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The Application of Synchronous Averaging to Renewable Energy Systems

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Abstract: - Synchronous or time-synchronous averaging is a technique used to improve SNR in cyclical systems. We describe the operation of synchronous averaging and highlight the advantages and disadvantages of the procedure. This information is then used to suggest how the technique should be most effectively applied when monitoring renewable-energy devices, particularly wind turbines and wave-energy generators. These devices have their own distinct characteristics that make this a worthwhile exercise.

Key-Words: - Time-Synchronous Averaging, Condition Monitoring, Vibration Analysis, Wind Turbine, Wave Energy

1 Introduction

There are many types of mechanical system that execute cyclical motion. Most common are reciprocating machinery such as motors and generators. It is now recognised that significant cost saving can be achieved in large rotating systems by implementing a condition-monitoring regimen with the objective of discovering problems as they are beginning to develop and before catastrophic failure occurs [1]. Condition monitoring is facilitated by fitting acoustic and vibration sensors at critical points such as bearing positions and gearboxes. The information coming from the sensors is analysed, usually by an automated system, and a change in signal quality is considered the early indication of an emerging problem.

The difficulty with such systems is that the sensors pick up vibration from all sources, with unrelated signals coupled through the frame of the machinery and via the air; signals may also be affected by electrical pick-up in what are often electrically noisy environments. Because of these accumulated effects, the signal is sometimes severely contaminated. A fault indication characterised by an anomalous frequency component growing over time may need to achieve significant amplitude to rise above the noise, with the result that problem detection is delayed.

Is there any way to improve the signal-to-noise ratio (SNR)? One obvious method is to acquire data over many data cycles, *N*, and average over each cycle, point for point. Extraneous noise will then be reduced by cancellation due to its random nature and only the signal synchronised with the rotation (which is reinforced) is retained. Theoretically, such a procedure should improve the SNR by a factor $\sqrt{N}$. The problem though is that rotating machinery, even if speed-regulated by a governor, will show significant cycle-to-cycle rotational speed variation. In conventional systems data is normally acquired at regular time intervals, and following this with a direct averaging procedure will simply smear the data. It is instead necessary to match the incoming data with the angular position of the machine (the crank angle) and average the values at the same set of regularly-spaced angular positions over many cycles. A position sensor normally identifies the 0^o reference position, in some systems called the top-dead-centre (TDC), and marks the beginning of each cycle. Early systems used a hardware PLL frequency multiplier applied to the reference signal to generate regular sampling pulses at the correct angular positions within the cycle [2], but recent increases in computer processing power means that current systems now interpolate the angular position from the analysis of an over-sampled data set [3]. The two methods are contrasted in Fig. 1.

The procedure described is called synchronous averaging (SA), and is very effective at improving SNR. It also obviates the need for a windowing correction when transforming into the frequency domain by a Fast Fourier Transform (FFT). However, whilst a useful technique, synchronous averaging must be carefully applied as it relies on some basic assumptions about the nature of the machine cycle, assumptions that are only approximated to in practice (though this fact is often overlooked). An understanding of these issues allows corrections to be made to the basic procedure, or if this is not possible, we can at the very least get a realistic estimation of the error.

