Condition Monitoring of Induction Slip Motors in high 50 Hz Noise Environments

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Abstract: Beran Instruments Limited have been monitoring induction slip motors for over 20 years in high electrical noise environments. Due to the high-temperature environment of certain customer installations, integrated electronics piezo-electric (IEPE) sensors are not employed, and charge sensors are installed to monitor the condition of the motors. Over the past 20 years, Beran have used a variety of techniques, including the development of specialist isolated analogue signal conditioning amplifiers, to enable the true vibration signals that occur around the drive frequency (which is coupled to, and therefore affected by, the mains frequency) to be visualised.

Beran Instruments Limited undertook a research and development programme, Machinery Health State Detection (mSTATE) supporting Future Net Zero Energy Generation. The goal of the programme was to develop a new capability to subtract electrical noise from sensor signals and was conducted in partnership with the University of Bristol and EDF Energy Torness Nuclear Power Station, with funding from the United Kingdom's innovation agency, Innovate UK.

The mSTATE project delivered a novel algorithm that allows complete subtraction of 50 Hz mains frequencies from the charge sensor signals allowing, for the first time, our end users, and future customers the ability to visualise the true vibration signals and the ability to trend machine health over time without the use of specialist and expensive analogue signal conditioning systems.

This paper outlines the history and development of condition monitoring of induction slip motors at Beran Instruments, and how the mSTATE project resulted in a new approach to subtract 50 Hz noise from accelerometer signals using the power of modern signal processing and data architectures.

Keywords: vibration monitoring, condition monitoring, induction motors, electrical noise, rotating machinery, machine diagnostics, data analysis

Introduction

Existing nuclear power generation operated by EDF Energy in the UK uses Advanced Gas-cooled Reactors (AGRs) [1]. Torness nuclear power plant produces low carbon, reliable and safe baseload electricity generation 24 hours per day, 365 days a year. Torness power station has two nuclear reactors each driving a steam turbine generator unit. The operational aim is to generate long-term electricity, refuelling the reactor whilst operational. Major service and inspection intervals are performed every three years, resulting in long operational service of complex key critical infrastructure and the necessity to use condition monitoring systems to understand plant operational behaviour.

Each reactor has eight gas circulators driven by an electric motor. The motor is driven by a three-phase 50 Hz 11 kV power feed and the motors run at a lower slip frequency slightly above 49.5 Hz. Due to the operational requirements and how gas circulators are installed, the machines cannot be removed from service without a full reactor shutdown.

The operational slip frequency is determined by the formula:

$$S = \frac{f_s - f_m}{f_s}, \tag{1}$$

where S is slip, f_s represents synchronous power grid frequency while f_m is mechanical frequency of the rotor [2].

Based on this expression, slip is the measurement of the difference between the rotor and stator input current. As motor speed increases to synchronous machine speed, the load on the motor decreases [3]. For safety reasons, the gas circulator motors run at very light loads, resulting in very low slip motors. However, as machine operation changes, factors such as Inlet Guide Vane (IGV) angles or reactor refuelling can alter the load on the motor affecting the slip frequency.

The vibration signal problem experienced on-site is the significant swamping of the machine vibration signal by the adjacent power drive cabling, which historically has masked the vibration signal [4]. At the same time, it is impossible for many vibration monitoring systems to distinguish between 50 Hz and 49.5 Hz due to the available resolution of the fast Fourier transform (FFT).

Beran has previously supplied analogue condition monitoring amplifiers which suppressed the 50 Hz noise generated by the electric drive signal allowing machinery diagnostic engineers the ability to see the gas circulator vibration signal. Advances in digital signal processing, computing power and development of algorithms allowed for new and novel technologies to be used, to determine machine faults and provide advanced warning resulting in improving machinery safety and reliability for asset owners, operators, and engineers.

