Sensor Measurement Strategies for Monitoring Offshore Wind and Wave Energy Devices

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Abstract

While the potential of offshore wind and wave energy devices is well established in terms of environmental impact, operations and maintenance issues are still not very well researched or understood. One of the important aspects in this regard is the lack of access to these devices since they are typically situated in high wind and wave conditions to generate more energy. Consequently, deployment of sensors for such devices is an important issue since they can measure the response of these devices in an as-deployed condition and assessments or intervention decisions may be made based on the fusion of data of such sensors and through the choice of intelligent markers or modelling. While scaled model testing of devices in ocean basin has gained popularity and wide acceptance over time, research in the direction of developing guidelines for sensor measurement or placement strategies are currently not in place. This paper addresses some specific aspects of sensor choice, measurement and placement. In this regard, the performances of the sensors are considered in terms of their receiver operating characteristics (ROC) and uncertainties related to measurements are addressed. The option of using multiple, cheaper sensors of seemingly inferior performance as opposed to the deployment of a small number of

expensive and accurate sensors is also explored. Practical aspects of testing are addressed in terms of exposure conditions and the performance of different sensors. Tests have been carried out in an ocean wave basin and the sensor placement for these tests has been used as a case study.

1 Introduction

Both offshore wind and wave energy technology has seen major advances in recent years. Wave energy in particular is growing in popularity (Falcão 2010; Mccullen et al. 2002). Operations and maintenance (O&M) costs are a highly relevant factor in the overall financial assessment of such projects, all the more so in offshore projects due to lower availability of the device (O'Connor et al. 2013). This has pushed the need for reliable structural monitoring systems for accurate and reliable information about the health of these energy conversion devices. With a move in recent times towards offshore energy solutions, loss in ease of accessibility may lead to damage going undetected, and the increased risk of catastrophic failure (Swartz et al. 2010).

There is clear financial benefit to optimizing time between inspections and scheduled maintenance work, which affects the uptime of systems while also coming with their own costs- an unscheduled maintenance event is five times more costly than one that is scheduled (Adams et al. 2011). However, high costs related to some sensing systems outweigh the benefits to O&M cost savings so the value of expensive sensing systems must be evaluated.

There are many forms of sensing systems, based on various technologies. Accelerometers have been successfully applied to identifying and locating the presence of structural damage in offshore structures (Mangal 2001), as well as motion cameras and load cells (V.JAKSIC; ref; ref) and Fiber Bragg

Grating (FBG) to measure strain. Cameras can even be employed in underwater situations to detect damage (O'Byrne et al. 2014) where marine growth exasperates fatigue damage. However, little is known of the relative merits of these technologies.

Wireless sensor networks (WSN) are a promising technology which have in recent years gained much attention from academia and industry alike. The application of WSN technology to structural health monitoring (SHM) has the potential to provide a substantial and quantifiable improvement to existing monitoring solutions for civil infrastructure (Boyle et al. 2011) .While wired SHM systems would require more maintenance and more frequent site visits as wires can be damaged over time, wireless SHM systems offer flexibility, even on difficult to access structures, and significantly reduced costs of installation and maintenance.

However, some of the existing wireless systems for SHM still have high power consumption. The high power consumption and the limited power budget make these systems unsuitable for long-term installation on a structure and requires frequent site visits for system maintenance.

WSN nodes are battery powered and because of their limited energy source they are not suitable for long-term structural health monitoring applications. With the focus on enhancing the life time of a wireless sensor node, a popular is by complementing an energy harvesting technique with an efficient energy management algorithm (Sharma et al. 2010). This approach has the potential to achieve self-sustainability of the node with harvesting energy from the environment and effectively managing the node activity (i.e. the sampling rate of the sensors) according to the energy levels and the dynamics of the phenomenon observed (Srbinovski et al. 2015unpublished)

2 Experimental Model

2.1 Model

A scaled Tension Leg Platform (TLP), a truss like structure with a hexagonal base, was tested in this study. This device consists of a gravity base connected by six mooring tethers to the Buoyancy Ring and the Upper Structure and the Tower and Nacelle, all as shown in fig 1.