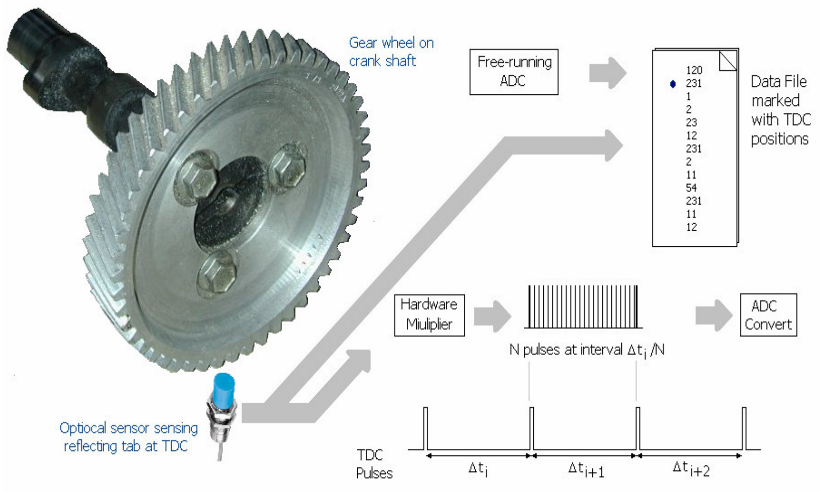

Figure 1 The sensor generates a single tachometer pulse at TDC. The bottom half of the diagram shows how, in this example, 24 equally spaced measurement pulses derived from the period between the previous two tachometer pulses and generated by hardware are used to directly activate the ADC. The pulses will be inaccurate if $\Delta t_i <> \Delta t_{i+1}$ but the advantage is that the software processing requirements are negligible. In the top half of the diagram, the ADC gathers data at high speed with the datum nearest each TDC is marked. The file is later post-processed to match each data point with an angular position using interpolation. This method is processor intensive, but potentially much more accurate because the sampling interval is based on the current cycle, not the previous one as is the case with the hardware multiplier.

We will show how the technique may be applicable to renewable energy systems; these are systems with their own distinctive mechanical characteristics and are worthy of separate consideration. We are reviewing the use of synchronous averaging as a tool used in currently active renewable energy research projects at the University of the Highlands and Islands and attempting to determine best practice.

2 Applications of SA

The first assumption underpinning synchronous averaging is that the time duration of the effect being measured scales linearly with rotation frequency. The second assumption is that the angular speed (which may vary between cycles) is constant over any particular cycle. If the system being measured does not satisfy these criteria, the averaged data will not be a true reflection of the performance of the system. The SNR will be improved regardless, but the final averaged trace may only be useful for a qualitative evaluation rather than a quantitative assessment. These issues are important as we can see by considering situations related to renewable energy system where synchronous averaging might be applied.

2.1 Conversion of Large Diesel Engines to Hydrogen

Large diesel engines are still of some interest as the world moves to the new and cleaner hydrogen economy. There are many functioning engines available (for example, as a result of the decommissioning of marine vessels), with power output ranging from 50 kW to 3 MW. It would be useful to adapt these to run on hydrogen as a backup in the event of problems with fuel cell systems (or power line faults).

However, there are some technical problems with the conversion of these machines to run on hydrogen. Diesel engines rely on the heat rise associated with the compression cycle to ignite the fuel mixture. The combustion temperature of hydrogen gas (585^{o}C) is much higher than that of a diesel aerosol (210-250^{o}C). Injecting hydrogen instead of diesel would not work: the hydrogen will simply not ignite [4]. One straightforward way of modifying the system is the development of a hybrid system using a fuel mixture, the major component of which is hydrogen. The mixture may include ether, which has a self-ignition temperature of only 188^{o}C, and diesel. However careful control of the quantity of fuel injected is necessary if the cylinders (and the engine) are not to be damaged by excessive pressure. In developing such a system, it is essential that a highly accurate indicator plot (a *p-V* diagram) be obtained by direct measurement. This information is used to carefully balance the mixture.

A piezoelectric pressure sensor connected into a small orifice drilled in the cylinder can be used to monitor the pressure over the cycle. The output from the pressure sensor may be noisy and it is difficult to see detailed features in the indicator plot such as the opening of closing of valves in the data from one cycle. A typical plot of the performance a single cylinder of a 2 MW Mirrlees V12 engine is shown in Fig. 2.

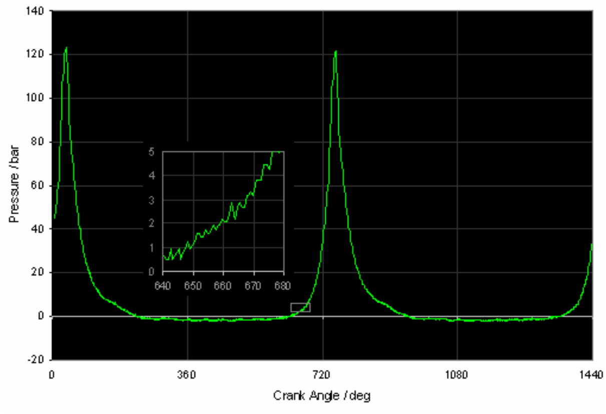

Figure 2 Typical indicator plot for a large diesel engine. Inset shows the noise level (Cylinder 3, Engine 1, Stornoway Power Station, 2005).

