ON THE MODELING ERRORS IN THE TIDAL POWER ASSESSMENT

Jean-François Filipot[1], Coline Delafosse[2], Thibault Marzin[2], Susana Baston[3]

[1]France Energies Marines, 15 rue Johannes Kepler, Brest France
E-mail : jean.francois.filipot@france-energies-marines.org

[2]DCNS, 415 rue Jurien de la Gravière, Brest, France,
E-mail : coline.delafosse@dcnsgroup.com,
thibault.marzin@dcnsgroup.com

[3] ICIT, Herriot-Watt University, Back Road, Stromness,
Orkney, KW16 3AW. E-mail :s.baston@hw.ac.uk

Abstract :

The present paper discusses the errors produced while estimating the tidal power with numerical circulation models. The study relies on the analysis of five model-data comparisons issued from the literature. As usually done in the tidal power assessment studies, statistics are first derived for the current velocities. The novelty of this work resides in the direct computation of power density statistics. The errors in the power density prediction are found to be significantly higher than for the current velocity, as expected since power density is a function of velocity cubed. This stresses the need to consider the uncertainties in the tidal energy estimation for the profitability assessment of potential tidal sites.

Keywords : Tidal power, numerical circulation models, ADCP, statistics

1. Introduction

Tidal power extraction profitability will drive the emergence of the tidal energy in the coming years. Therefore, accurate estimation of the tidal energy potential is required to spot the most favorable sites for tidal farm sitting. This has been addressed by a number of studies, from country-scale (e.g. Grabbe *et al.*, 2009) to site specific Pham & Martin (2009), Baston & Harris (2011) resource estimation. As the tidal power is proportional to the tidal current velocity cubed, the tidal resource is commonly estimated using measurements and/or model prediction of the current velocities (e.g. Carballo *et al.* 2009, Chen *et al.*, 2013). The measurements are generally taken as the ground truth and serve to calibrate the numerical models. Once tuned, these models are in turn assumed to provide a reliable spatial representation of the current field.
Although the calibration process aims at minimizing the model deviation from the observations, significant errors remain (e.g., Briere *et al.*, 2007, Carballo *et al.*, 2009) due to, for instance the spatial (horizontal and/or vertical) resolution of the computation grid, the inherent inaccuracy of the numerical schemes or the inability to represent some of the physical processes (e.g. 3D flow patterns).

Because the tidal power is linear function of the flow velocity cubed, one may intuitively infer that errors in the power estimation will be larger than those in the velocity estimation. Of course, the nonlinear relation between power and velocity prevents straightforward relations between their statistics. The purpose of the present paper is to go one step forward in comparison with the existing studies dealing with the tidal power assessment, that restrict themselves to the modeled velocities validation.

We shall here investigate the models accuracy in the power estimation through direct comparisons of observed and modeled tidal power time series. This study was motivated by the need to quantify the uncertainties in the tidal power assessment that in turn feeds the economic models used to estimate the site profitability.

The paper structure is as follows: first of all the metrics or statistical parameters used in this study are introduced, followed by the analysis of five different datasets and calculation of its power error statistics. Finally, the typical power errors and their implications to the financial assessment in this emergent sector of the ocean energy will be discussed.

2. Metrics

The typical model to data validation consists in a comparison of the model and data time series from which a range of statistics can be computed. We shall here employ the following metrics to compare N modeled to N observed data:

The root mean square error:

$$RMSE(X)=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{i,mod}-X_{i,obs})^2}, \tag{1}$$

The normalized root mean square error:

$$NRMSE(X)=\sqrt{\frac{\sum_{i=1}^{N}(X_{i,mod}-X_{i,obs})^2}{\sum_{i=1}^{N}X_{i,obs}^2}}, \tag{2}$$

the bias:

$$BIAS(X)=\frac{1}{N}\sum_{i=1}^{N}(X_{i,mod}-X_{i,obs}), \tag{3}$$

the normalized bias:

$$NBIAS(X)=\frac{\sum_{i=1}^{N}(X_{i,mod}-X_{i,obs})}{\sum_{i=1}^{N}X_{i,obs}}, \tag{4}$$

and the linear Pearson's correlation coefficient:

