Online-Algorithm using Adaptive Filters for Short-Term Wave Prediction and its Implementation

B. Fischer, P. Kracht, and S. Perez-Becker

Fraunhofer IWES,
Division Control Engineering and Energy Storages,
Koenigstor 59, 34119 Kassel, Germany
E-mail: {boris.fischer, peter.kracht, sebastian.perez-becker}@iwes.fraunhofer.de

Abstract

The control of wave energy converters can be significantly improved by taking into account the future incident wave elevation. For optimized energy yield it is, therefore, highly desirable to include wave prediction algorithms in the real-time control system. Recent research has shown that it is possible to predict up to one wave period with reasonable accuracy using rather simple autoregressive models, forecasting the wave elevation based on the past time series measured at the device itself. So far, the focus has been on the theoretical feasibility of short-term wave prediction. Comparably less publications deal with issues related to the real-time implementations of these prediction algorithms: causality, simplicity and robustness. In this study, adaptive filters are employed to estimate the future wave elevation. It is shown that they achieve about half a wave period with reasonable accuracy. Their real-time implementation is undemanding. Furthermore, their adaptability makes them robust to changing environmental conditions and only a minimum of supervisory control is required. The real-time feasibility is demonstrated by an example implementation on a programmable logic controller and measurement data from a wave rider buoy located in the North Sea.

Keywords: adaptive filter, wave energy converters, control, short term wave forecasting

1. Introduction

In order to make wave energy conversion commercially successful different control methods have been studied in recent years. Most of the proposed methods depend on the knowledge of the future wave elevation, whereas the required prediction horizon differs with respect to the specific method.

For example, in [1] the required horizon for the so-called complex-conjugate or reactive control [2] is given as ’well above 20s’. In [3] ‘some’ seconds ahead are asked for an ‘approximate optimum’ control. A fuzzy-logic based control is proposed in [4], whereas a prediction of 1 second in the future is passed to the controller. In [5] the potential control optimization for a turbine with movable guide vanes used in an oscillating water column device is described, requiring a prediction horizon in the range of approx. 0.5 to 1 seconds ahead.

At present, mainly two different options to predict the wave elevation are discussed.

The first one is the spatial prediction of the wave elevation based on measurements located some distance ahead of the device, see for example [6-8]. This method is reported to forecast quite long prediction horizons with high accuracy. In [7] promising results from tests in a wave tank have been gained looking at unidirectional waves, while in [8] a possible forecasting horizon above 1 minute is reported. On the other hand, this approach is likely to become very complex since effects like multidirectionality of waves, the presence of radiated and diffracted waves and nonlinearities in the wave propagation must be taken into account. Therefore, an array of sensors in front of the device is probably required [9].

A second approach is to predict the wave elevation using the past time series measured directly on (or with) the converter itself [4,9,10]. This approach is appealingly simple because there is no need for additional measurement devices. Some successful efforts have been made by Fusco and Ringwood in [9], where different prediction methodologies such as Kalman filters, artificial neural networks and linear autoregressive models are compared.

By using real measurement data they showed that the relatively simple linear, autoregressive models perform quite well. After filtering the data with zero-phase low-pass filters it was possible to predict up to 2 wave periods ahead. Between 0.5 and 1 wave periods could be predicted with reasonable accuracy in [1]. To the best of the authors' knowledge, no specific investigations have addressed aspects like the computational costs for on-line prediction or the adaption to time-varying sea states.

In our study, we focus on these real-time implementation aspects of wave prediction algorithms that are based on the past history of the wave elevation or another appropriate signal at the converter. That is, we consider causality, complexity and the robustness of the algorithms from an implementation point of view.

Linear, autoregressive models have been chosen because of their relative simplicity and the promising prediction results reported in the said references. The performance of different adaptive predictors based on these models has been investigated, using wave elevation time series from a wave rider buoy in the North Sea. These investigations showed that the continuously adapted versions perform slightly better than the predictors with once-in-a-while adaptation. Around 0.5 wave periods could be forecasted at this site with reasonable accuracy.

The continuous adaptation of predictors based on linear, autoregressive models leads to the notion of adaptive filters. As they are computationally undemanding they can be easily run on typical real-time control hardware. Additionally, they offer continuous adaptation to the changing sea states, thus solving the question of when to change their parameter sets and how to realise a bumpless transfer between these parameter sets.