The noise also makes it difficult to see the exact injection point. In cases like this, synchronous averaging could significantly improve the data quality. There is also considerable variation between curves over each firing cycle (because of a variation in the injection point), therefore an average is more representative of the performance of the engine than any single trace. The first requirement for the use of synchronous averaging is absolutely met: The engine cycle is tied into the movement of the drive shaft – there is direct coupling between the engine volume and the crank angle. What this means in practice is that if the pressure–time curve takes on a certain shape at rotational speed ω then the pressure curve is squeezed by a factor of two (in time) when the speed is 2ω. The dependence on time is later removed by the synchronous averaging rescaling procedure.

Fig. 3 shows the effectiveness of the averaging procedure. The trace is significantly improved. However, it was found in this example that energy and work calculations from the graph were in error by several percent. This is a big problem when we are planning to adopt the same method to optimise the performance of the engine by tweaking the fuel mixture and injection time (or indeed for doing any scientific work). It emerges that the source of the error is that the second requirement for the effective use of synchronous averaging is not met: The rotation speed changes significantly within a engine cycle because of the impulse acceleration effect as each cylinder fires. In the Mirrless V12 engine, a cylinder fires every 60 degrees and disrupts the even motion of the shaft. The effect is never completely smoothed, regardless of the nature of the load or the size of the flywheel.

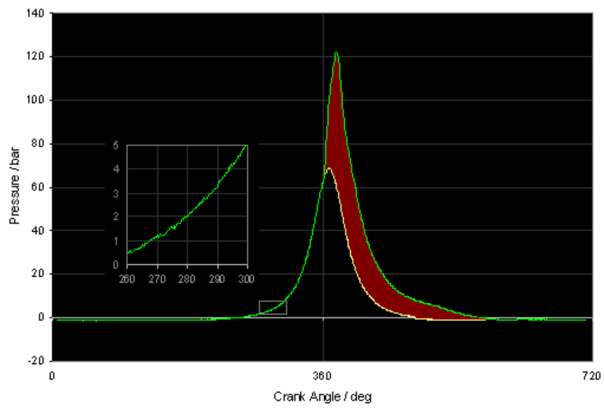

Figure 3 SNR improvement with 50 cycles of synchronous averaging. The red area is the difference between the pressure trace with and without fuel injection and is a measure of the work done (Cylinder 3, Engine 1, Stornoway Power Station, 2005).

This problem is completely resolved by extracting secondary angular information from a gear wheel on the shaft using an inductive sensor (or any toothed wheel, perhaps one used to manually turn the engine). This is digital re-sampling [2] and gives absolute angular reference points within the cycle and allows a profile of the angular acceleration to be obtained[1]. The modified procedure is extremely effective and gives plots that are consistent with calculations by other means of the work being done by the piston. This solution is now available on commercial diesel engine monitoring systems [5]. Using this system, it is possible to experiment with fuel mixtures whose dominant content is hydrogen to fine-tune the performance of large diesel engines following conversion.

Where the curve is very distinctive (as is the case here with only two turning points per engine cycle), one might ask if a TDC sensor is required at all; after all the angular information is technically already contained in the trace (though admittedly contaminated by noise). The pressure rise during the pressure stroke prior to ignition is a feature of the geometry of the cylinder and will be identical for each cycle. Only the shape of the curve around and after injection will vary. Can we lock onto a true angular reference point by data analysis alone and avoid having to fit a TDC sensor? This will then be the basis of a synchronous averaging process implemented in software. We can certainly define a threshold pressure that will be identified as the beginning of the cycle. The problem is that if the

[1] It is also possible to get absolutely accurate using an optical position sensor attached to the shaft. There are Gray Code or grating wheels that can generate 3600 pulse per cycle. However, connecting such a sensor arrangement to the system is technically difficult.

mean noise amplitude is ψ bar then there will be angular error around the threshold of $\delta\phi$, equivalent to trigger source jitter. This is given by

$$\delta\phi = \pm\psi \frac{\partial\phi}{\partial p}, \qquad (1)$$

where p is the pressure. The optimal trigger level is where the rate of pressure increase is greatest, and for many applications software triggering based on a noisy threshold is viable if one can accept the associated angular error. In the specific example of Fig. 2 and 3, the maximum pressure rise is 2 bar/deg and the noise amplitude is about 0.5 bar. The angular error represents a relatively variation of 1 degree in our estimate of the fuel injection point.

