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Measurement Based Flow Speed Estimation for Tidal Turbine Control

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Abstract: This work aims to explore effective online torque estimation techniques for tidal turbine control under varying flow conditions. A modified Kalman filter with adaptive features is developed to estimate hydrodynamic torque from a tidal turbine's available measurements, based on which a modified Newton-Rapson method is employed to calculate the effective flow speed. The rotor speed reference signal required for tidal turbine control can be produced using the estimated torque and flow speed. The Kalman filter model is constructed using on a low frequency lumped parameter model of a horizontal-axis, fixed-pitch, two-bladed variable speed tidal turbine, established from a fully characterised model of a real turbine. The adaptive feature of the Kalman filter allows the tracking of the spatial-temporal variations of the effective flow speed caused by turbulence. Simulation studies are implemented to test the developed algorithm over the full envelope of the flow speeds.

Keywords: Torque estimation, flow speed estimation, tidal turbine control, Kalman filtering techniques, Newton-Rapson method, tidal turbine modelling, time-varying disturbance.

1. INTRODUCTION

Tidal energy systems are becoming a fast emerging technology in offshore renewable energy domain. In the evaluation of tidal power resources, the prediction of achievable energy at given sites is important. Sufficiently fast flowing currents are rare and tend to be concentrated in areas where the topography of the land causes the currents to be constrained or channelled, such as in straits, estuaries, in between islands or around the end of large headlands. Sites worth exploring should have mean spring peak speeds between 2 to 3m/s (Winter, 2011). One advantage of tidal flows is that speeds can be accurately predicted, since they occur at some point between the high and low tides and have the same periodicity as the vertical movement (Whitby and Ugalde-Loo, 2014). Extremely high flow speeds are statistically uncommon, requiring the use of hydrodynamic power limiting at values above the design flow speed.

Prediction of tidal flows over a region can be split into two categories: short–term prediction and long–term prediction. These two categories are also called operational and planning (Jahromi et al., 2011), respectively. Planning in the sense that the available power in a region is proportional to the cubic flow speed, thus accurate flow prediction leads to accurate resource characterisation. Long–term prediction algorithms used for planning are reviewed in (Jahromi et al., 2011), they are beyond the scope of this paper. Short-term tidal current speed prediction can be developed based on the recorded tidal current speeds data or using turbine operational data. For the purpose of this paper, short-term prediction using turbine operational data is called short-term estimation as the methods used do not have prediction capabilities.

Prediction using recorded tidal current data has been reported in a number of works (Jahromi et al., 2010; Kavousi-Fard, 2017b; Kavousi-fard, 2017; Yang et al., 2017; Qiao et al., 2020). Preferred models for this type of prediction include neural networks, fuzzy systems, support vector regression, auto-regression and auto-regression moving average models. The last two methods based on identification techniques are found to be less suitable for large datasets (Jahromi et al., 2010). For the other methods it was found that the prediction accuracy is mostly dependent on the optimisation design (Qiao et al., 2020) and is affected by the presence of uncertainty in the measurement data (Kavousi-Fard, 2017a). Hybrid models have been proposed to overcome these issues, for instance, local optimal solutions of neural networks can be avoided using genetic algorithms with global optimisation abilities, and progressing from deterministic prediction to probabilistic prediction, to account for prediction uncertainty, can improve neural networks' forecasting accuracy. In wind industry, similar hybrid models have been proposed as well as other simpler statistical techniques, e.g. using Kalman filtering for wind turbine control, and particularly, to compensate components' time lags a few seconds ahead, or for start/stop actions several minutes ahead (Bossanyi, 2000).

In the short-term current estimation, turbine operational data is commonly used to calculate hydrodynamic torque, either at the converter level or the rotor level. In both cases, the tidal current speed estimation can be taken as a

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by-product of the torque estimation. The control scheme is often called sensorless control when the estimator is implemented at the converter level.

