# Real-time monitoring of unmanned FOWT by using sensors and algorithms

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# Abstract

The current line-monitoring technology in deep water is based on battery-powered sensors and post-processing of sensor signals, in which real-time monitoring is not possible. Even when real-time multiple-sensor signals are available, the robust algorithms for the real-time monitoring of profile, stress, and fatigue are very rare. In this paper, three new technologies are presented, i) real-time inverse estimate of incoming incident random wave by using adaptive Kalman filter, ii) real-time estimate of line profiles and stresses by using multiple inclinometers and robust algorithm, iii) real-time estimate of line profiles and stresses by using multiple inclinometers and ANN-based machine-learning algorithm. The first two items have been developed by authors as briefly demonstrated in this paper and the development for the third item is in progress, for which the first and second items are essential. The corresponding big data necessary for training the developed machine-learning algorithm is generated by the reliable turbine-floater-mooring-powerline coupled dynamics simulation program developed by authors.

Keywords: line monitoring, floating wind turbines, sensors, digital twins, machine learning, inclinometers, inverse wave estimate, Kalman filter, turbine-floater-mooring-powerline coupled dynamics simulation

# 1. Introduction

Offshore Wind Energy is gradually becoming an important part in the energy mix in many countries. Compared to fixed offshore wind turbines, FOWTs (floating offshore wind turbines) have many attractive features. For instance, they are much less restricted by regulation and opposed by coastal residents. FOWTs have significantly higher-quality (stronger and steadier) wind and are less sensitive to space/size/noise/visual/foundation restrictions. They are to be safe against earthquakes and tsunamis. In this regard, there may be bigger potential market with FOWTs in the coming years. However, unmanned FOWTs are located far away from land and thus survey, monitoring, and maintenance may require high human effort/time, number of service vessels, and cost especially when wind farm consists of hundreds of units. Therefore, big saving in operation and maintenance is very crucial to lower LCoE (levelized cost of energy).

In this regard, its remote health monitoring capability by using various sensors is very crucial to maintain its functionality, structural robustness and reduce operational costs. Most underwater line tracking systems used so far are based on battery-powered sensors distributed along the entire line. It is difficult to get real-time sensor signals from them because expensive acoustic signal sender-receiver has to be used. Its continuous service is not possible because the battery needs to be replaced and the corresponding operation is technically very difficult and expensive. After the sensor is retrieved, it requires a lot of human effort and time for its post-processing. The monitoring by a visual camera is only superficial and limited by darkness and bad weather. Therefore, it would be very nice if we could develop a very efficient real-time monitoring technique and algorithms by using only essential sensors near free surface. Wind farms typically consist of numerous identical units. If an optimal smart monitoring system is developed for a single unit, then it can be repeatedly used for the whole units. Therefore, if we develop a smart monitoring scheme using minimum number of sensors, the overall cost saving will be huge.

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As mentioned in the above, the structural health monitoring of underwater components, such as mooring and power lines. are highly expensive and problematic. To solve this issue, we suggest in this paper a highly cost-effective real-time minimum-sensor monitoring system with ANN-based machine learning technique. To generate the corresponding big data for training, author-developed turbine-floater-mooring fully-coupled dynamic simulation program is used ([1]-[7]). Recently, several researchers (e.g. [8]) including authors ([9]-[11]) investigated the feasibility of that kind of monitoring based on machine-learning algorithms. The current state of the art shows that most of them utilized the machine-learning algorithm to estimate the variation of mooring top tensions from floater motions ([12], [13]).

The minimum requirement of the present system includes GPS sensor on the floater and inclinometers on the top portion of lines. Those signals are used to estimate the overall real-time profiles of the lines by using the trained algorithm. To train the developed machine-learning algorithms from a big data, a reliable FOWT simulation program is essential, for which the first author has developed a turbine-floatermooring fully coupled dynamic simulation program during the past decade. The inverse estimate of incoming waves can also be done by using the author-developed Kalman-filter method ([11]). Since authors have developed fully coupled dynamics simulations including floater, cables, and elastic beams, the similar digital-twin-based big data for training can be developed. The proposed research is innovative in that 1) incident wave is real-time predicted by PI-developed adaptive Kalman filter technology from motion sensor, 2) digital-twins technology with minimum sensors and machine learning, which results in minimal cost, 3) real-time estimation of accumulated fatigue of lines and beams.

# 2. Methodology, Numerical Results, & Discussions

## 2.1. Real-time Inverse wave estimation by using Adaptive Kalman filter

The real-time inverse estimation of the ocean wave spectrum and elevation from a vessel-motion sensor is of significant practical importance but is still in developing stage. The Kalman-filter method has the advantage of real-time estimation, cost reduction, and easy installation than other methods. In view of covering various sea states, reasonable estimation of high-frequency waves is important. However, if the vessel is less responsive for high-frequency waves, amplified noise may occur and cause overestimation problem there. Despite the inherent advantages of the Kalman filter, it has rarely been used for the inverse estimation of incident waves from motion sensors in the open literature. Authors recently developed a new method to obtain both real-time wave spectrum and elevation through an adaptive Kalman-filter algorithm. The developed methodology and algorithm are summarized in Fig. 1.