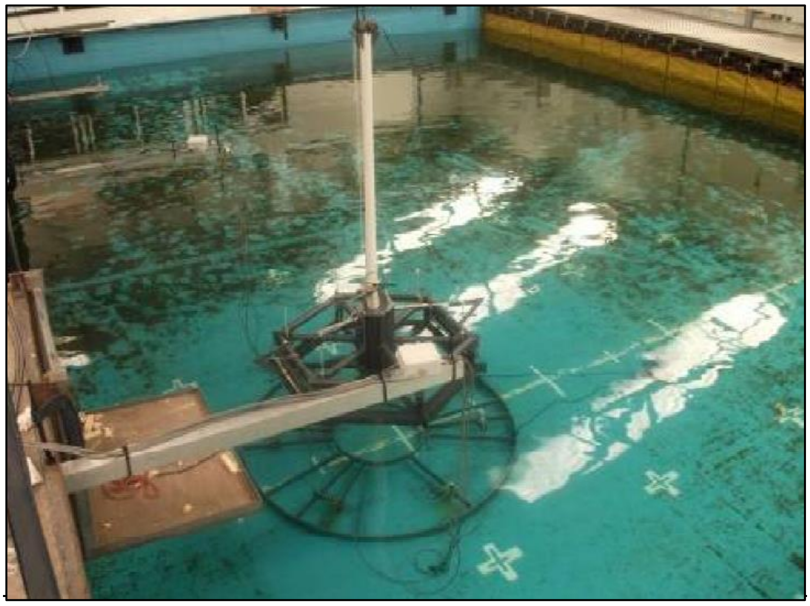


Figure 1 TLP Model

2.2 Instrumentation and Testing

The model was instrumented with 6 Tedea-Huntleigh stainless steel single ended bending beam load cells which were attached to the six mooring line cables and bolted to the gravity base. These measured the cable tension in Newtons (N). The instantaneous positions of 3 reflective markers, which were attached to the six corners of the hexagonal base, were monitored by 4 Qualisys 3-Series Oqus Marker Tracking Cameras with a sampling frequency of 32Hz. A Laser Doppler Vibrometer (LDV) was also employed during testing to record the velocity of the TLP. This high resolution technology samples at a rate of 480 Hz. Displacements and velocities were recoded in the wave direction, as this was considered the most critical plane.

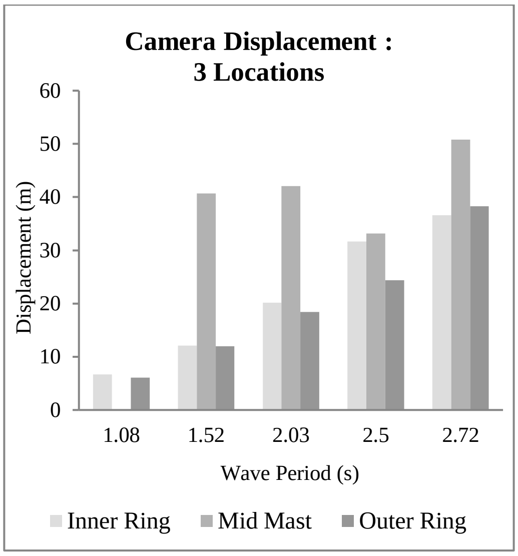
The model was tested at the Hydraulics and Maritime Research Centre (HMRC), University College Cork (UCC), Ireland in its Ocean Wave Basin. A variety of periods and wave amplitudes were used and the Bret Schneider wave spectrum was chosen, to best represent a true sea state.

3 Results

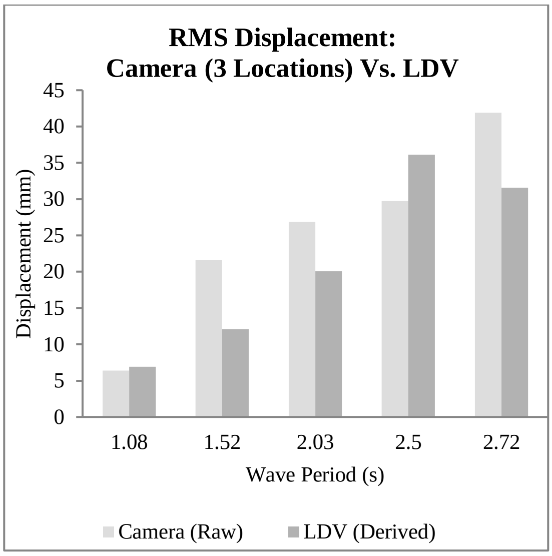
Displacement

The camera recorded the position of the TLP at 3 different locations; the Inner Ring, the Outer Ring and the Middle Mast. The velocity of the structure as recorded by the LDV was used to find displacement values.