Torque estimation for tidal turbines has been suggested in (Whitby and Ugalde-Loo, 2014) following experiences in wind turbines. In wind turbine estimators, the turbine dynamics models are used to build either a simple filter as presented in (Leithead and Connor, 2000), an observer as in (Cardenas-dobson et al., 1996), or a stochastic technique such as Kalman filter as used in (Bourlis and Bleijs, 2010). The controller-estimator interaction has been found to constrain the speed bandwidth, and consequently reduce the controller's tracking capability. Observers for tidal turbines have been implemented in (Jung et al., 2010) using a sliding mode observer, and in (Azelhak et al., 2021) using a Luenberger observer. Both estimators are designed off-line and implemented at the power converter level to estimate generator speed and hydrodynamic torque, respectively. The latter also uses a Newton-Rapson (NR) algorithm to estimate flow speed based on hydrodynamic torque estimations. The NR algorithm can be replaced by a look-up table to reduce computational complexity but at a cost of reduced accuracy. There are very few methods fully developed to achieve online torque estimation in the presence of flow disturbance.

In this work, we aim to tackle the online estimation problem for tidal turbine control by developing a modified Kalman filter, to estimate hydrodynamic torque, and a modified NR algorithm to calculate the flow speed. The modified Kalman filter should have the feature to accommodate the spatial-temporal variations of flow speed caused by turbulence, whereas the modified NR algorithm is meant to speed up the calculation of flow speed without compromising the accuracy. The estimates of hydrodynamic torque and flow speed are then used to determine the reference speed, for the tidal turbine's speed controller, across the whole operating envelope, i.e., below rated variable speed operation and above rated stall regulation.

The remaining part of the paper is organised as follows. In Section 2 a low order lumped parameter model of the turbine dynamics is presented, and the overall control scheme is given. The turbine control strategy is defined and its link with hydrodynamic torque estimation to improve the turbine operation efficiency is discussed. The proposed method to estimate both hydrodynamic torque and flow speed is presented in Section 3. Simulation studies and results, using time series data for a 100kW tidal turbine, are presented in Section 4. Finally, conclusions are drawn in Section 5.

2. TURBINE MODEL FOR ESTIMATION AND CONTROL

2.1 Tidal Turbine Model

The turbine to be controlled is a stall regulated variable speed tidal turbine from the H2020 project industrial partner. The turbine rotor comprises of two blades with bidirectional operation capability, and the drive-train has a direct drive permanent magnet synchronous generator (PMSG) configuration. With this configuration, rotor speed is equal to generator speed, which is the output of the turbine dynamics model.

For the purpose of model-based estimation, a well-suited linear model of the turbine is required with emphasis on low frequency dynamics. In this work, a linear tidal turbine model is developed following a similar work for wind turbine modelling (Leithead and Rogers, 1996) to accommodate the dynamics of the drive-train of a direct drive tidal turbine. The rotor can be interpreted as a single blade attached to the hub by a massless shaft, which is then attached rigidly to the generator. The approximated inertia of the hub is added to the generator.

The developed lumped parameter model is a multi-input single-output (MISO) model with two inputs, hydrodynamic torque, T_h, and generator torque, T_G, and one output, generator speed, Ω_G. During machine operation, the generator reaction torque and speed are two available measurements at the turbine drive. In this model, the generator reaction torque can be replaced by the demanded reaction torque, T_d, since the generator dynamics are sufficiently fast to make any difference insignificant, and to avoid high frequency noise from the drive train. Control is therefore attained with a speed feedback loop as shown in Fig. 1, where the system output is given by

$$y = \Omega_G - \Omega_{\text{ref}}. \tag{1}$$

Here Ω_{ref} is the reference speed.

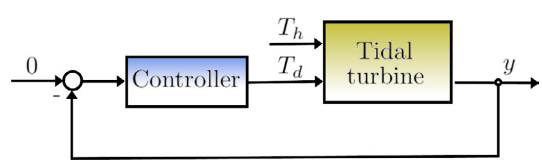

Fig. 1. Turbine speed control loop

Hydrodynamic torque measurements are not readily available but can be inferred from drive-train torque (mechanical torque) measurements for steady state conditions. However, under varying flow speed conditions, an estimate of hydrodynamic torque is required to track the turbine hydrodynamic efficiency over the full envelope. Hydrodynamic torque can be assumed to be slowly varying and the stochastic variation due to flow speed variation can be modelled as a random walk process as (Bourlis, 2011)

$$\dot{T}_h(t) = m(t), \tag{2}$$

where m is a white noise sequence with probability distribution $p(m) \sim N(0, Q)$, and Q is sufficiently large to provide freedom for the variation.