A predictor has been implemented and tested on a programmable logic controller (PLC) to test its real-time performance, showing that wave forecasting based on adaptive filtering can easily be performed on state-of-the-art real-time control hardware.

The paper is organized as follows. Section 2 gives a description of the methodology, i.e. the autoregressive model, plug-in and direct predictors, and once-in-a-while vs. continuous adaptation. In Section 3 the wave data used for our study is briefly described. The prediction results in terms of prediction accuracy are discussed in Section 4. Based on these results, the continuously adapted, direct predictor is chosen for the implementation on the PLC, which is described in Section 5. In the conclusion the main results are discussed.

2. Prediction Methods

The prediction algorithms considered in this paper use linear combinations of past measurement samples to estimate future samples one or more steps ahead. Their theoretical background assumes that the signal $\eta(k)$ to be predicted can be modelled by a linear autoregressive model

$$\eta(k+1) = \sum_{i=0}^{N-1} a_i \cdot \eta(k-i), \qquad (1)$$

with the parameters a_i and the model order N, see [4,9, 10].

As for the control of wave energy converters it is desired to predict more than one step ahead, so called multi-step predictors have to be applied. Two categories of multi-step predictors are usually classified: “plug-in” and “direct” multi-step predictors.

Plug-in multi-step predictors are obtained by the successive application of a single-step predictor, where the predicted value of the subsequent single-step prediction is treated as a measured one in the following single-step prediction:

$$\begin{aligned}
\hat{\eta}(k+1|k) &= \sum_{i=0}^{N-1} a_i(k) \cdot \eta(k-i) \\
\hat{\eta}(k+2|k) &= a_0(k) \cdot \hat{\eta}(k+1|k) \\
&\quad + \sum_{i=1}^{N-1} a_i(k) \cdot \eta(k-i+1) \\
\hat{\eta}(k+3|k) &= \cdots,
\end{aligned}$$

where $\eta(k)$ is the measured sample at the k-th time step, $\hat{\eta}(k+L|k)$ is the predicted sample L steps ahead of the k-th time step. The model order N determines the number of real measured samples that are used for the prediction. The possibly time-varying coefficients $a_i(k)$ are determined by optimisation procedures discussed below.

Direct multi-step predictors directly predict the sample L steps ahead, using only the samples measured up to the current time step. They have a set of coefficients $a_{i,L}(k)$ that is optimised for this prediction horizon:

$$\hat{\eta}(k+L|k) = \sum_{i=0}^{N-1} a_{i,L}(k) \cdot \eta(k-i).$$

Note that in a strict theoretical sense the direct predictor is rather loosely related to the model in Eq. (1). However, it can be regarded as a generalisation of the plug-in predictor. The empirical tests carried out showed that the direct multi-step predictors have a slightly improved prediction performance when compared to the direct plug-in predictors.

Two different methods for determining the coefficients of both multi-step predictors have been investigated in this study: once-in-a-while and continuous adaptation.

For the first method a number of samples from the near past are used for an identification procedure. During this identification procedure, a least squares optimisation problem is solved:

$$\min_{a_i}\left(\hat{\eta}(k+1|k)-\eta(k+1)\right)^2 \qquad (2)$$

in case of the plug-in predictor, and

$$\min_{a_{i,L}}\left(\hat{\eta}(k+L|k)-\eta(k+L)\right)^2 \qquad (3)$$

in case of the direct predictor. Here, $\hat{\eta}(k+L|k)$ is the estimated wave elevation L steps ahead and $\eta(k+L)$ the actual (measured) wave elevation at that time. After the identification, the coefficients remain fixed while the actual prediction is performed. It is clear that the identification procedure has to be repeated after a certain period of time to account for the time-varying properties of the wave spectrum. Although these change rather slowly, several implementation issues have to be addressed. For example, it must be considered how and when this procedure has to be triggered and how a bumpless transfer between two sets of coefficients can be obtained.

The second method answers those questions by solving the optimisation problem recursively and updating the predictor coefficients smoothly every time step. Thus, the predictor implicitly adapts to the time-varying wave properties. There is no need for an additional supervisory control action.

For the realisation of the continuous adaptation we applied the recursive least squares algorithm (RLS), borrowed from adaptive filter theory [11]. In the terminology of digital signal processing, this is an adaptive FIR-filter (Finite Impulse Response filter).