Figure 2(a) shows the displacements recorded by the camera at the 3 tracked positions. Due to the far larger amplitude of displacement at the mid mast position, due to the flexible nature of the mast and its sensitivity, these readings were omitted from the average value shown in figure 2 (c), as they were viewed to be skewing the data (see figure 2 (b)).



2(a)



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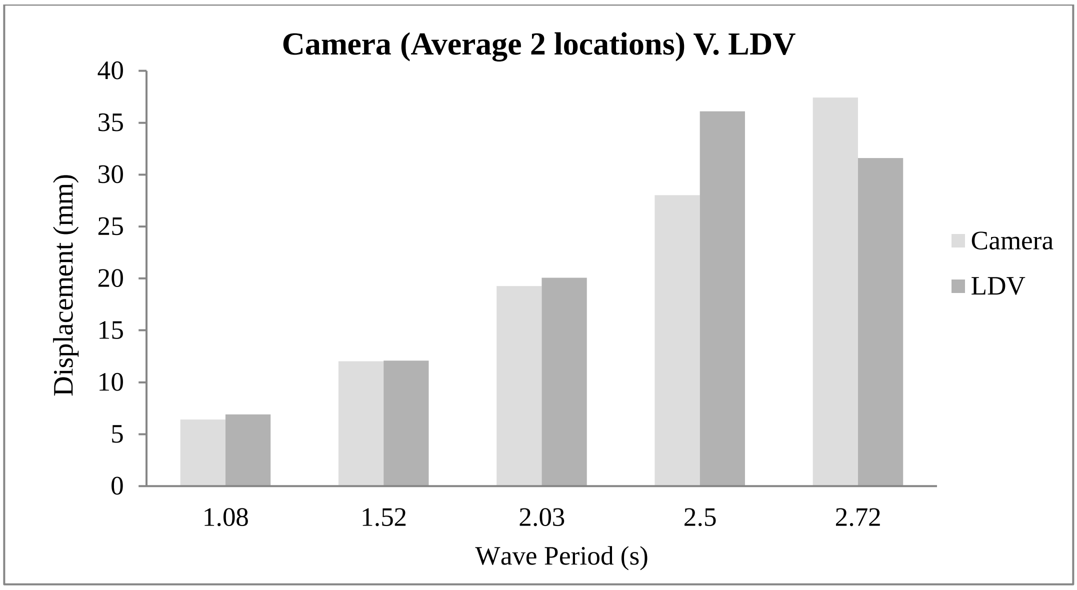

2(c)

Figure 2 Displacment

Velocity

The LDV records velocity, and the displacement data recoded by the camera is used to derive its velocity. In figure 3, the RMS values of velocity for each test are shown for both the motion camera and the LDV.

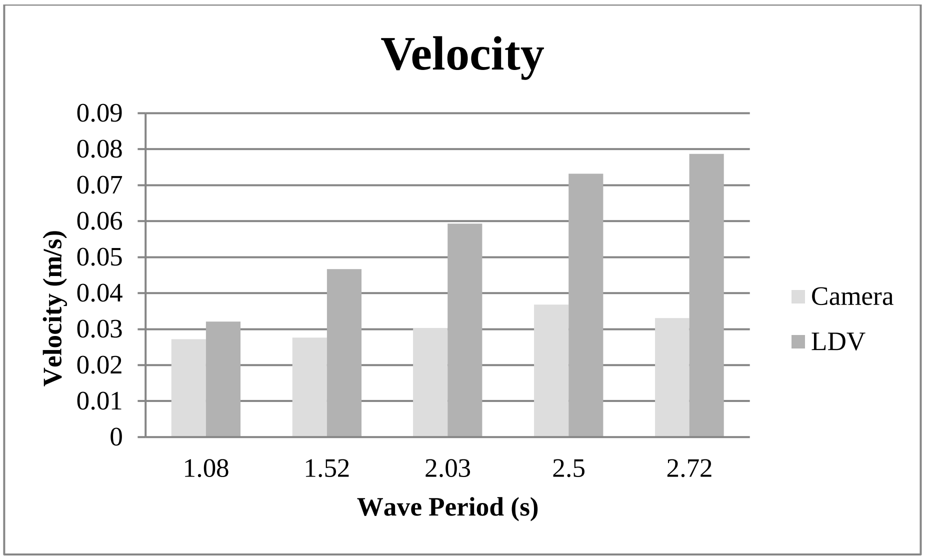

Figure 3 RMS Velocity of Camera and LDV data

Values recorded for the LDV are increasingly higher than those derived from the camera for each successive test of increased wave period. The camera's data here is inaccurate in that it doesn't increase proportionally with the increase wave loading.