Extensive prior work has identified the slip frequency as being challenging to identify and remove [5-7], particularly in the presence of broken rotor fault bars embedded within the electrical machine. Many of the approaches in the literature aim to address this issue through fixed frequency spectral line removal using the wavelet transform [8-10]. This approach is entirely understandable given the wavelet transform can be formed to remove individual spectral components aligned with the shape of the mother wavelet [11-13]. Our study looked at using an array of techniques to resolve the issue of the power signal overriding the vibration signal, including continuous wavelet transform, adaptive frequencies, modified Kalman filters and spectral subtraction resulting in the spike removal of 50 Hz caused by the mains generation. The advantage of this approach is to track any variation in the underlying grid carrier frequency which is known to change under variable grid loading.

Data acquisition

To acquire data for the research, signals were collected from Gas Circulators installed at EDF Energy Torness Nuclear Power Station using Prosig P8000 and Prosig DATS application software. Current clamps were applied to the three-phase motor power drive of the Gas Circulator, with data collected from the current clamps and installed vibration sensors.

The real machine-acquired data was run through machine simulations and algorithms that had been created and modified in MATLAB, where the closely coupled power grid frequencies present in the vibration signal were able to be removed allowing the true dynamic response signature of the induction motor to be observed.

Algorithm development

To support the works, a continuous wavelet transform was applied as a pre-filter, which is an alternative to a bandpass infinite impulse response (IIR) filter, in the analysis of the acceleration vibration data. The continuous wavelet transform is a signal processing method which processes the signal into multiple overlapping frequency bands from 0 Hz to the Nyquist frequency. Figure 1 shows the FFT of the vibration signal before the pre-filtering, FFT after pre-filtering, application of the continuous wavelet transformation and comparison to the 4th Order Butterworth filter output. The benefit of using the continuous wavelet transform is that more of the unwanted frequencies are removed from the signal and the signal is not subjected to a phase change.

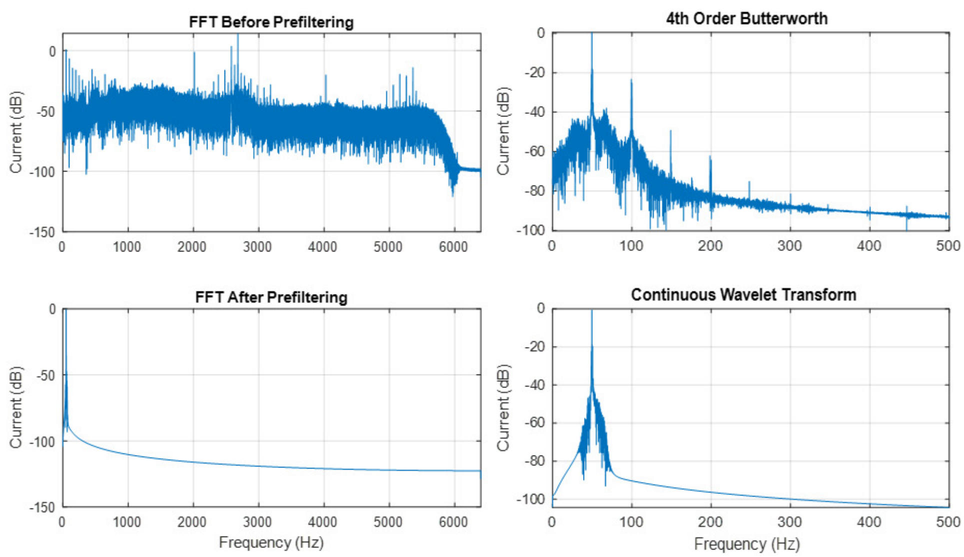


Figure 1: FFT of the vibration signal before the pre-filtering, FFT after pre-filtering, application of the continuous wavelet transformation and comparison to the 4th Order Butterworth filter output

Using a model to estimate the output of a system that is not possible to directly measure resulted in the selection of the Kalman filter technique to enable comparison between anticipated and measured data [14-16]. Scaling factors were applied to extract filtered data from the Kalman filter. The Kalman filter allows for the signal input into a system with noise to be compared with the output of an estimator removing the noise from the system, essentially providing two outputs, consisting of the noisy output and the filtered output.

