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Adaptive Wave Energy Converter Excitation Force Predictor in the Support Vector Machine Framework

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Abstract: The performance of Wave Energy Converters (WECs) depends on the capability of the control system to effectively predict the force of excitation, caused by the dynamics of sea waves acting on the system. This is of particular importance in the case of advanced control policies, as for constrained and predictive control algorithms, that makes explicit use of the predicted dynamics of controlled system and related disturbances acting on it for developing the control law. This paper proposes a prediction algorithm, developed within the Support Vector Machine framework, able to provide an effective prediction of the excitation forces acting on WECs. The proposed data-driven algorithm can be designed by off-line training but, due to the unpredictable long-term dynamics variability of sea conditions, pre-trained data-driven algorithms cannot effectively consider such a varying conditions. To overcome this limit, the proposed approach is featured by the capability to adapt the prediction to unknown dynamics by learning from on-line measured or estimated data. This feature also allows to limit the computational complexity of the algorithm while its prediction capabilities are adapted to time-varying sea state conditions evaluated in real-time. The proposed approach is tested on simulated data generated from a high-fidelity WEC simulator.

Keywords: Model Predictive Control, Disturbance Estimator, Linear Systems

1. INTRODUCTION

In the last years, several technologies have been proposed to support climate-neutrality targets, such as the European Green Deal, allowing the transition to a renewable energy source with a quasi-zero carbon footprint. This revolution involves different fields and several technical challenges to be addressed. Transports, power distribution, energy storage, and generation are only a few of the different sectors subject to radical changes related to the decarbonization process (Infield and Freris, 2020). If green power generation represents one of the main possibilities for reducing pollution, marine power generation is probably one of the most suitable and effective solutions to consider in the next few years to achieve the green energy production targets (Basit et al., 2020). Wave Energy converters (WECs) are marine systems involved in the extraction of energy from sea waves movement and are rapidly diffusing among several countries in the world, in particular in those nations bathed by oceans. WEC systems could differ for several features, mainly their mechanical structure and their position in the sea (Zhang et al., 2021). In terms of performance, the goal to be achieved by control systems engineers in the WEC controller development is to optimize the system performance, maximizing the energy extracted by the power generator according to the wave dynamics, while guaranteeing the safety of the system in such an unpredictable operating scenario. Several control systems have been proposed in the last years to increase the energy generation performance of WEC. The proposed control techniques included the application of different control theories, including Passive (Proportional) control (Gallutia et al., 2022), reactive (Windt et al., 2021) (Proportional-Integral) control, latching (Wang and Zhu, 2024) and declutching control (Garcia-Rosa et al., 2020).

Among different methods, Model Predictive Control (MPC) and similar constrained predictive control methods emerge across different fields as the most suitable and effective control strategies to optimize the performance of plants while ensuring physical and logical constraints characterizing controlled systems (Zidek et al., 2021; Cavanini et al., 2023b). Several studies demonstrated the ability of MPC to improve the performance of WEC systems (Richter et al., 2012). This can be achieved only by having the ability to predict the wave excitation force acting on the WEC system over a certain horizon of interest (Hals et al., 2011). Several techniques have been proposed to predict such dynamics that affect system performance, using model-based methods (Davis and Fabien, 2020), data-driven techniques (Shi et al., 2020), and their combination (Falnes, 2007). This paper proposes a new data-driven prediction algorithm developed within the Support Vector

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Machine framework (Cavanini et al., 2024) to predict the wave excitation force acting on the WEC over a prediction horizon of interest. The algorithm, trained off-line on available wave excitation force data, is exploited on-line to provide an effective estimation of the excitation force. This is a common approach, usually referred to as supervised machine learning paradigm. In these terms, the policy capability is limited to learn only from available off-line training data, which are neither accessible nor diverse enough to encompass the wide range of operating conditions related to the sea state and waves. In order to overcome this limit, the proposed SVM-based prediction policy can exploit information given by the measured or estimated instantaneous excitation force, commonly available by standard estimators, such as observers based on Kalman Filter (KF) (Jama et al., 2020). The proposed on-line update approach, based on Low-Rank matrix approximation (Corrini et al., 2024; Cavanini et al., 2023a), enables automatic updating of the SVM's knowledge base while running online, preserving the original computational complexity and memory footprint of the off-line-designed prediction algorithm. Simulation results have been collected by testing the algorithm on data generated by the WEC-Sim simulation software (Ruehl et al., 2024a) provided by NREL (Lawson et al., 2014). Reported results show the superior performance of the proposed approach with respect to baseline SVM, demonstrating the effectiveness of the proposed approach and the capability of the proposed method to adapt the prediction to varying and unpredictable sea conditions.