In particular, when vessel's motion RAO (response amplitude operator) is small in the high frequency region and there is sensor error, a problem of amplified noise occurs in the zone associated with the Kalman filter. A new solution to the problem was developed so that the small gain in the RAO increases by a certain amount by using Winer filter. Then, the overestimation of real-time wave spectra in the high-frequency region can be suppressed. The real-time incident wave profile can also be inversely estimated.

The vessel's motion transfer functions and numerically generated motion-sensor signals with artificial noise were used to validate the developed Kalman-filter processes. Using the modified TF (transfer function) through Wiener filter, the Kalman filter has been tested for various sea states and different vessel types. The test results were promising. Fig.2 illustrates the motion=sensor signals and the corresponding actual and inversely-estimated incoming wave profile in the case of a turret-moored FPSO (floating production storage offloading) platform [11]. The real-time predicted signal matches well against the actual incident (generated) random-wave profile. This real-time-inverse-wave-estimate capability is essential in the development of real-time mooring/powerline monitoring with minimum sensors, as explained in Sec. 2.3.



Fig.1. Wave elevation estimation process using Kalman filter



Fig. 2. Input heave motion & Estimated wave elevation using Modified TF (significant wave height Hs = 2 m, peak period Tp = 7 sec, frequency range.:  $0.1 \sim 2.0$  rad/s)

## 2.2. Real-time estimation of line profile, fatigue, and stress by multiple sensors

During the past decade, first author has developed the leading-edge FOWT-simulation computer program CHARM3D-WT, which solves fully-coupled dynamics among the floating platform, mooring system, and wind turbine including control in time domain ([1]-[7]). The CHARM3D-WT has extensively been compared and successfully verified against several experiments including DeepCWind and KRISO tests. The CHARM3D-WT has successfully been used for the design of smart structural health monitoring system for FOWTs by using numerical simulations and numerical sensors.

In this section, real-time evaluation of riser bending response using multiple inclinometers is briefly explained. Using basic beam FEM theory with high-order elements, the discretized bending moment distribution can be deduced from the sensor signals so that the real-time stress and fatigue monitoring is possible. The slope signals measured by the inclinometers are generated by the simulation program for a given random wave. Then, the bending moment and stress are evaluated along the line. The methodology can be summarized as follows.

Let us consider the Euler beam element with four boundary conditions, displacements and inclinations at both ends, assuming twisting is negligible, as shown in Fig. 3. A cubic interpolation function is used to approximate the displacements along the element, as shown in Eq. (1). Inclination along the line can then be obtained by the first derivative of the displacement function with respect to the generalized coordinate s.



#### Fig. 3. Beam element

Applying boundary conditions, as shown in Eq. (2), to Eq. (1), the coefficients in (1) can be computed. The result is given in Eq. (3).

$$v(s) = f(v_1, v_2, \theta_1, \theta_2, s) = a_0 + a_1 s + a_2 s^2 + a_3 s^3$$
(1)

$$v(s = s_1) = v_1, \quad v(s = s_2) = v_2, \quad \frac{dv}{ds_{s=s_1}} = \theta_1, \quad \frac{dv}{ds_{s=s_2}} = \theta_2$$
 (2)

Displacement equation can be arranged in matrix form, as shown in Eq. (4), where  $N_1N_2N_3N_4$  is called interpolation (shape) function, which expresses the displacement distribution in terms of nodal values as vector  $\{\xi\}$ :

$$v(s) = (1 - \frac{3s^2}{L^2} + \frac{2s^3}{L^3})v_1 + (s - \frac{2s^2}{L} + \frac{s^3}{L^2})\theta_1 + (\frac{3s^2}{L^2} - \frac{2s^3}{L^3})v_2 + (\frac{s^3}{L^2} - \frac{s^2}{L})\theta_2$$
(3)

$$v(s) = [\mathbf{N}_1 \mathbf{N}_2 \mathbf{N}_3 \mathbf{N}_4] \begin{cases} v_1 \\ \theta_1 \\ v_2 \\ \theta_2 \end{cases} = [\mathbf{N}] \{\xi\}$$
(4)

Once the beam-element displacements are determined, bending moment can be obtained by Eq. (5):

$$\sigma_s(s) = \frac{My_{\text{max}}}{I} = y_{\text{max}} E \frac{d^2[\mathbf{N}]}{ds^2} \{\xi\} = y_{\text{max}} E[(\frac{12s}{L^3} - \frac{6}{L^2})v_1 + (\frac{6s}{L^2} - \frac{4}{L})\theta_1 + (\frac{6}{L^2} - \frac{12s}{L^3})v_2 + (\frac{6s}{L^2} - \frac{2}{L})\theta_2]$$
(5)

where L is the inclinometer installation length interval. Combining Eqs. (5) and (3), bending moment can be calculated by Eq. (6):

$$\mathbf{M} = \mathbf{EI}[(\frac{12s}{L^3} - \frac{6}{L^2})v_1 + (\frac{6s}{L^2} - \frac{4}{L})\theta_1 + (\frac{6}{L^2} - \frac{12s}{L^3})v_2 + (\frac{6s}{L^2} - \frac{2}{L})\theta_2]$$
(6)