$$NCORR(X)=\frac{\sum_{i=1}^{N}(X_{i,mod}-\langle X_{i,obs}\rangle)\sum_{i=1}^{N}(X_{i,mod}-\langle X_{i,obs}\rangle)}{\sqrt{\sum_{i=1}^{N}(X_{i,mod}-\langle X_{i,obs}\rangle)^2\sum_{i=1}^{N}(X_{i,mod}-\langle X_{i,obs}\rangle)^2}}, \tag{5}$$

where <.> stands for the time average here. Other metrics exist to quantify model errors but we believe the above formulas provide enough information for our purpose. The use of normalized metrics will further help in the objective comparison of velocity data of different magnitude. High

NRMSE(X) values indicate large model-to-observation deviations. In the meantime, if the NBIAS(X) scores are large as well, this reveals systematic model over or under-predictions. In our study, the correlation CORR(X) may further provide information on the phase shifts between model and observation.

3. Model errors in the power prediction

3.1 Dataset

The literature provides a number of model-based tidal resource assessment papers and some of them propose a validation of the modeled current against field data (e.g. Carballo *et al.* (2009), Defne *et al.* (2011), Chen *et al.* (2013), Lalander *et al.* (2013) (see figure 1).

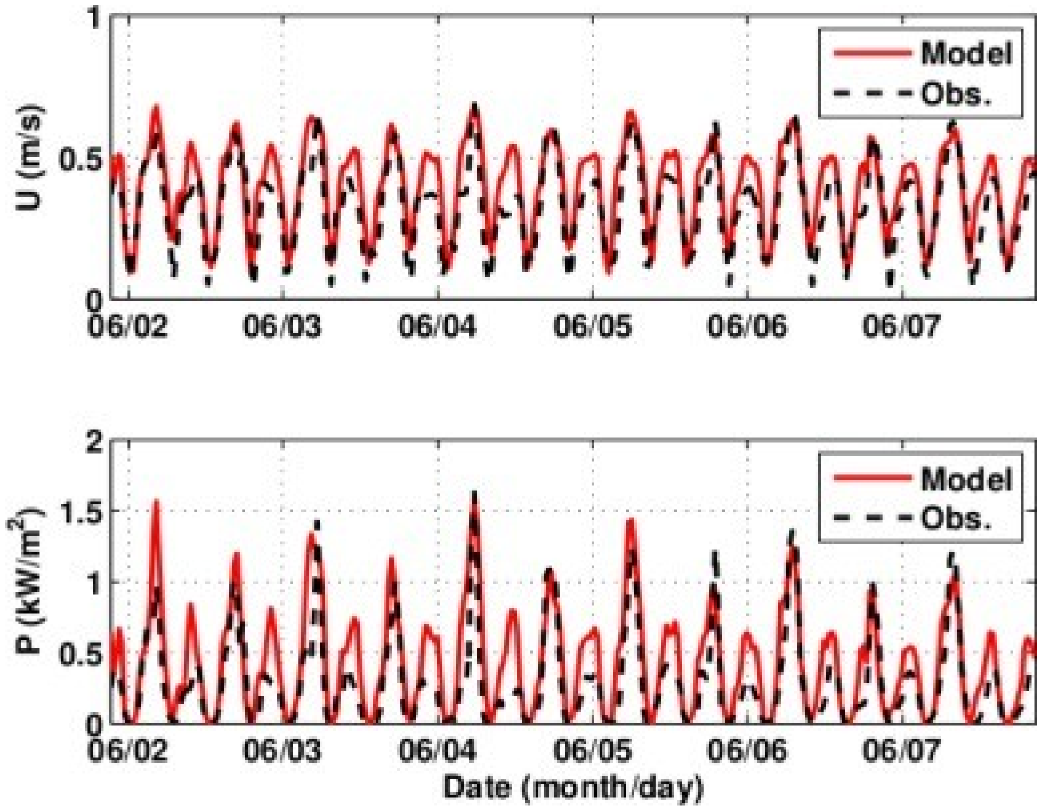

Figure 1: Top panel, modeled (red line) and measured (dashed black line) current magnitude, computed from the data presented in Lalander et al. (2013). Bottom Panel: modeled(red line) and measured (dashed black line) current power density computed from the current magnitudes given in the top figure.