The following lumped parameter state-space model is established for the tidal turbine that includes three states, $x_1 = \theta_G$, $x_2 = \Omega_G$ and $x_3 = T_h$.

$$\begin{bmatrix}\dot{x}_1(t)\\ \dot{x}_2(t)\\ \dot{x}_3(t)\end{bmatrix} = \begin{bmatrix}0 & 1 & 0\\ -\gamma_1 & -(I_1+I_2) & 1\\ 0 & 0 & 0\end{bmatrix}\begin{bmatrix}x_1(t)\\ x_2(t)\\ x_3(t)\end{bmatrix} + \begin{bmatrix}0\\1\\0\end{bmatrix} T_d(t) + \begin{bmatrix}0\\0\\1\end{bmatrix} m(t) \tag{3}$$

$$\Omega_G(t) = [0\ 1\ 0]\begin{bmatrix}x_1(t)\\ x_2(t)\\ x_3(t)\end{bmatrix} \tag{4}$$

θ_G is the generator angular position. The lumped inertias I_1 and I_2 are the sum of all inertias in the drive-train reflected to the hub, that is, $I_1 + I_2 = J_R + J_H + J_G$, with the inertia of hub J_H, the generator inertia I_G and the rotor inertia J_R. The lumped damping is $\gamma_1 = B_R + B_S$, with B_S representing the losses from the shaft. The hydrodynamic damping B_R can be omitted since other sources of damping in the drive-train are generally much larger (Leithead and Rogers, 1996). Under these assumptions, the resulting lumped parameter model is time-invariant across the loci of equilibrium points, and only the changes in the hydrodynamic torque in response to changes in flow speed, at any equilibrium point, is time-varying.

2.2 Full Envelope Switching Control Scheme

Expressions for hydrodynamic torque, T_h, and flow speed, v, are given using Blade Element Momentum (BEM) theory as follows:

$$T_h = \frac{1}{2}\rho\pi R^5 \Omega_R^2 \cdot \frac{C_p(\lambda, \beta)}{\lambda^3}, \quad (5)$$

$$v = \frac{R\Omega_R}{\lambda}, \quad (6)$$

where ρ is the water density, $1,027 kg/m^3$, R is the rotor radius, Ω_R is the rotor speed and $C_p(\lambda)$ is the power coefficient, which is a function of the pitch angle, β, and the tip speed ratio, λ. In stall regulated turbines, the pitch angle is kept constant for above-rated operation, hence the power coefficient is only a function of tip speed ratio, $C_p(\lambda)$.

A suitable control strategy for the tidal turbine under study is described in Fig. 2, where the reference speed, across the whole operating envelope, is given by

$$\Omega_{\text{ref}}(t) = \begin{cases} \Omega_0 & ; T_{\text{loss}} \le T_h \le T_0 \\ \sqrt{\dfrac{T_h(t)}{K_{\text{opt}}}} & ; T_0 \le T_h \le T_1 \\ \Omega_1 & ; T_1 \le T_h \le T_{\text{rated}} \\ \dfrac{P_0}{T_h(t)} & ; T_{\text{rated}} \le T_h \le T_{\text{stall}} \end{cases} \quad (7)$$

Ω_0, Ω_1 are constant speed values, P_0 is the turbine rated power, and K_{opt} is an optimal gain given by (5) for tracking the maximum turbine efficiency, $C_T(\lambda_{\text{opt}})$. The four torques, T_0, T_1, T_{rated} and T_{stall} are labelled in Fig. 2. The stalling front is a hydrodynamic constraint imposed on the turbine design and splits the above rated operation in stall operation (right hand side of the stalling front) and deep stall operation (left hand side of the stalling front). The use of an additional controller during deep stall was suggested in Whitby (2013) since the turbine dynamics may change significantly in that operation region.