For precise work, more discriminating strategies are available - we might try to fit the expected shape of the curve from 10% to 30% of the peak pressure to the data and get a best fit. This is only possible if the shape of the compression curve is precisely known – it is a complex function of the dynamics and geometry of the engine

One very interesting alternative is to use a neural network to learn the shape of the portion of the curve up to the injection point. A backpropagation network using a small number of log-sigmoid neurons in the first layer will force the network to converge to the underlying shape of the curve and ignore the noise [6]. If too many layer 1 neurons are used, the network will over train and try to learn about the noise. This is undesirable. The structure of an appropriate network is shown in Fig. 4.

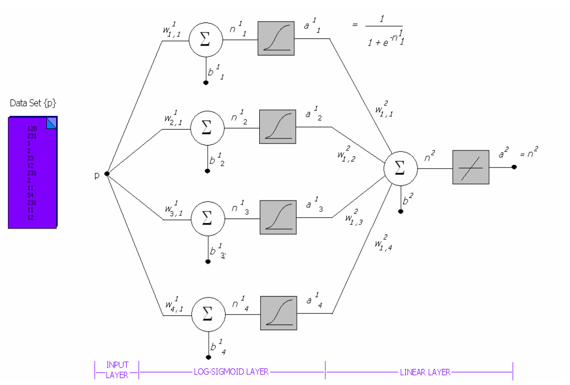

Figure 4 A neural network to learn the underlying structure of the indicator curve. The number of neurons in the Log-Sigmoid layer can be between 3 and 10.

Tests are being conducted using this procedure to accurately define a reference point by software analysis methods only and the results will be reported elsewhere. Although software triggering is possible, there is still the problem of speed variation over the cycle to be addressed.

2.2 Vibration Analysis of Wind Turbines

Vibration analysis of rotating machinery can detect wear or cracks in gear teeth, or problems with bearings. These problems are often brought on by rotor misalignment or a balancing problem, or just by normal wear [7]. In contrast to the previous section, the signal output from a vibration sensor is in general of low amplitude and very noisy – there is no characteristic 'shape' to the data. This is a real problem because the characteristic noise associated with a faulty bearing is very small, particularly if the bearing is large and slow moving. Synchronous averaging has proved an extremely effective noise-reduction technique for gear teeth problems allowing tiny spectral features to emerge following an FFT [8], but is only effective in special circumstances when diagnosing bearing (and drive belt) problems. This is because the rolling of bearings is generally not synchronised with the rotation frequency of the shaft. Problems with gears are strongly coupled with the rotation and scale with it. Moreover bearing problems do not necessarily scale because of slippage and resonance effects. A recommended approach when applying averaging to bearing problems is to convert each cycle to a normalised spectrum and perform a spectral average.

We have seen that changes in angular velocity over a cycle cause a problem when we are implementing synchronous averaging. The causes may be the firing acceleration of the cylinders of an engine or changes in the load on motorised systems. The wind turbine is no exception; it is vulnerable to rapid variations in speed because of the gusting nature of strong wind [9]. The effect might seem less problematic in larger turbines (2 – 3 MW), but not so. The larger blades turn slower and the duration between tachometer pulses is correspondingly longer. As in the previous section, it is necessary to use secondary pulses obtained from gear wheels to effectively implement synchronous averaging with wind turbines.

However wind turbine differs from most machinery in the range of speed variation in its normal modes of operation. Most machinery works at more-or-less the same speed or set of speeds, but the wind turbine is at the mercy of the elements. This need not be a disadvantage because it permits us to examine the operation of the system over a range of stresses and conditions, effectively adding a dynamical element to the monitoring process.

We can illustrate how this might work by considering the human heart as an analogy. The rate at which the heart beats can vary from 0.6-5 Hz but the action of the pump does not linearly scale – the speed of muscle contraction is largely constant as are recovery times. A characteristic electrical trace of the heart (the EKG or ECG) can be used to diagnose problems [10]. A typical trace is shown in Fig. 5 and is generally noisy because of the low amplitude of the signal picked up by sensors on the surface of the skin.

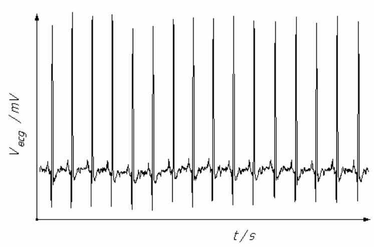

Figure 5 A typical trace from an ECG recording.