The Kalman filter rapidly synchronises with the expected output with minimal errors in the computations. The frequency domain shows the reduction in the magnitude of the power frequency when the noise was removed as shown in Figure 2.

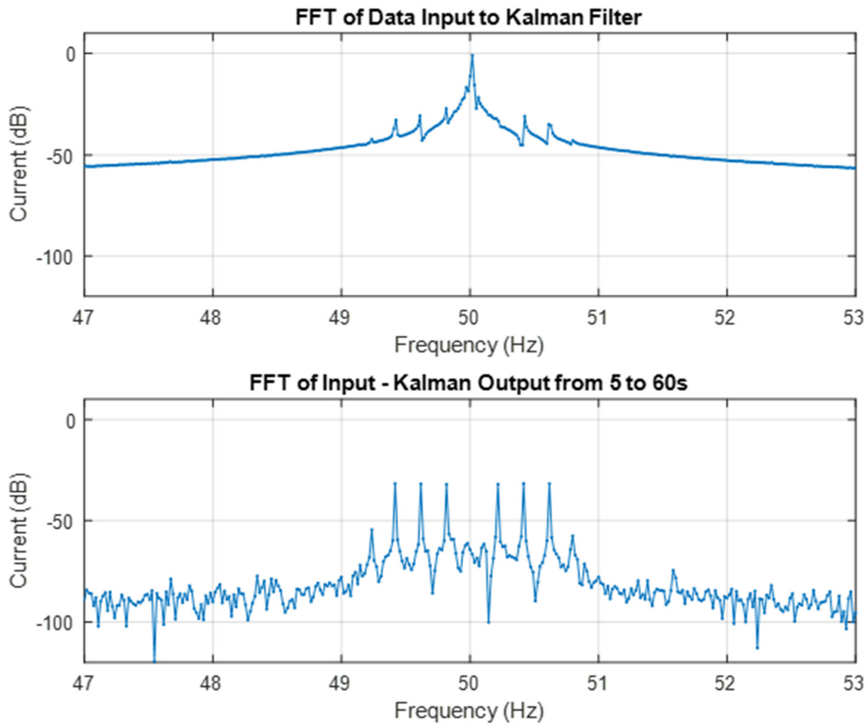


Figure 2: top image shows the FFT of data input to the Kalman filter, bottom image shows output of the Kalman filter successfully removing 50 Hz power drive signal

Alternatively, as the unwanted portions in the vibration signals were directly caused by the interference from the input currents, it may also be possible to simply subtract some modified versions of the input current signals from the vibration signals so that these interferences could be removed, which is a typical application of spectral subtraction [17-21]. This approach would yield a straightforward and computationally efficient solution that is ideal given the limited computational capability of the current on-site equipment.

To achieve this, both the amplitudes and the phases of the input signals needed to be adjusted. There existed three input current signals with overall almost identical characteristics. Each of the three signals may be used independently while major differences should not be expected.

Using the measured current signals, the input frequency could be calculated conveniently first. The amplitudes of the signals, including the input signals and the vibration signals, were then extracted at the determined input frequency. For each of the three input signals, its amplitude could then be scaled accordingly. Similarly, the respective phase angles at the input frequency could be obtained as well, after which the phase angles of the modified input signals could also be adjusted to match those of the vibration signals.

Eventually, a modified version of each input signal was generated for every individual vibration signal. This modified input signal could simply be subtracted and so the interference caused by the input current to the measured vibration data could be eliminated.

To demonstrate the robustness of this approach, the results of four vibration signals using three input current signals are to be presented. With each input signal, four modified versions would be generated to match the amplitudes and phases of the four vibration signals. Each modified signal would then be subtracted from the corresponding vibration signal. With three input current signals, three sets of results would be obtained. The frequency spectra of the vibration signals before and after the subtraction are shown in Figures 3 and 4.