As seen in (7), the reference speed is a function of the hydrodynamic torque, which is unavailable at the turbine drive-train. Under steady state conditions, the shaft torque is similar to the hydrodynamic torque, however, with flow speed variations, the hydrodynamic torque is needed to improve the tracking performance. To estimate the hydrodynamic torque, we propose to use the simplified linear model developed in Section 2.1 together with the BEM equations for torque. The BEM equations are nonlinear, thus requiring a suitable algorithm for its solution.

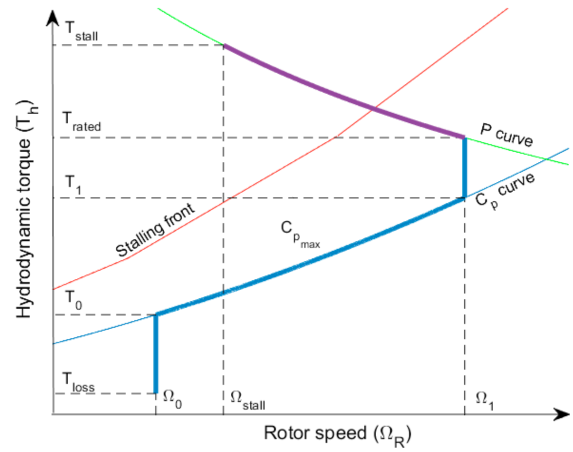

Fig. 2. Turbine control strategy in the torque/rotor speed plane

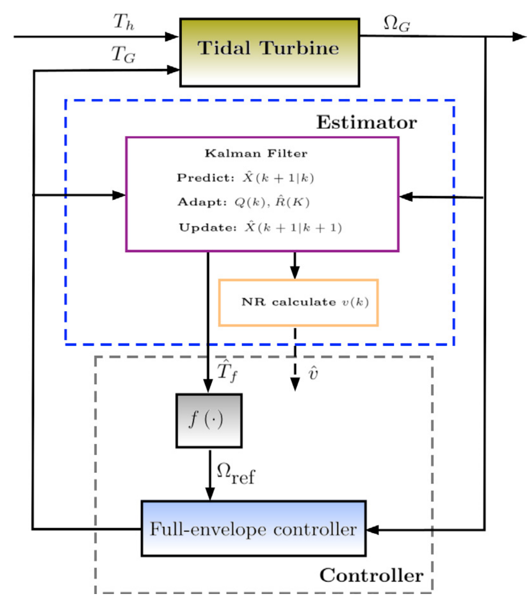

Fig. 3. Hydrodynamic torque and flow speed estimation using Kalman filter

3. ESTIMATION WITH MODIFIED KALMAN FILTER

3.1 Hydrodynamic Torque Estimation

A modified Kalman filter with adaptive features is developed to estimate hydrodynamic torque. The inputs are the generator speed and the generator torque, both are available at the drive-train. The formulation of the Kalman filter follows the work in (Bourlis, 2011) for wind turbine advanced control. The estimated hydrodynamic torque can be used to calculate flow speed using a Newton Rapson (NR) routine, and to generate reference operating points with high accuracy. The proposed estimation scheme is presented in Fig. 3.

The modified Kalman filter algorithm including predict, update and adapt, are given in the following.

(i) Predict

$$\hat{X}(k+1|k) = A\hat{X}(k|k) + BU(k) \quad (8)$$

$$\hat{P}(k+1|k) = A\hat{P}(k|k)A^T + Q(k) \quad (9)$$

(ii) Update

$$\hat{X}(k+1|k+1) = A\hat{X}(k+1|k) + K(k+1)r(k+1) \quad (10)$$

$$\hat{P}(k+1|k+1) = A(I - K(k+1)C)\hat{P}(k+1|k) \quad (11)$$

$$K(k+1) = \hat{P}(k+1|k)C^T S^{-1}(k+1) \quad (12)$$

where $\hat{X}(k+1|k)$ and $\hat{P}(k+1|k)$ are the a-priori state vector and estimation error covariance, respectively, and $\hat{X}(k+1|k+1)$, $\hat{P}(k+1|k+1)$ are the a-posteriori ones. During prediction, the estimated state vector, $\hat{X}(k|k)$ at time k, which is the mean of the true state vector, is dynamically projected forward to time $k+1$. The projected state vector, $\hat{X}(k+1|k)$, is then used to update the a-posteriori mean $\hat{X}(k+1|k+1)$. The Kalman gain $K(k+1)$ is used to correct the a-posteriori mean at time $k+1$. The correction is applied to the innovation sequence $r(k+1)$, which represents the estimation error between the measured output and its estimated value, i.e.,