The paper is structured as follows. In Section 2, the WEC model dynamic is presented. Section 3 presents KF estimation algorithm and the SVM-based prediction approach with the proposed on-line update capabilities. Section 4 reports simulation results and achieved performances. Finally, Section 5 concludes the paper.

2. WAVE ENERGY CONVERTER

The WEC considered in this paper is a floating point absorber subject to incoming sea water waves. The simulation model of this system is provided within the WEC-Sim (Wave Energy Converter SIMulator), an open-source software (Ruehl et al., 2024a) provided by the National Renewable Energy Laboratory (NREL) and Sandia National Laboratories (Sandia) (Ogden et al., 2022). The simulation model is developed in MATLAB/Simulink by

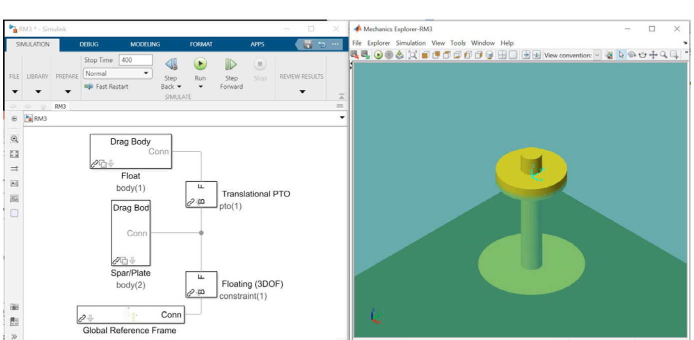

Fig. 1. The WEC-Sim MATLAB/Simulink simulation model, from Ruehl et al. (2024b)

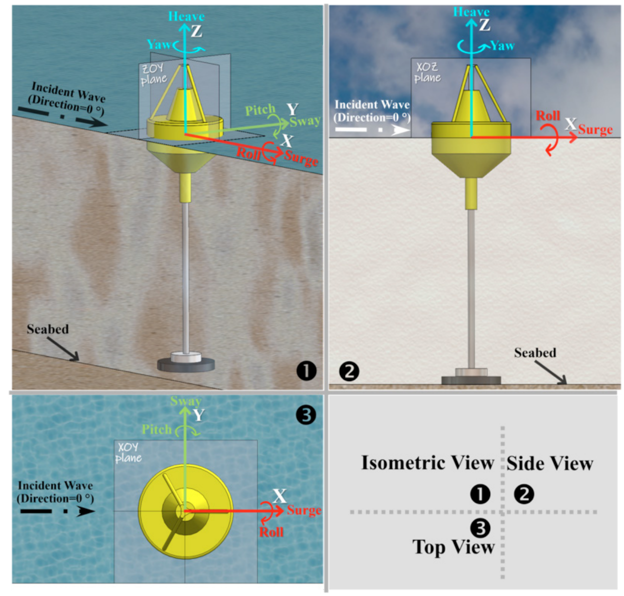

Fig. 2. The WEC-Sim model reference system, from Ruehl et al. (2024b)

MathWorks® (see Fig. 1) and the reference systems considered in the modeling approach are shown in Fig. 2. In the following, we present the essentials of the simulation model. The reader can refer to (Ruehl et al., 2024a) for further details.

The WEC-Sim code scales the hydrodynamic coefficients according to Eq.(1) , where ρ is the water density, ω is the wave frequency in rad/s, and g is gravity:

$$\overline{|F_e(\omega)|} = \frac{|F_e(\omega)|}{\rho g} \tag{1a}$$

$$\overline{A(\omega)} = \frac{A(\omega)}{\rho} \tag{1b}$$

$$\overline{B(\omega)} = \frac{B(\omega)}{\rho\omega} \tag{1c}$$

$$\overline{K_{hs}} = \frac{K_{hs}}{\rho g} \tag{1d}$$

where, F_e is the wave excitation force and torque vector, A and B are the added mass and radiation damping coefficients, respectively, and K_{hs} is the linear hydrostatic restoring coefficient. Due to the simplified model structure, the WEC system is reduced to a single degree of freedom, considering only vertical PTO motion for both simulation and control. Wave forcing is computed using linear coefficients from a frequency-domain BEM solver based on potential flow theory (Babarit et al., 2012), which solves the Laplace equation assuming inviscid, incompressible, and irrotational flow.