Frequency

The displacement time series for the LDV and the motion camera were converted into the frequency domain with a Fourier Fast Transform (FFT). The dominant input to the series, the waves acting are the dominant frequency in this output, seen as the largest peaks (Figure 4).

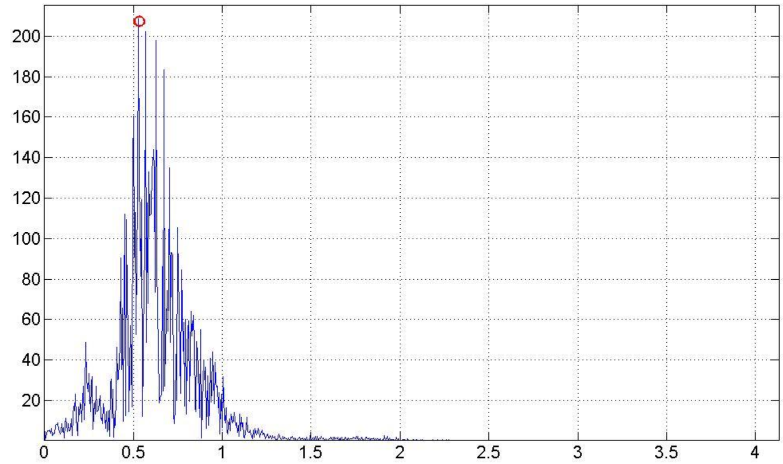

Figure 4 Fourier Fast Transform of Camera Displacement Time Series

By comparing analysis outputs to known inputs for two different technologies, we can compare the retained accuracy of each. In Figure 4, the response of frequency of the output for the two different instruement is compared to the known frequency of the wave input to the system. The peak frequency of the velocity output of the LDV is, on average, 18.7% lower than the wave frequency of each particular test. Whereas the peak frequency of the camera's displacement is an average of 31.9% higher than the same inputs.

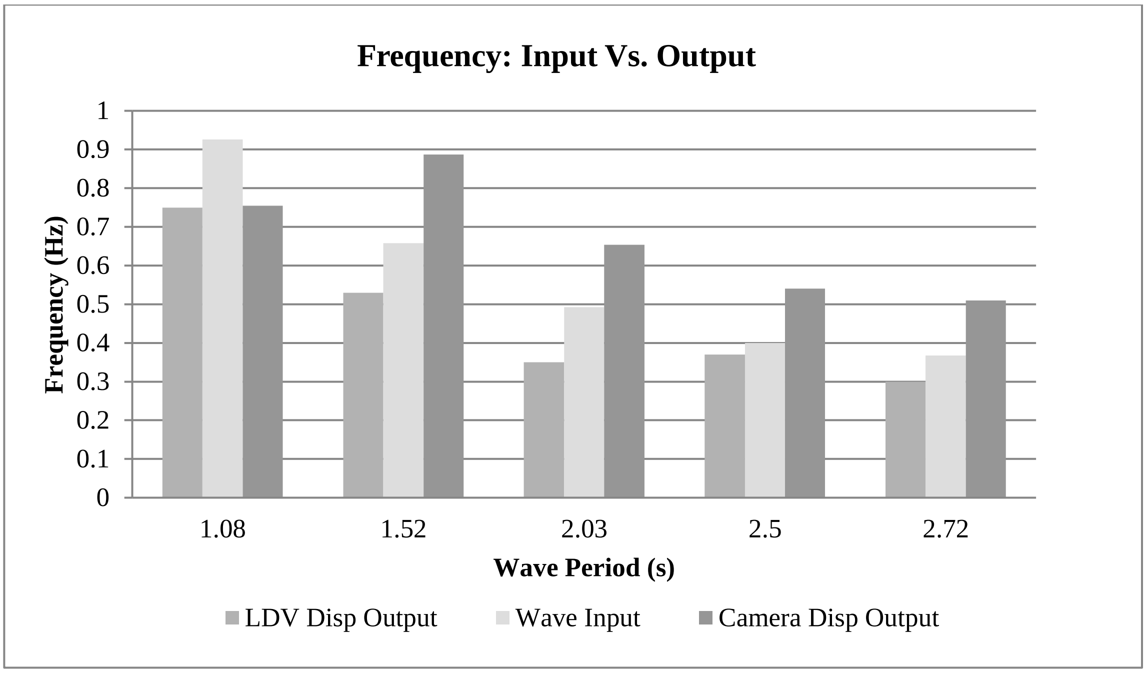

Figure 5 Frequency comparison of input wave to frequency of LDV and camera displacement outputs