$$r(k+1) = Z(k+1) - C\hat{X}(k+1|k). \quad (13)$$

The estimation error covariance is also dynamically projected and updated, but depends on $Q(k)$, which for tidal turbines, varies due to turbulence intensity, and may require a recursive correction.

(iii) Adapt

In (Bourlis, 2011), an innovation adaptation estimation method is used to provide adaptability to the Kalman filter for time-varying process noise. A non-recursive $Q(k)$ adaptation criterion, based on PI control, was found to be useful when the noise variance is also time-varying and needs to be adapted. The equations to provide adaptation to the Kalman filter are as follows.

$$Q(k) = Q(k-1) + (K_p + K_i T_s)e(k) - K_p e(k-1) \quad (14)$$

$$e(k) = trace\left\{C\hat{P}(k|k-1)C^T\right\} - trace\left\{C\tilde{P}(k|k-1)C^T\right\} \quad (15)$$

$$C\hat{P}(k|k-1)C^T = S(k) - \hat{R}(k) \quad (16)$$

$$C\tilde{P}(k|k-1)C^T = S_0(k) - \hat{R}(k) \quad (17)$$

$$S_0(k) = \frac{1}{N}\sum_{i=k-N}^{k} r_i r_i^T \quad (18)$$

$$\hat{R}(k+1) = \frac{1}{N-1}\sum_{i=k+1-N}^{k+1}(r_i - \tilde{r})(r_i - \tilde{r})^T \quad (19)$$

$$\tilde{r} = \frac{1}{N}\sum_{j=k-N}^{k} r_j \quad (20)$$

In the adapt scheme, the PI controller gains, K_p and K_i, are determined by testing the performance of the algorithm for the lowest and highest expected Q values. Variable $e(k)$ is the controller input error, $S(k)$ is the predicted innovation error covariance, and $S_0(k)$ is the innovations autocovariance computed from samples $r(k)$.

When the Kalman filter is optimum, the innovations are zero mean white noise, i.e. $S(k) = S_0(k)$, which is not the case for spatial-temporal flow speed variations. Furthermore, measurement noise variance $\hat{R}(k)$ is also time-varying and needs to be updated. The mean noise variance can be calculated from data measurements, however, variations due to model mismatch are expected since the simplified turbine model might omit unknown dominant modes. The adaptation of $\hat{R}(k)$ is achieved by keeping the consistency between the innovation error covariance and the innovations auto covariance, which makes the Kalman filter algorithm to converge. The adaptation of $\hat{R}(k+1)$ is given in (19) and (20) of the adapt scheme. The relationship between the estimated hydrodynamic torque and flow speed, through BEM equations, can be exploited to find a numerical solution for flow speed.

3.2 Effective Flow Speed Calculation

Flow speed can be determined numerically by solving the nonlinear hydrodynamic torque equation in (5), e.g., using the NR method, as presented in (Bourlis and Bleijs, 2010; Azelhak et al., 2021). The solution requires the $C_p - \lambda$ characteristics of the rotor be represented by a suitable polynomial that accurately approximates the power coefficient. In practice, the selected control strategy does not sweep the full $C_p - \lambda$ characteristics, thus the order of the polynomial can be reduced to provide accurate approximation only in the range of operation. A suitable polynomial approximation of the turbine power coefficient regarding the tip speed ratio is written as

$$C_p(\lambda) = \sum_{i=0}^{4} p_i \lambda^i \quad (21)$$

where p_i are polynomial coefficients.