It is possible to perform synchronous averaging because the large peak can act as a trigger point for use by software (a described in Section 2.1), but to do so would merely distort the signal because the characteristic electrical activity does not conveniently scale. The solution is to monitor a subject over a long period. The quantity of data acquired is then large and it is feasible to group each trace in bins of single integer heartbeat rate. Averaging in each bin is now possible with little distortion. Following averaging, we can show all the clean traces as a waterfall diagram to reveal the dynamic features. Fig. 6 shows the output from a program developed to group, average and display ECG data.

The ECG example is an extreme case, but this method of grouping cycles may be applicable to all mechanical systems where there is a large and varied range of data available. A change in characteristic with speed can provide important information about the operation of the system. With wind turbines, where we are also awash with data, cycles can be grouped by speed in bins of width 1 to 10% (depending on memory). The cycles in each bin are averaged using synchronous averaging to give a characteristic trace for that speed. One can compare the averaged clean trace as it changes with speed to find speed dependent effects.

Why would this be important? It permits us to find resonances in the system, possibly associated with the bearings, and discern frequency-dependent effects that are destroyed by the indiscriminate application of synchronous averaging. It is proposed therefore that, the wide range of data available from wind turbines should be exploited to provide more information about the system to the diagnostic engineer. It is possible to improve SNR whilst retaining effects that do not scale with speed. This idea is currently being tested with medium-sized wind turbines.

Vibration information is best interpreted in the frequency domain and efforts have been made to create automated fault diagnosis systems from vibration analysis data using neural networks. A Self-Organising Feature Map has been used effectively to monitor large cranes [11]. Such systems could be applied to wind turbines monitoring.

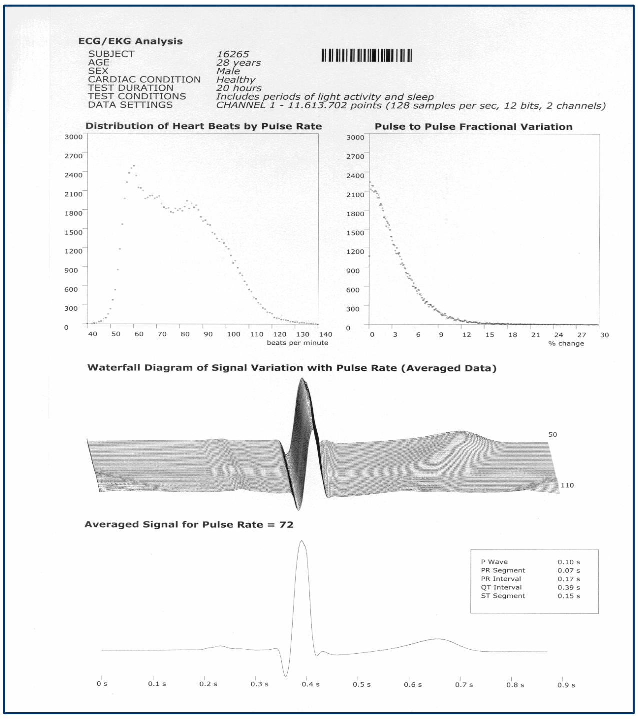

Figure 6 A graph of averaged binned ECG data showing the changing shape with pulse rate.

2.3 Energy from Waves

Waves and tides are two distinct sources of energy. Tidal power originates from the force of gravity but waves are generated by the action of wind on the surface of the oceans. Of the two, wave power is potentially a more promising source of renewable energy, not least because the characteristic frequency is around 0.3 – 0.05 Hz compared to the diurnal variation in the tides. Although water waves are longitudinal, the vertical motion is converted into a surge flow as the waves hit land.

Although there are very few operational devices, the energy can theoretically be extracted in a variety of ways. One technique is the oscillating column method [12]. The rise and fall of the water at the base of column partially submerged in the water acts as a piston compressing and decompressing enclosed air, the resulting pressure difference driving a turbine at the end of the column. In effect, wave power is converted back to wind power. This may seem inefficient is that only a small proportion of the energy available in the wave is utilised, but the energy is more controllable because of the air buffer – many previous attempts to utilize wave energy have failed because of the destructive power of waves under storm conditions [13].