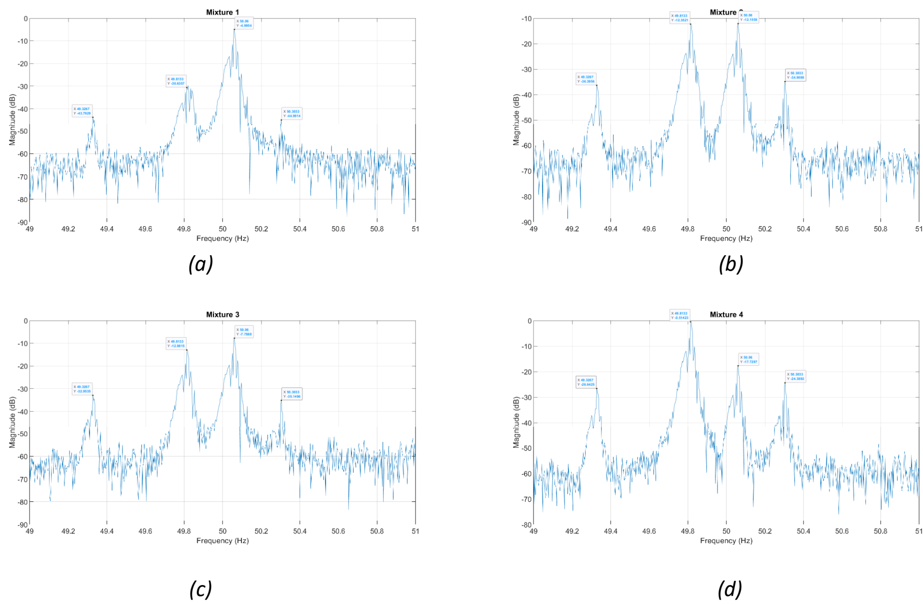
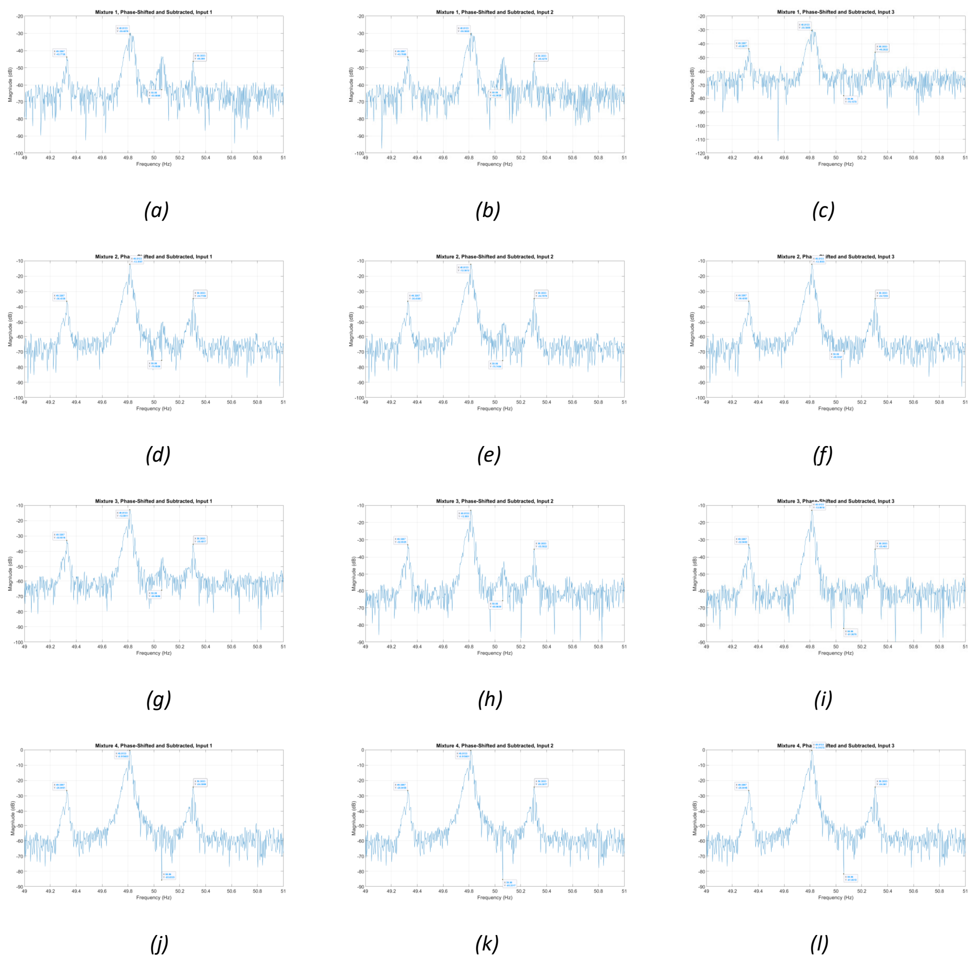