Other approximations for the power coefficient can be found in (Carpintero-renteria et al., 2020). However the polynomial approximation from (21) simplifies the implementation of the NR algorithm. Additionally, the modified NR algorithm presented in (Abbasbandy, 2003) is used to reduce the number of iterations required to obtain the solution. The modified NR algorithm to solve (5), as $f(\lambda) = 0$, is given by

$$f(\lambda) = \frac{2\hat{T}_h}{\rho\pi R^5\Omega_R^2}\lambda^3 - C_p(\lambda) \quad (22)$$

$$\lambda_{n+1} = \lambda_n - \frac{f(\lambda_n)}{f'(\lambda_n)} - \frac{f^2(\lambda_n)f''(\lambda_n)}{2f'^3(\lambda_n)} - \frac{f^3(\lambda_n)f''^2(\lambda_n)}{2f'^5(\lambda_n)} \quad (23)$$

where $f'(\lambda_n)$ and $f''(\lambda_n)$ are the first and second derivative of $f(\lambda_n)$, since the modified NR algorithm uses a Taylor series expansion of the traditional NR method. The subscript n is the iteration number in the NR search progress. The numerical solution of (23) using the modified NR algorithm is valid for the range of tip speed ratio defined to obtained the polynomial approximation of the

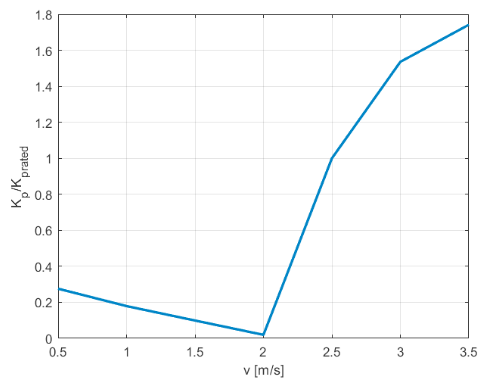

Fig. 4. PI controller gain-scheduled

$C_p - \lambda$ characteristics of the turbine. If no solution is found at any time step, the algorithm may return to the previously calculated value of tip speed ratio.

The flow speed can therefore be calculated by (6). The tip speed ratio initial condition is set up by $\lambda_0 = \frac{R\Omega_0}{v_{\text{rated}}}$, where v_{rated} is the rated flow speed for turbine operation.

4. SIMULATION RESULTS

The proposed lumped parameter model and the estimation process (modified Kalman filter and modified NR algorithm) are tested using simulation software DNV Tidal Bladed. The turbine is a two-blade stall regulated variable speed turbine. A PI controller is used to control the turbine's generator speed across the full envelope of flow speed from 1m/s to 3.5m/s. The controller gain is made to follow the variation of the partial derivative of the hydrodynamic torque with respect to the flow speed, to implement a gain-scheduled controller, as shown in Fig. 4.

Figures 5 to 9 are comparisons of the flow speed estimates against the simulated flow speeds at the hub height. Percentage of fit is common practice in tidal flow prediction and is calculated as in (Jahromi et al., 2010).

$$\%\text{FIT} = \left(1 - \frac{|v - \hat{v}|}{|v - \bar{v}|}\right) \times 100 \qquad (24)$$

where $\hat{v}$ is the estimated flow speed and $\bar{v}$ is the mean value of of the flow speed, v, obtained using Tidal Bladed.

Fit percentages and estimated flow speed mean values are presented in Table 1. The estimator performs well at flow speeds between $1.0m/s$ and $2.0m/s$. At higher flow speed values above $2.5m/s$, the fit percentage drops due to numerical instability. The NR method produces negative estimates at tip speed ratio values below 2.5 and fails to converge. The main cause of these unrealistic estimates may come from the stiff characteristic of the performance coefficient at that range of tip speed ratios. It is important to note that, the estimator is still tracking the variation in flow speed at $3m/s$. The spikes in flow speed estimates at 250s and 310s represent a sustained change in generator speed, however, the estimator continues to track after its transient response.