However, though the relation between power and current velocity is fairly straightforward ($P \alpha U^3$), it is not linear and the power statistics can not be directly inferred from the velocity statistics. Modeled and measured power data are thus computed using five current velocity time series presented in Defne et al. (2011), Chen et al. (2013) and Lalander *et al.* (2013) (see table 1). These three papers were chosen as they provide model-data comparisons based on instrument measurements collected in close vicinity of potential farm sitting sites.

Case	Paper	Instrument	Model
Case 1	Lalander et al. (2011)	ADCP1	TELEMAC-2D
Case 2	Defne et al. (2013)	ADCP 1597	ROMS
Case 3	Defne et al. (2013)	ADCP 1693	ROMS
Case 4	Chen et al. (2013)	ADCP S1	SELFE
Case 5	Chen et al. (2013)	ADCP S2	SELFE

Table 1: Cases studied

3.2 Results

In the present study, the current magnitude and power density were computed from the data of the three studies cited above. The metrics presented in section 2 were derived from the model-data comparisons found in the literature (see Table 1), both for the current magnitude and power density and are reported in Table 2 and 3. They show significantly higher prediction errors for the power density than for the velocity. This trend is rather intuitive, considering the cubic relation between power and velocities. However an exact quantification of the errors in the tidal power prediction was not accessible from the current velocity statistics only, as the metrics are in general non linear operators.

Case	RMSE (m/s)	NRMSE (%)	BIAS (m/s)	NBIAS (%)	CORR (%)
Case 1	0.10	27.75	0.07	21.16	88.57
Case 2	0.22	32.42	-0.04	-7.14	71.79
Case 3	0.15	29.78	-0.01	-3.17	79.16
Case 4	0.13	26.93	-0.06	-14.49	73.97
Case 5	0.11	22.65	-0.04	-8.47	74.91

Table 2: Velocity magnitude statistics

Case	RMSE (kW/m^2)	NRMSE (%)	BIAS (kW/m^2)	NBIAS (%)	CORR (%)
Case 1	0.24	55.84	0.15	52.30	85.48
Case 2	2.03	72.60	-0.04	-2.07	56.29
Case 3	0.90	59.36	-0.03	-2.90	70.90
Case 4	0.38	46.44	-0.19	-28.49	73.97
Case 5	0.30	43.76	-0.11	-19.49	73.88

Table 3: Tidal power statistics

NRMSE scores are roughly twice as larger for the power density as for the velocity and the power density correlation is systematically weaker than that of the velocity. These results illustrate the large uncertainties underlying the tidal power assessment preceding tidal farms sitting. It is worth noting that high NRMSE values are not always associated with high BIAS (e.g. cases 2 and 3), meaning that a simple model tuning (e.g. by increasing the bottom friction) will not lead to straightforward improvements. For case 2, the high NRMSE combined with low BIAS and correlation CORR advocate for phase shifts between the model and observed signals. This may be attributed to to an insufficient number of tide constituents in the model forcings. Figure 2 gives further information on the error distribution as a function of the velocity magnitude. The NRMSE and NBIAS (in absolute value) typically decrease with increasing velocity magnitude. The bottom panel of Figure 2 also shows that the contribution of these "slack flow" (velocities less than 0.2m/s) errors do not contribute much to the mean error as they concern only a small subset of the data (typically less than 10 %).