Figure 3: The four raw vibration signals in the frequency domain before the subtraction.

By comparing the raw vibration signals in Figure 3 with the results in Figure 4, the peaks at the input frequency (50.06 Hz) have been noticeably reduced while the characteristics including the magnitude and shape of the other regions of the signals were mostly unchanged.

It could also be observed that using the three different input signals yielded slightly different results. When the third input signal was utilised for the subtraction, the overall quality of the results appeared to be higher. It was additionally validated that the calculations were completed correctly, so the differences in the results should be attributed to the slight but still existent discrepancies among the input signals, which were likely caused by factors such as noise during the data collection.

Nevertheless, using this modification and subtraction approach, it was demonstrated that the peaks at the input frequency were reduced effectively at a very low computational cost.



(a) (b) (c)

(d) (e) (f)

(g) (h) (i)

(j) (k) (l)

Figure 4: The (a)-(c) first, (d)-(f) second, (g)-(i) third and (j)-(l) fourth vibration signals in the frequency domain after the subtraction using the first, second and third input signals.

Practical implementation

The theoretical modelling and calculations performed in MATLAB showed that the power drive noise signal could be successfully removed from the vibration signals.

The next step was to embed the algorithms into Beran's PlantProtech Condition Monitoring System and proved the functionality of the algorithms can be applied to both a real instrument and a real-life complex machine.

Data was acquired from existing installed vibration sensors and a power clamp was applied to the input motor drive power connection.

Beran's PlantProtech Condition Monitoring System with the embedded mSTATE algorithms successfully removed the noise from the motor power drive.

Figure 5 shows the uncorrected machine vibration data with a significant 50 Hz component while Figure 6 demonstrates the output following the application of the embedded algorithms which successfully removed the 50 Hz Power Drive signal from the vibration data.