Bending moment at mid-point of element (s/L =0.5) can be calculated by substituting in Eq. (6), resulting in Eq. (7):

$$M = EI[\frac{1}{L}(\theta_2 - \theta_1)] \tag{7}$$

As shown in Eq.(7), the bending moment at element mid-point can be estimated without knowing displacements at end points. This means that the distribution of bending moment and stress can be found when multiple inclinometers are properly arranged along the line. The tension variation can also be obtained by using ANN-based machine-learning algorithms or by using tension meter at the top and best estimating the rest of points. With the real-time estimated bending stress and tension, the real-time cumulative fatigue monitoring is also possible.

Fig. 4 shows the real-time profiling of bending moments along the SLWR (steel lazy-wave riser) by using only a series of inclinometers. Fig. 5 shows the time histories of bending moments at a point. The real-time estimation by the above method matches well against the actual bending moment distribution. Here, we demonstrated that by using multiple inclinometers the real-time stress monitoring is possible. By using a parallel algorithm with quadratic interpolation function, it is also possible to recover the real-time shape of line. The use of inclinometers instead of accelerometers is beneficial in that the sensor noise effects can be minimal. In case of using accelerometers, sensor noises can be increasingly harmful when the signal is integrated twice to get the corresponding displacements.



Fig. 4. B.M. Comparison, SLWR, XZ plane, WD (water depth =100m), Irregular Wave (EX), snap shots at 5268s & 10321s



Fig. 5. Bending moment comparison time series at arclength=97.5m, 6000s~7000s, Irregular Wave (OP)

#### 2.3 Real-time estimation of line profile, fatigue, and stress by minimum sensors and machine learning

In the previous section, we explained that the real-time distribution of bending moment/stress along the line of any shape can be estimated by using multiple inclinometers along the line. When the water depth is large, getting the real-time signal from the deep portions of inclinometers can be problematic and challenging. We suggest a real-time minimum-sensor-based FOWT monitoring system with machine learning utilizing artificial neural network (ANN) algorithms. The minimum combination includes a GPS/motion sensor on the floater and inclinometers on the top portion of lines. Those signals are used to estimate the overall real-time profiles and stresses of the lines by using the ANN trained on big data. The big data are to be established by using TAMU simulation program CHARM3D-WT after being fully tuned against any available measured data. The simulation program can be repeatedly used to generate a big data necessary for the training of the developed machine-learning algorithm. The procedure can be summarized as in Fig. 6. When using this approach, the real-time inverse estimate of incoming wave, as described in Sec.2.1, plays an important role.

This approach is now in progress and some preliminary results will be published in the near future. The proposed research is innovative in that 1) incident wave is real-time predicted by PI-developed adaptive Kalman filter technology from motion sensor, 2) digital-twins technology with minimal number of sensors and machine learning, which results in minimal cost, 3) it is remotely operated i.e. smart real-time sensor- and target signals can be collected and monitored on land, 4) real-time estimation of accumulated fatigue of lines, towers, and blades, 5) no battery replacement and no human effort for post-processing.



Fig. 6. Mooring/power-line monitoring with numerical sensors using ANN method

# 3. Conclusions

The present state-of-the-art of line monitoring in deep water is i) install sensors along the line, ii) collect sensors when battery is gone and replace a new one, iii) do postprocessing with the collected sensor signals, in which real-time monitoring is not possible. On the other hand, the sensor signals can be transmitted to a surface platform by using acoustic-signal sender/receiver. They use such a high-cost method since it is hard to use electrical lines with sensors by numerous reasons. Even when real-time multiple-sensor signals are available, the robust algorithms for the real-time monitoring of profile, stress, and fatigue are very rare. In this regard, we presented three new technologies, i) real-time inverse estimate of incoming incident random wave by using adaptive Kalman filter, ii) real-time estimate of line profiles and stresses by using multiple inclinometers and robust algorithm, iii) real-time estimate of line profiles and stresses by using minimal number of inclinometers and ANN-based machine-learning algorithm. The first two were well developed by authors as briefly demonstrated in this paper and the third is in progress, for which i) and ii) are essential and their estimated values matched well against the actual values. For the machine learning algorithm, a big simulation data is necessary for training and that was generated by the reliable turbine-floater-mooring-powerline coupled dynamics simulation program developed by authors.

## **Conflict of Interest**

The authors declare no conflict of interest.

## **Author Contributions**

MooHyun Kim and Woo Chul Chung conducted the research; MooHyun Kim wrote the paper. All authors had approved the final version.

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