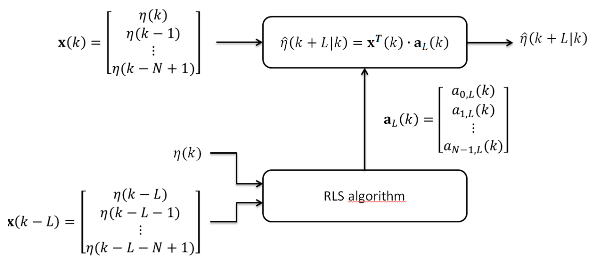

Fig. 1: Schematic of the direct predictor with continuous adaptation.

Fig. 1 exemplarily shows the direct version of the multi-step predictor with continuous adaptation. The current measured sample $\eta(k)$ and past measured samples from $\eta(k-L-N+1)$ to $\eta(k-L)$ are used to update the vector of the predictor coefficients $\mathbf{a}_L(k)$. Then, the actual prediction $\hat{\eta}(k+L|k)$, based on the last N samples, takes place. To predict a whole time-series consisting of more than a single sample (e.g. the time-series of the next 10 samples, or $L = 1, \ldots, 10$), a bank of these direct predictors has to be implemented, see Fig. 2.

Overall, we have investigated four different variants of predictors:

1. plug-in, once-in-a-while adaptation,
2. direct, once-in-a-while adaptation,
3. plug-in, continuous adaptation,
4. direct, continuous adaptation.

To this end, we applied real, measured wave elevation data from a wave rider buoy.

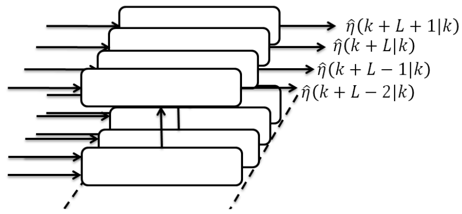

Fig. 2: A filter bank of direct, adaptive predictors is used for predicting a whole time series.

It should be noted that the cost function in Eq. (2) only accounts for the prediction performance one step ahead. In [9] the application of a more sophisticated cost function has been proposed for the optimisation of the plug-in predictor's coefficients. It takes several steps of prediction into account. The resulting prediction performance lies between that of a plug-in predictor optimised with Eq. (2) and that of a direct predictor using the cost function in Eq. (3).

3. Wave measurement data

The wave data utilized for this study was measured with a wave rider buoy located in the North Sea at approximately 54° 0.86´ N, 6° 35.03´ E (water depth around 30 m). The buoy was installed during the FINO project ([12]) and is operated by the German Federal Maritime and Hydrographic Agency (BSH). The data, which is free of charge for research purposes, consists of 30 min data sets, collected at a sampling frequency of 1.28 Hz. For this study data sets from a three month period were evaluated (October to December 2010).

A status flag is given in the data sets along with the wave elevation. This flag indicates if the current sample is valid, repaired or irreparable. For the study all data sets containing one or more data point not marked as correct were excluded from the evaluation, resulting in remaining data corresponding to 2140 hours. By calculating the significant wave height and the peak spectral period a first analysis of the data was carried out, showing that the data covers a broad range of sea states (Fig. 3), which can be considered a representative range of sea-states for the North Sea (see e.g. [13]).

4. Prediction results

Using these wave measurement data, comprehensive offline calculations have been carried out to compare the four different algorithms and to find appropriate model orders N. These calculations showed that the prediction performance of all four variants is similar, while the direct predictor with continuous adaptation slightly outperforms the other three variants. Therefore, we only present the results of the latter in this paper.

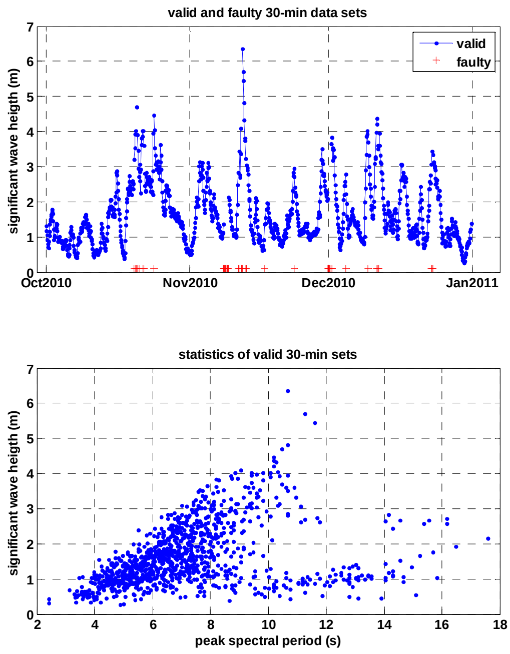

Fig. 3: 30-min measurement data sets. Top: Significant wave height during the whole measurement period. A red symbol indicates a corrupted data set. Bottom: Significant wave height and peak spectral period of all valid 30-min data sets.