The displacement of the surface can be described by a sum of sinusoids over a range of frequencies. The peaks are not therefore simply periodic but a particular wind speed produces a characteristic (and distinct) spectrum [14]. It is known that water waves are slow to develop and persist over great distances. Monitoring the water level and performing a Fourier Transform to extract the spectral detail can be used for prediction. Whilst there are advantages in merely monitoring the height and frequency of waves, for example to learn about the conditions at sea where they originated, or to maximise energy transfer by the resonant coupling of the air column with the driving force, our focus here is on the effective monitoring of the generators used to produce the power.

The oscillating column turbine is exposed to a quite different driving force to a standard wind turbine and this must influence the way it is monitored. The driving force is oscillatory with clear peaks and troughs and will be subject to different wear conditions and will be exhibit different failure modes. Whilst the noise associated with the rotating parts can be reduced as before by applying synchronous averaging using the tachometer pulse from the rotating shaft, it should be recognised that the this motion will not be synchronised with the driving force. If, in parallel, we also synchronise averaging with the driving force, we will detect the effect of the impulsive force on the blades and other parts of the system. It is therefore possible to synchronise with any available trigger to isolate factors from different sources. This technique becomes be especially useful if extended to wave energy generators in direct contact with the sea water where the forces are very much greater and potentially damaging. Although planned and predictive maintenance is very much more complex when we have no real control of the driving forces, monitoring in these situations is especially important.

3 Conclusion

With the urgent need for renewable sources of energy, we can expect dedicated machinery to proliferate. Although these machines are by no means novel or based on any new principle, they differ from the machines we routinely monitor. They have operational rather than functional characteristics that are sufficiently distinctive that we must modify the standard monitoring methods to making the monitoring of the renewable systems effective.

The fundamental distinction is that conventional machines are under our control; the power source of renewable energy generators is not. This is a fundamental difference that should be recognised in condition monitoring.

We have proposed that synchronous averaging is applicable to engines converted to run hydrogen, the monitoring of wing turbines and wave energy systems, in each case with modifications that both recognise the limitations of synchronous averaging and the salient and often distinct characteristics of the renewable energy systems.

Acknowledgments

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References

[1] Moubray, J., *Reliability-Centred Maintenance*, Butterworth-Heinemann, 1997

[2] McFadden, PD., Interpolation Techniques for Time Domain Averaging of Gear Vibration, *Mechanical Systems and Signal Processing* **3**(1), 1989, pp.87-97.

[3] Decker, HJ. & Zakrajsek, JJ., Comparison of Interpolation Methods as Applied to Time Synchronous Averaging, NASA TM-1999-209086, ARL-TR-1960, 1999

[4] Akihama, K., Takatori, Y., Inagaki, K., Saaaki, S., & Dean, AM., Mechanism of Smokeless Rich Diesel Combustion by Reducing Temperature, SAE World Congress (2001-01-0655), 2001

[5] Icon Research, Doctor DK Series Operating Manual, http://www.iconresearch.co.uk/, 2002, pp. 32-40.

[6] Hagan, MT., Demuth, HB., & Beale, M., *Neural Network Design*, PWS Publishing, 1996.

[7] Adams, ML., *Rotating Machinery Vibration: From Analysis to Troubleshooting*, CRC, 2000.

[8] Wowk, V., *Machinery Vibration: Measurement and Analysis*, McGraw-Hill, 1991.

[9] Park, J., *The Wind Power Book*, Prism Press, 1981.

[10] Houghton, AR. & Gray, D., *Making Sense of the ECG*, Hodder-Arnold, 2003.

[11] See http://www.neroresearch.fi/

[12] Dorrell, DG., Kazi, S., & Papadopoulos, M., Wave Generator Modelling using an Oscillating Water Column and a Wells Turbine, *Power and Energy Systems* 409, 2003.

[13] de O. Falcão, AF., First-Generation Wave Power Plants: Current Status and R&D Requirements, *Journal of Offshore Mechanics and Arctic Engineering* **126**(4), 2004, pp. 384-388

[14] Pierson Jr., WJ, Neumann, G., & James, RW., A Proposed Spectral Form for Fully Developed Seas based on the Similarity Theory of S.A. Kitaigorodskii, *Journal of Geophysical Research* **69**, 1964, pp. 5181-5191.