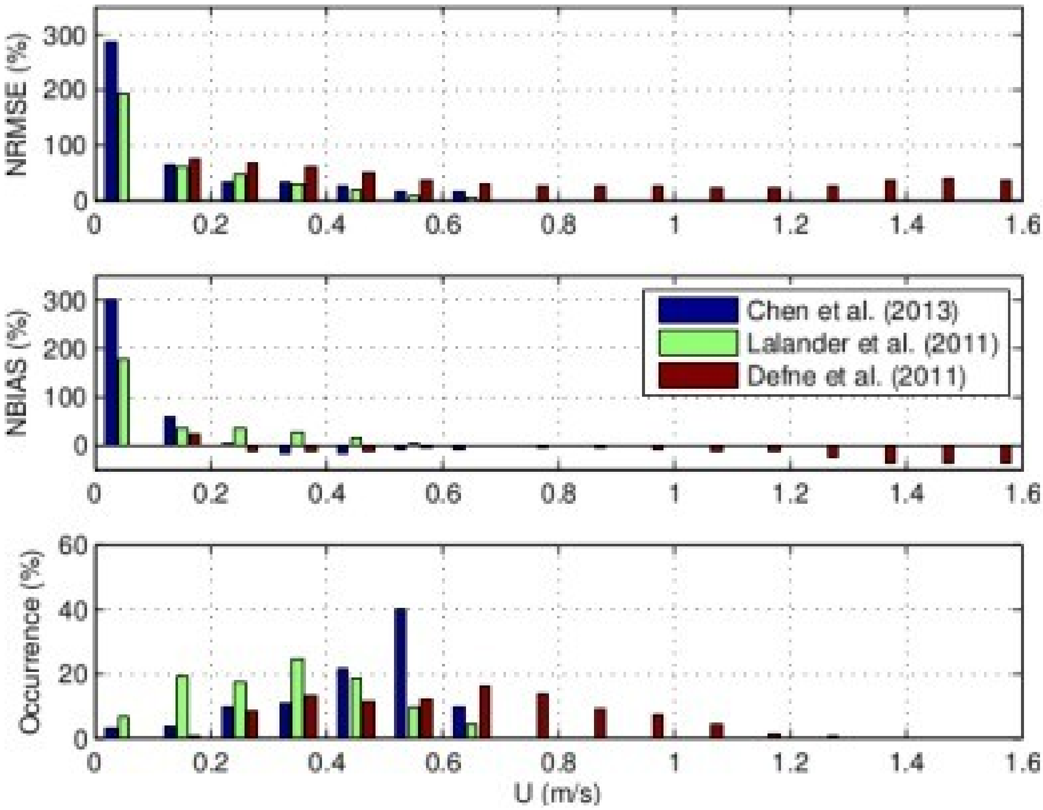

Figure 2: Top panel, NRMSE as function of current velocity. Middle panel, NBIAS as a function of current velocity. Bottom panel, probability of occurrence, in % as a function of current velocity. For the sake of clarity, the dataset are grouped by papers.

The same approach can be applied to the power estimation (figure 3). Qualitatively, similar conclusions can be drawn, the model scores typically improve with increasing power density values. The errors for the lowest power densities ($P < 1$ kw/m^2) are however dramatically high, reaching nearly 400 % for the NRMSE. At least two reasons can be advanced to explain the high model deviation at low power densities or velocities: first the models ability to simulated slack flows is questionable, second, the instrumental noise may cause larger (spurious) model deviation. The weight of these errors is besides significant when considering the probability of occurrence (Figure 3). These findings confirm that errors in the power estimation are much higher than for the velocities.

3. Conclusion

The results presented in this paper demonstrate that the tidal power assessment with state of the art datasets is subject to high statistical errors. NRMSE and NBIAS values exceeding respectively 70 % (case 2) and 50 % (case 1) were found in the course of the study. To our knowledge, such model to data tidal power comparisons has not been done before. Quantifying the error presented by numerical models on the tidal power estimation is an important achievement and we feel that this information can be useful in the context of tidal farm sitting, where slight variations in the estimated tidal power may greatly impact the potential profitability.

Further research will be conducted to:

- investigate the errors inherent to the measurements and the way they should be taken into account in the models accuracy assessment,
- provide similar statistics across the water column,
- explore other sources of observation for model validation.