It should be noted that for the comparison of the algorithms, the identification procedure of the once-in-a-while adaptation was triggered every 2 hours. The transient periods due to the adaptation of the predictor coefficients have been omitted for the evaluations.

The prediction accuracy is evaluated with the goodness-of-fit (GOF) criterion

$$GOF(L) = 1 - \sqrt{\frac{\sum_k \left(\eta(k+L) - \hat{\eta}(k+L|k)\right)^2}{\sum_k \eta^2(k)}}.$$

This criterion has also been used in [9].

Fig. 4 exemplifies how the GOF varies with the model order N for a 2 h sample measurement period. For this sea state and prediction horizon (H_s = 2.65 m and L = 3 samples, i.e. 2.34 s) the accuracy increases rapidly at low model orders and saturates at about N = 50. Although the saturation value changes depending on the sea state and the prediction horizon, see also Fig. 5 below, the model order at which the saturation occurs was found to be generic. Hence, we used N = 60 for further analysis and the real-time implementation.

Fig. 5 shows the GOF during the whole measurement period of 3 months for L = 3 samples in the upper diagram and for L = 8 samples in the lower diagram (2.34 s and 6.25 s, respectively). It can be seen that the prediction accuracy decreases as we increase the prediction horizon.

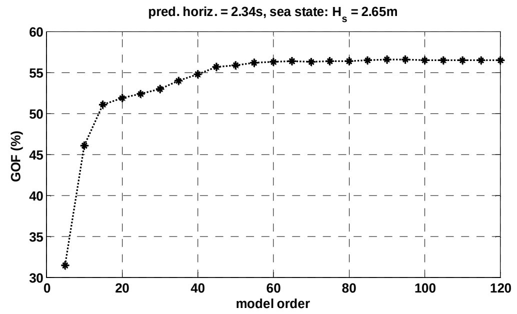

Fig. 4: Variation of GOF with the model order for a 2 h measurement sample with 2.65 m significant wave height. Prediction horizon: 3 samples, i.e. 2.34 s.

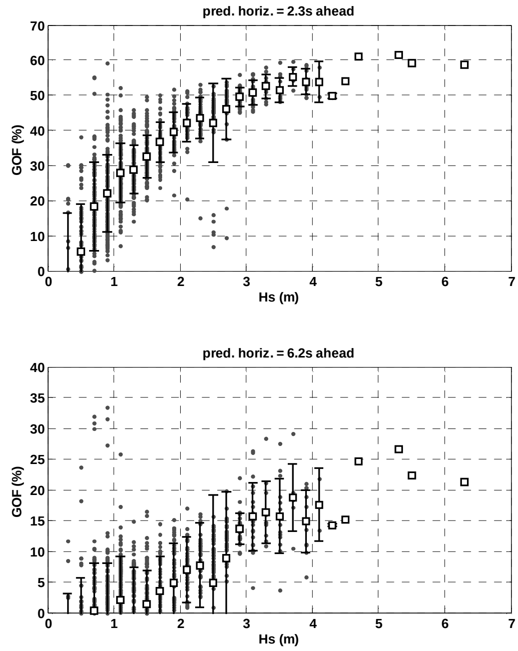

Fig. 5: Variation of GOF with respect to sea state and prediction horizon. A grey dot indicates the GOF of a 2 h measurement period, the squares are the mean values and the error bars are the standard deviation of each sea state bin. Model order: N = 60. Prediction horizon: 3 samples, i.e. 2.34 s, (top), 8 samples, i.e. 6.25 s, (bottom).

A grey dot indicates the result of a 2 h measurement period. These results have been sorted according to the significant wave height. An error bar is added to show the mean and the standard deviation in each sea state bin.

The figure also shows that the accuracy of the predictions becomes higher for increasing significant wave height. This is probably due to the fact that higher sea states have a narrower spectral band and a better signal to noise ratio.