The same comparison, but for the frequency of the LDV's velocity output yielding a difference of only 7%, on average, from the wave input.

Load Cells

Load cells were placed at Bow Port, Bow Starboard, Mid Starboard, Stern Starboard, Stern Port, Mid Port and were accordingly labelled White, Red, Yellow, Green, Brown and Blue.

The average Peak and RMS load values for each load cell for 20 different tests are represented in Figure 6. The highest loads are recorded in the direction of the wave, at the bow and at the stern of the structure. Analysis of the effect of removing different load cells to the overall data was carried out, a sample of which is shown in Figure 7.

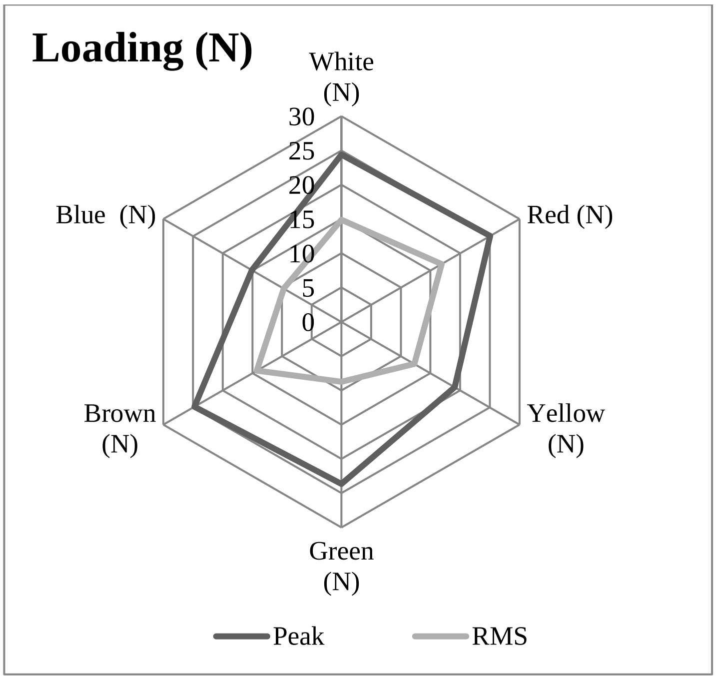

Figure 6

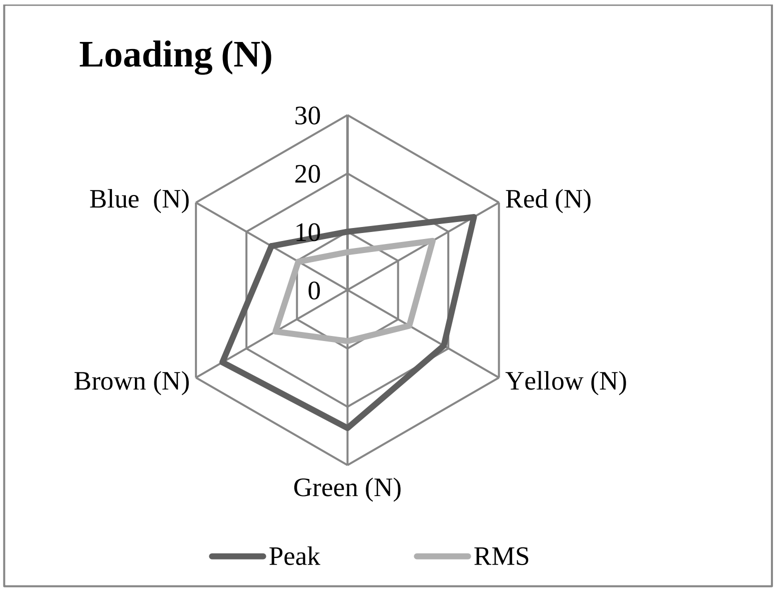

Figure 7

Data obtained from the white cell at Bow Port was removed, and the estimate shown for loading at this position shows a loss in accuracy of the loading on the structure.