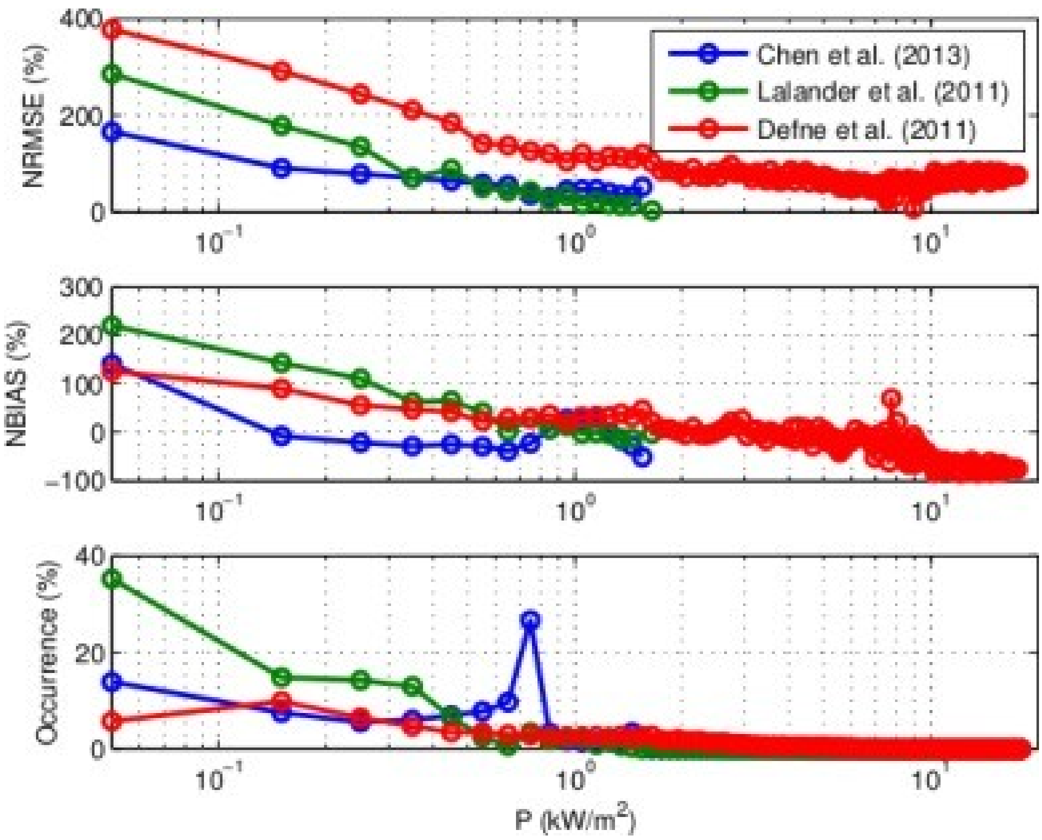

Figure 3: Top panel, NRMSE as a function of power density. Middle panel, NBIAS as a function of power density. Bottom panel, number of data, in % as a function of power density.

4. Acknowledgments

The authors are grateful to Dr. Zafer Defne for having kindly provided the data of his paper. We further thank, Dr. Youen Kervella who suggested to compute the scores as a function of the velocity or power magnitude. Marc Boeuf is acknowledged for the discussion that initiated this study.

5. References

Baston, S., Harris, R., 2011. Modelling the hydrodynamic characteristics of tidal flow in the pentland Perth. EWTEC 2011, Southampton, UK, 5-9 September 2011 .

Briere, C., Abadie, S., Bretel, P., Lang, P., 2007. Assessment of telemac system performances, a hydrodynamic case study of anglet, France. Coastal engineering 54, 345-356.

Carballo, R., Iglesias, G., Castro, A., 2009. Numerical model evaluation of tidal stream energy resources in the ria de muros (nw spain). Renewable Energy 34, 1517-1524.

Chen, W.B., Liu, W.C., Hsu, M.H., 2013. Modeling assessment of tidal current energy at kinmen island, taiwan. Renewable Energy 50, 1073-1082.

Defne, Z., Haas, K.A., Fritz, H.M., 2011. Gis based multi-criteria assessment of tidal stream power potential: A case study for georgia, USA. Renewable and Sustainable Energy Reviews 15, 2310-2321.

Grabbe, M., Lalander, E., Lundin, S., Leijon, M., 2009. A review of the tidal current energy resource in norway. Renewable and Sustainable Energy Reviews 13, 1898-1909.

Lalander, E., Thomassen, P., Leijon, M., 2013. Evaluation of a model for predicting the tidal velocity in fjord entrances. Energies 6, 2031-2051.

Pham, C.T., Martin, V.A., 2009. Tidal current turbine demonstration farm in paimpol-brehat (brittany): tidal characterisation and energy yield evaluation with telemac, in: Proceedings of the 8th European Wave and Tidal Energy Conference, Uppsala, Sweden, pp. 7-10.