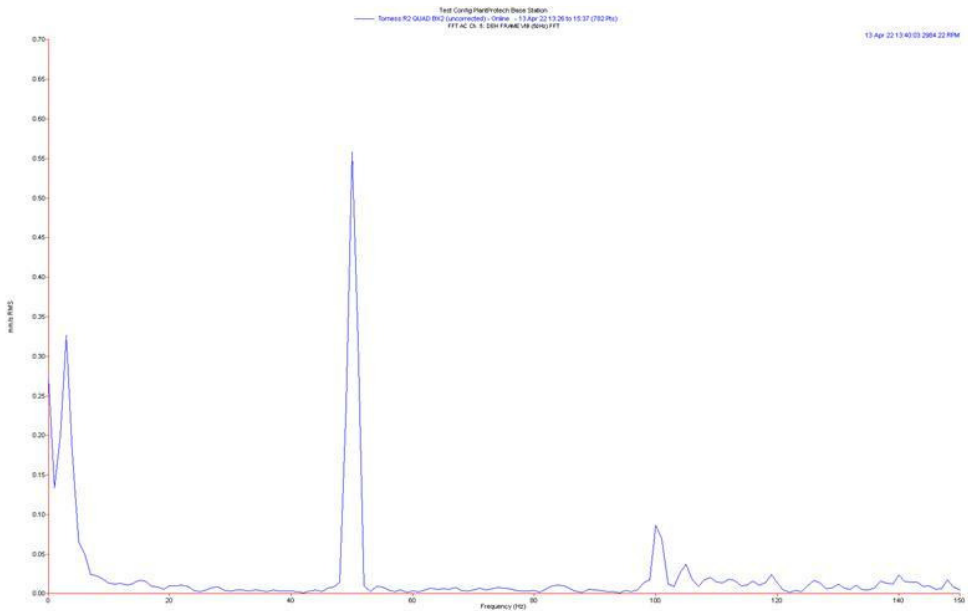


Figure 5: existing vibration data from Gas Circulator

Figure 6: Gas circulator corrected vibration data with 50 Hz power drive noise removed

Discussion

As shown in Figures 5 and 6 the carrier signal at the underlying grid frequency is completely removed via this process, enabling identification of the adjacent slip frequencies emanating from rotor motion lagging the carrier signal. The advantage of this approach is that subsequent analysis of any potential degradation of the rotor cage becomes possible by close inspection of eddy current behaviour at these discrete frequencies.

Other areas of consideration which are beyond the initial scope of this work are to apply the tools to synchronous motors where coupled behaviour may interfere further with individual machine response. Furthermore, the approach can easily be adopted to achieve signal noise cancellation in other vibration signals where rotating machinery may be operating at a different speed which is not necessarily coupled to the host machine response, and noise cancellation in signals of other frequencies such as multiple harmonics of the fundamental carrier signal.

Conclusion

A practical tool has been deployed to remove problematic slip frequencies to assist the analysis of closely aligned frequencies in electrical machines. The approach has been demonstrated on three-phase 50 Hz 11 kV gas circulator data from Torness Power Station in the UK.

The mState project has delivered a novel algorithm that allows complete subtraction of 50 Hz mains frequencies from the sensor signals allowing, for the first time, end users to visualise the true vibration signals. By removing noise from the signal with very low computational costs, the capability now exists to trend machine health over time without the use of specialist analogue signal conditioning systems.

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References

[1] "How an AGR power station works," British Energy Group plc, 2006.

[2] D. Miljković, "Brief Review of Motor Current Signature Analysis," CrSNDT Journal, vol. 5, pp. 14–26, Jun. 2015.

[3] S.-H. Kim, "Chapter 3 - Alternating current motors: Synchronous motor and induction motor," in Electric Motor Control, S.-H. Kim, Ed. Elsevier, 2017, pp. 95–152.

[4] H. Henao et al., "Trends in Fault Diagnosis for Electrical Machines: A Review of Diagnostic Techniques," IEEE Industrial Electronics Magazine, vol. 8, Art. no. 2, 2014.

[5] P. Gangsar and R. Tiwari, "Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review," *Mechanical Systems and Signal Processing,* vol. 144, pp. 1–37, 2020.

[6] D. Torregrossa, F. Peyraut, M. Cirrincione, C. Espanet, A. Cassat and A. Miraoui, "A new passive methodology for reducing the noise in electrical machines: Impact of some parameters on the modal analysis," *Transactions on Industry Applications,* vol. 46, no. 5, pp. 1899–1907, 2010.

[7] R. Supangat, N. Ertugrul, W. L. Soong, D. A. Gray, C. Hansen and J. Griegger, "Broken rotor bar fault detection in induction motors using starting current analysis," in *European Conference on Power Electronics and Applications*, 2005.

[8] R. Patil, "Noise Reduction using Wavelet Transform and Singular Vector Decomposition," Procedia Computer Science, vol. 54, pp. 849–853, Dec. 2015.