Note that the predictor has been continuously applied to the whole measurement period without any supervisory control action. Where the status flag indicated corrupted measurement data, a zero wave elevation is passed to the input of the predictor. These measurement periods have been removed for the evaluation of the prediction accuracy in Fig. 5.

How accurate are these presented specific values of the GOF in terms of the control of wave energy converters? As it is pointed out in the introduction, the required prediction accuracy is heavily dependent on the particular control application. Fig. 6 gives a general idea of what a GOF of 20% or 50% means.

It shows measured and estimated time series at two different sea states. The two prediction horizons of the estimated time series are the same as in Fig. 5. In the upper diagram, where $H_s = 4.01$ m, the GOF of the 2.3s-ahead prediction is 56.9%, and that of the 6.2s-ahead prediction is 19.7%. In the lower diagram, where $H_s = 2.34$ m, the GOF of the 2.3s-ahead prediction is 51.6%, and that of the 6.2s-ahead prediction is 19.0%.

The visual inspection of the 2.3s-ahead prediction (GOF >50%) reveals that almost all extreme values are captured with only slightly lower amplitude and the zero-crossings coincide very well with those of the measurement.

The 6.2s-ahead prediction (GOF 19%), which is about half a wave period, predicts amplitudes that are clearly smaller than the measured ones. However, the instants of the extreme values and zero-crossings are estimated almost as accurate as for the smaller prediction horizon.

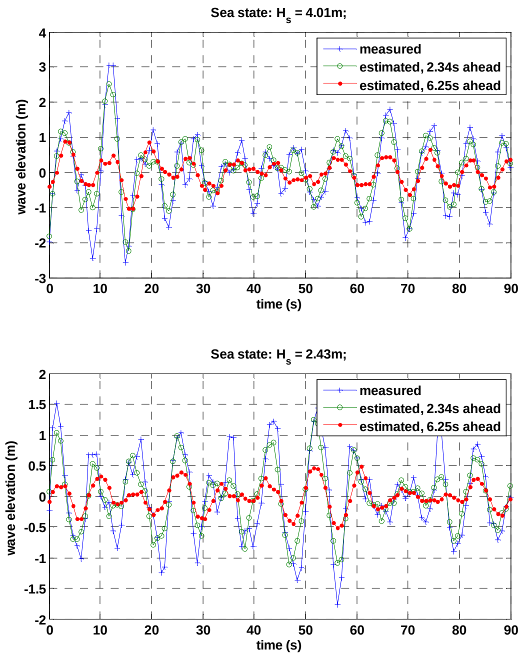

Fig. 6: Example time series of measured and predicted wave elevation. Sea states with 4.01 m (top) and 2.43 m (bottom) significant wave height. In both cases, the GOF of the 2.34s-ahead prediction is >50%, and the GOF of the 6.25s-ahead prediction is about 19%. Model order: $N = 60$.

Finally, it has to be pointed out that the measurement data of the wave rider buoy has been directly passed to the predictor without any non-causal low pass filtering. This has been done e.g. in [1] to account for the low pass effect of an oscillating device. Low pass filtering can further increase the prediction accuracy by a great amount, as this reduces measurement noise and removes high frequency content in case of wide banded sea states.

5. Real-time implementation

The tests on real-time control hardware aimed at evaluating the feasibility of the methods under real-time conditions. Following the results of the offline evaluation of the different prediction methods the direct predictor with continuous adaptation was chosen for these tests.

A Beckhoff CX1030 programmable logic controller (PLC) was chosen from the large number of available off-the-shelf real-time controllers. It has already been used on a wave energy converter under real sea conditions [5]. The core of the PLC is an Intel Pentium© processor clocked at 1.8 MHz. The software development environment supports different programming languages – including Structured Text, which is quite similar to high-level languages like C – and the execution cycle time t_c of the PLC-program can be set to multiples of 50 µs.

Using Structured Text, the direct predictor with continuous adaptation was implemented and tested in real time on the PLC, using the following configuration:

- 7.81 s-ahead prediction (10 separate filters),
- Filter order N = 60,
- PLC execution cycle time $t_c = 0.78125$ s (1.28 Hz).