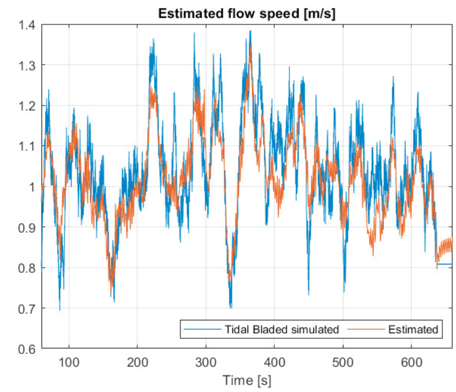

Fig. 5. Flow speed estimation at 1.0m/s

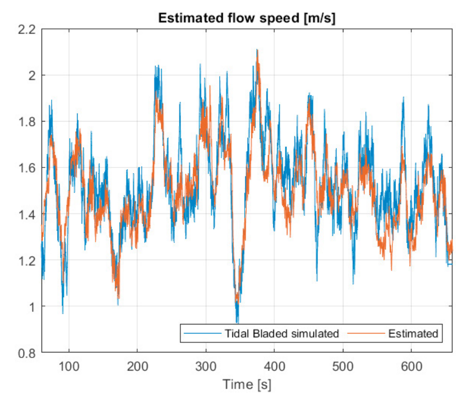

Fig. 6. Flow speed estimation at 1.5m/s

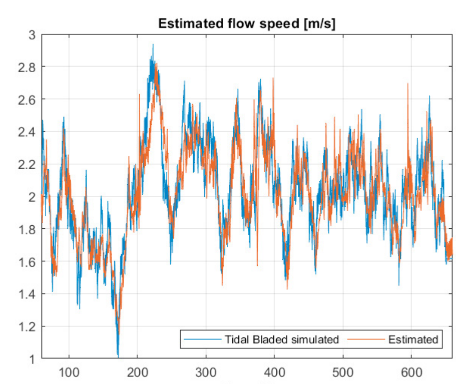

Fig. 7. Flow speed estimation at 2.0m/s

Table 1. Flow speed estimates fit percentage

$\bar{v}$ (m/s)	$\bar{\hat{v}}$ (m/s)	FIT (%)
1.0	1.0528	57.7348
1.5	1.5119	59.0974
2.0	2.0204	63.4374
2.5	2.5891	36.5828
3.0	2.9724	13.7391
3.5	3.0762	1.5403

5. CONCLUSIONS

In this paper, our recent work on tidal turbine estimator design is reported. A low order lumped parameter model of the direct drive permanent magnet tidal turbine has been developed to implement an adaptive Kalman filter.

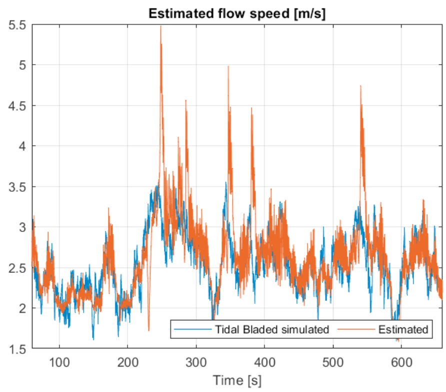

Fig. 8. Flow speed estimation at 2.5m/s

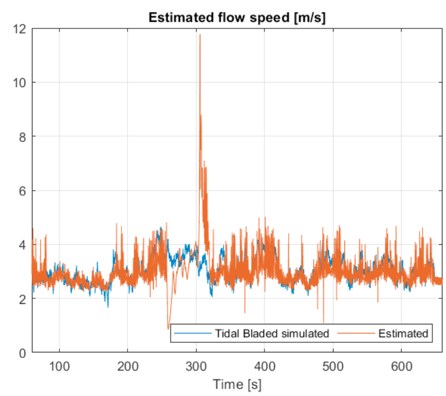

Fig. 9. Flow speed estimation at 3.0m/s

The model development is a novel contribution from the H2020 ELEMENT project. The adaptive Kalman filter is designed to estimate the hydrodynamic torque and the estimated hydrodynamic torque is then used to calculate the effective flow speed. The filter has an adaptive step that improves the estimation process of the spatial-temporal variations of the flow speed.

In simulation studies, it was found that the flow speed estimates are satisfactory for flow speed values between $1m/s$ and $2.0m/s$. Beyond these flow speed values, the estimator algorithm needs to be refined to overcome numerical instability that may come from the polynomial approximation of the power coefficient. The current estimator tuning will be explored for feedback control in a future paper.

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