[9] K. Bnou, S. Raghay, and A. Hakim, "A wavelet denoising approach based on unsupervised learning model, " EURASIP Journal on Advances in Signal Processing, vol. 2020, Art. no. 1, Jul. 2020.

[10] R. Aggarwal, D. J. Singh, V. K. Gupta, S. Rathore, and A. Khare, "Noise Reduction of Speech Signal using Wavelet Transform with Modified Universal Threshold," International Journal of Computer Applications, vol. 20, pp. 14–19, Apr. 2011.

[11] A. Sapena-Bano, M. Pineda-Sanchez, R. Puche-Panadero, J. Martinez-Roman and D. Matic, “Fault diagnosis of rotating electrical machines in transient regime using a single stator current's FFT,” *IEEE Transactions on Instrumentation and Measurement,* vol. 64, no. 11, pp. 3137–3146, 2015.

[12] A. Sapena-Bano, M. Pineda-Sanchez, R. P. Panadero, J. Perez-Cruz, J. Roger-Folch, M. Riera-Guasp and J. Martinez-Roman, “Harmonic order tracking analysis: A novel method for fault diagnosis in induction machines,” *IEEE Transactions on Energy Conservation,* vol. 30, no. 3, pp. 833–841, 2015.

[13] E. H. E. Bouchikhi, V. Choqueuse and M. E. H. Benbouzid, “Current frequency spectral subtraction and its contribution to induction machines’ bearings condition monitoring,” IEEE Transactions on Energy Conversion, vol. 28, no. 1, pp. 135–144, 2013.

[14] K. H. Eom, S. J. Lee, Y. S. Kyung, C. W. Lee, M. C. Kim, and K. K. Jung, “Improved Kalman Filter Method for Measurement Noise Reduction in Multi Sensor RFID Systems,” Sensors (Basel, Switzerland), vol. 11, Art. no. 11, Oct. 2011.

[15] G. G. Rigatos and P. Siano, “Sensorless Control of Electric Motors with Kalman Filters: Applications to Robotic and Industrial Systems,” International Journal of Advanced Robotic Systems, vol. 8, Art. no. 6, 2011.

[16] S. Praesomboon, S. Athaphaisal, S. Yimman, R. Boontawan, and K. Dejhan, “Sensorless speed control of DC servo motor using Kalman filter,” in 2009 7th International Conference on Information, Communications and Signal Processing (ICICS), 2009, pp. 1–5.

[17] S. Boll, "Suppression of acoustic noise in speech using spectral subtraction," in IEEE Transactions on Acoustics, Speech, and Signal Processing, vol. 27, no. 2, pp. 113-120, April 1979.

[18] S. V. Vaseghi, “Spectral Subtraction,” in Advanced Signal Processing and Digital Noise Reduction, Wiesbaden: Vieweg+Teubner Verlag, 1996, pp. 242–260.

[19] N. Upadhyay and A. Karmakar, “Speech Enhancement using Spectral Subtraction-type Algorithms: A Comparison and Simulation Study,” Procedia Computer Science, vol. 54, pp. 574–584, 2015.

[20] Y. Lu and P. C. Loizou, “A geometric approach to spectral subtraction,” Speech communication, vol. 50, Art. no. 6, 2008.

[21] K. C. D. Kompella, M. V. G. Rao, and R. S. Rao, “Bearing fault detection in a 3 phase induction motor using stator current frequency spectral subtraction with various wavelet decomposition techniques,” Ain Shams Engineering Journal, vol. 9, Art. no. 4, 2018.

Biographies:

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Nick Lieven – is professor of Aircraft Dynamics at the University of Bristol with 30 years’ experience in Structural Health Monitoring and has over 150 published papers.

Alex Niciecki – System Engineering Team Leader, Beran Instruments, with over 15 years’ experience working in safety critical product development. He acted as Technical Lead on the mSTATE project supporting the system development.

Duncan Affleck – Beran Sales Manager, has been working in the condition monitoring world for almost 3 decades supplying machinery vibration diagnostic systems around the world.