In order to simulate the application of the wave prediction as realistic as possible, a second PLC, representing the wave rider buoy or a sensor on a wave energy converter, was used to transfer the samples of the wave data time series step-by-step to the first PLC on which the prediction algorithms were run. The results of the online predictions were verified by a comparison with the offline results, showing exact compliance except minor deviations due to numerical effects.

During the online tests an evaluation of the calculation time required for both prediction of the future wave elevation and adaptation of the predictor coefficients was carried out. The required calculation time for the entire set of 10 separate adaptive filters sums up to around 1.2 ms, which is less than 1% of the PLC cycle time. Even though the control of a wave energy converter will require shorter cycle times and a higher prediction horizon might be necessary, this result indicates that adaptive filters are a fairly feasible method for online wave prediction.

6. Conclusion

This study is focussed on the real-time aspects of short-term wave forecasting based on linear auto-regressive models. Adaptive filters were proposed as a computationally undemanding prediction method, which additionally offer continuous adaptation to changing sea states.

Concerning prediction accuracy, continuously adapted predictors slightly outperform their equivalents with once-in-a-while adaptation on a comprehensive set of wave data from a wave rider buoy located in the North Sea. The algorithm is able to predict up to half a wave period in the future with reasonable accuracy. It shall be pointed out that the measurement data of the wave rider buoy was directly passed to the predictor without any non-causal low pass filtering. If the low pass effect of an oscillating device is taken into account, the achievable prediction horizon is very likely to be increased, e.g. when the predicted quantity is the wave excitation force on a point absorber type wave energy converter.

Testing of the adaptive filters under real-time conditions showed that online prediction and coefficient adaptation can easily be performed on a standard state-of-the-art control hardware, leaving more than enough processor resource for feedback and operational control tasks.

Acknowledgements

The authors thank the BSH for providing the real sea data from the wave rider buoy installed for the FINO project. The FINO project is funded on the base of an act of the German Parliament by Federal Ministry for Environment, Nature Conservation and Nuclear Safety.

Just as much, the authors gratefully acknowledge the financial support from the Danish Council for Strategic Research under the Programme Commission on Sustainable Energy and Environment (Contract 09-067257, Structural Design of Wave Energy Devices).

References

[1] F. Fusco, J. V. Ringwood. (2012): A Study of the Prediction Requirements in Real-Time Control of Wave Energy Converters, IEEE Transactions on Sustainable Energy 3(1), pp. 176-184

[2] J. Falnes (2002): Ocean Waves and Oscillating Systems. Cambridge University Press.

[3] J. Falnes (2007): A review of wave-energy extraction. Marine Structures, Vol. 20, Issue 4, pp185-201.

[4] M.P. Schoen, K. Hals, T. Moan (2011): Wave Prediction and Robust Control of Heaving Wave Energy Devices for Irregular Waves. IEEE Transactions on Energy Conversions 26 (2), pp. 627-638

[5] F. Thiebaut, D. O. Sullivan, P. Kracht et al. (2011) : Testing of a floating OWC device with movable guide vane impulse turbine power take-off. Proc. EWTEC 2011, CD-ROM, Paper no. 159

[6] J. Tedd, P. Frigaard, (2007), Short term wave forecasting, using digital filters, for improved control of wave energy converters, Proc. ISOPE 2007, pp. 388-394

[7] F. Ferri, M. T. Sichani, P. Frigaard. (2012): A case study of short-term wave forecasting based on FIR filter: optimization of the power production for the Wavestar device, Proc. ISOPE 2012, pp. 628-635

[8] J. Dannenberg, K. Hessner, P. Naaijen, H. Van Den Boom, K. Reichert (2010): The On Board Wave and Motion Estimator OWME. Proc. ISOPE 2011, pp. 424-431

[9] F. Fusco, J. V. Ringwood. (2010): Short-Term Wave Forecasting for Real-Time Control of Wave Energy Converters, IEEE Transactions on Sustainable Energy 1(2), pp. 99-106

[10] U. A. Korde. (1999): Efficient primary energy conversoin in irregular waves, Ocean Engineering 26, pp. 625-651

[11] S. Hayken. (2002): Adaptive Filter Theory. Prentice-Hall.

[12] BSH: FINO, http://www.bsh.de/de/Meeresdaten/Projekte/FINO/index.jsp

[13] C. Beels, J.C.C. Henriques, J. De Rouck, M.T. Pontes, G. De Backer, H. Verhaeghe, Wave energy resource in the North Sea, Proc. EWTEC 2007