that is equivalent to the signal standard deviation, from the vibrations.  The two are related by | |

**Step 4**

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| **Input range** |  |
| **Sampling rate** |  |
| **Number of points** |  |
| **Observations:**  By tweaking the motor parameters with the above specifications, we observed that the power voltage affects the main vibration frequency, the unbalancing weight produces an oscillation at lower frequencies whereas a worse gear health lead to additional different vibration frequencies. | |

**Step 9**

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| **Feature to estimate the rotation speed**  The rotation speed, directly related to the supply voltage, can be estimated by the most powerful peak at higher frequencies (so besides the constant signal component). At different voltages in the range , this peak appears to be almost linear in power but perfectly linear in its corresponding frequency. The corresponding linear interpolation gives that can be easily inverted to estimate the corresponding voltage input knowing the peak frequency. |
| **Feature to estimate the unbalancing weight**  Adding a weight to the rotating motor produces an additional periodic force at low frequency, on top of the always present motor vibrations. This frequency is at for all differnet values of the weight, so the only way to reverse-estimate it is by looking at its power spectrum. This manifests a linear behavior according . So once the power of this frequency is known, gauge the unbalancing weight is just a matter of inverting the above expression. |
| **Feature to estimate the gear’s health condition**  Worsening the gear’s health condition adds 4 additional frequencies to the signal. This phenomenon is visible for when these components have fixed frequencies (at 12 and no weight) of , whereas this is neglectable for better conditions. Indeed, we can also affirm that below that threshold the power of these components increases exponentially, up to the worst-case scenario of health. This can be modeled by taking the average of the 4 peaks and use a linear regression for the values in the range , giving . |

**Step 10**

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| **Rotation**  **Speed**  **[V]** | **Feature:**  **Max Peak Freq. [Hz]** | **Unbalancing**  **Weight**  **[g]** | **Feature:**  **Power 3 Hz [W/Hz]** | **Gear health condition**  **[%]** | **Feature:**  **Average power of Peaks [W/Hz]** |
| 1 | 13 | 0 | 0.0004 | 0 | 0.0086 |
| 2 | 26.9 | 10 | 0.0083 | 5 | 0.0077 |
| 3 | 40.8 | 20 | 0.0166 | 10 | 0.0069 |
| 4 | 54.7 | 30 | 0.0247 | 15 | 0.0061 |
| 5 | 68.5 | 40 | 0.0329 | 20 | 0.0055 |
| 6 | 82.4 | 50 | 0.0412 | 25 | 0.0048 |
| 7 | 96.3 | 60 | 0.0494 | 30 | 0.0042 |
| 8 | 110.2 | 70 | 0.0578 | 35 | 0.0036 |
| 9 | 124.1 | 80 | 0.0661 | 40 | 0.0031 |
| 10 | 138.0 | 90 | 0.0745 | 45 | 0.0027 |
| 11 | 151.9 | 100 | 0.0826 | 50 | 0.0022 |
| 12 | 165.8 |  |  | 55 | 0.0017 |
|  |  |  |  | 60 | 0.0013 |
|  |  |  |  | 65 | 0.0010 |
|  |  |  |  | 70 | 0.0007 |
|  |  |  |  | 75 | 0.0006 |
| **Observations:**  As already discussed above, these features allow us to build linear models to estimate the experimental setup properties, based only on the output power spectrum.  One possible algorithm has been proposed on the attached Matlab script. | | | | | |

**Conclusions**

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| In conclusion, we were able to analyze and discuss spectrums for different signals, while dealing also with spectral leakage and Nyquist Theorem. We could also characterize a physical experiment and designed an algorithm to guess its relevant features from the raw acquired data. Although this was successful, we must state that this was a simulated scenario where only certain conditions combinations have been tested and uncertainties have been neglected. Nevertheless, a similar rationale can be extended to more complex real cases. |