4 Energy Aware Adaptive Sampling Algorithm for Energy Harvesting WSNs

The development of WSNs technology is hindered by their limited energy supply. In the case of SHM applications, sensors are extremely expensive with respect to energy requirements. It is desirable to develop protocols that effectively manage the sensor power consumption while still meeting the requirements of the application. Adaptive sampling algorithms (ASA) are often used as a tool to minimize the communication between the sensor nodes within the network and at the same time to minimize the power consumed by the sensors by reducing the sampling rate according to the needs of the phenomenon observed.

An ASA presented in (Alippi et al., 2010) was implemented in Matlab and evaluated using data collected with sensor for DISPLACEMENT as recorded by the motion cameras.

The algorithm used evaluates the maximum frequency of the signal using FFT and then decides the sampling frequency by multiplying the maximum frequency with a constant which is ≥2 satisfying the Nyquist criterion. A detailed description of the implemented algorithm with all relevant parameters explained can be found in (Alippi et al., 2010).

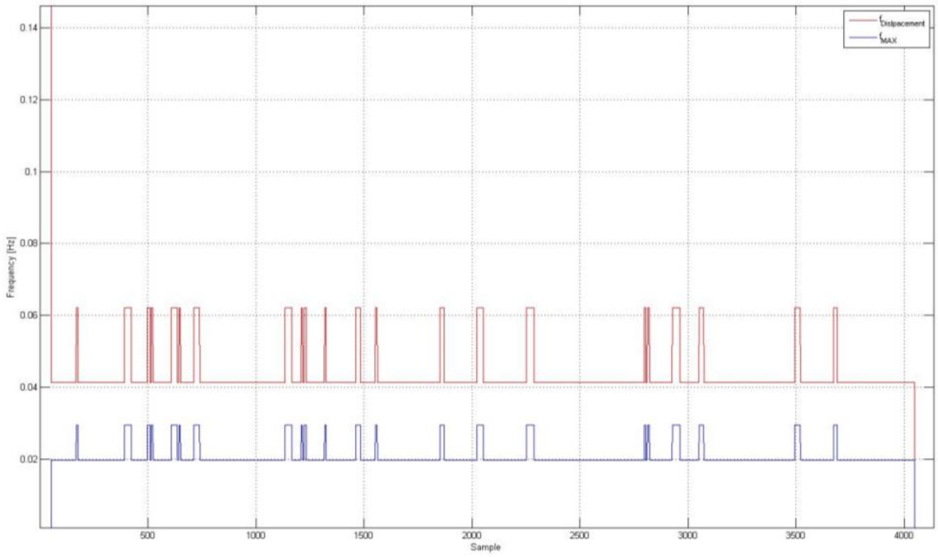

Figure 8 Matlab ASA Implementation of Camera Displacement Data

In figure 8, the sampling frequency according to the ASA and the maximum frequency of the signal are presented. The graph was generated by implementing ASA in Matlab with the following values for the relevant parameters: c = 2.1, h = 5, W = 50, δ = 0.1%. Details for each of these parameters are explicitly given in (Alippi et al., 2010). The time between successive frames was 0.3125, thus the starting sampling frequency was 32Hz. As shown in figure X, using the ASA reduces the number of acquired samples with respect to the traditional fixed sampling rate approach and hence saves energy.

9 Discussions and Conclusions

A comparison was made between high quality LDV data and lower quality motion camera data which recorded 3 different locations on the structure. It was initially thought that the multiple positions being tracked would increase accuracy, but due to physical characterists of the mid mast location, the extra data was misleading of the overall structure and reduced overall accuracy of results. Fewer, better placed markers which took into account physical set up of model would have been more effective. However, for the load cells, a higher number of locations monitored leads to a better understanding of the structure under wave loading.

Section 4 deals with the optimisation the number of acquired samples to save energy. In applications where a battery powered system is used to interface a power hungry sensor, reducing the sampling rate when possible will extend the life of the battery while still maintaining the application data requirements. Dynamically changing the sampling frequency according to the needs of the phenomenon under observation can also improve the data quality. Using fixed sampling rate can cause undersampling of the signal, hence introducing error in the measurement and difficulties in reconstructing the signal and this method helps to avoid this.

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