The system's dynamic response is evaluated using linear wave theory, which models the wave field as the superposition of incident, radiated, and diffracted wave components. Accordingly, the equation of motion for a floating body, defined about its center of gravity, can be expressed as:

$$m\ddot{X} = F_r(t) + F_b(t) + F_e(t) + F_{pto}(t) \tag{2}$$

whre m represents the nominal mass of the system, F_r is the radiation force, F_b is the buoyancy force, F_e is the wave excitation force, and F_{pto} is the power take-off (PTO) force. The radiation force F_r comprises an added-mass component, represented by the matrix $A(\omega)$, and a wave damping component, represented by the matrix $B(\omega)$, both of which are functions of the wave radian frequency ω and are obtained from the BEM solver. These components are associated with the body's acceleration and velocity, respectively. The excitation force F_e includes the Froude-Krylov contribution due to the undisturbed incident wave field, as well as a diffraction component arising from wave-body interactions. The buoyancy force F_b depends on the hydrostatic stiffness coefficient K_{hs}, the displacement of the floating body, and its mass.

3. FORCE PREDICTION POLICY

The force prediction proposed in this work follows a two-step process. First, the wave-excitation force F_e at the current time step is estimated using a KF. Then, the wave-excitation force prediction for future time steps is carried out using a SVM-based algorithm.

3.1 Kalman Filter Estimator

As the the excitation force is usually not measured, the objective of the KF is to estimate the excitation force F_e acting on the model (2). As first, we cast the model (2) in a state-space form to exploit the estimation capabilities of a the KF framework (So et al., 2017), such that

$$\dot{x}(t) = Ax(t) + Bu(t) \tag{3a}$$

$$y(t) = Cx(t). \tag{3b}$$

where

$$A = \begin{bmatrix} 0 & \dfrac{-k}{m+A_\infty} & \dfrac{1}{m+A_\infty} & 0 & \dfrac{1}{m+A_\infty} \\ 1 & 0 & 0 & 0 & 0 \\ -\dfrac{c_{aa}}{c_{ba}} & -\dfrac{c_{ab}}{c_{ba}} & -\dfrac{c_{bb}}{c_{ba}} & -\dfrac{c_{bc}}{c_{ba}} & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4a}$$

$$B = \begin{bmatrix} \dfrac{1}{m+A_\infty} & 0 & 0 & 0 & 0 \end{bmatrix}^T, \; C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix}. \tag{4b}$$

The state array is $x = [\dot{X}, X, F_r, F_b, F_e]^T$, where F_e is the disturbance signal to be estimated, $u = F_{pto}$ is the control action defined by the controller, and $y = [\dot{X}, X]^T$ are measured PTO velocity and position, respectively. Details of this modeling approach and related matrices components can be found in (So et al., 2017). Based on the state-space model of Eq.(4), the KF-based disturbance estimator considered in this work is the extended KF filter for uncertain state array estimation.

3.2 SVM-based Predictor

To design the wave-excitation force predictor, we assume that the wave-excitation force is available instantaneously. Therefore, the estimated/measured excitation force is used as the input dataset to develop the SVM-based prediction algorithm. If a measure is not available, we assume that the wave-excitation force estimation from a KF, as shown in Section 3.1, provides an effective estimate of the excitation force acting on the WEC. Therefore, we neglect the KF estimation error at this stage for simplicity.

The wave-excitation force from previous simulations or experiments can be collected into a training dataset, that is suitable for the off-line training phase of the SVM predictor presented in the following. Furthermore, the possibility to estimate on-line the excitation force makes possible to update the base of knowledge of the SVM estimator to the varying operating conditions, that are not considered by the initial dataset used to train off-line the prediction algorithm.

The SVM-based prediction algorithm is detailed in the following. It consists in a Least Square (LS)-SVM which solves the regression equation according to the following optimization problem:

$$\min_{w;e;b} J(w;e) = \frac{1}{2}w^T w + \frac{1}{2}\gamma \sum_{i=1}^{n} e_i^2 \tag{5a}$$

$$\text{s.t.} \;\; y_i = w^T \phi(x_i) + b + e_i, \;\; i = 1, \ldots, n \tag{5b}$$

where w is the vector of weights, $b \in \mathbb{R}$ is the bias, γ is the regularization constant, $\phi(x_i)$ is the feature map to the high dimensional feature space, and e_i is the prediction error. The Lagrangian results in

$$L(w;b;e;\alpha) = J(w;e) + \sum_{i=1}^{n} \alpha_i \left(y_i - w^T \phi(x_i) - b - e_i \right) \tag{6}$$

where α_i, for $i = 1 \ldots, n$, are the Lagrange multipliers. The related Karush-Kuhn-Tucker (KKT) conditions for optimality are:

$$\frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{i=1}^{n} \alpha_i \phi(x_i) \tag{7a}$$

$$\frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{n} \alpha_i = 0 \tag{7b}$$

$$\frac{\partial L}{\partial e_i} = 0 \rightarrow e_i = \frac{\alpha_i}{\gamma} \tag{7c}$$

$$\frac{\partial L}{\partial \alpha_i} = 0 \rightarrow y_i = w^T \phi(x_i) + b + e_i \tag{7d}$$

By substituting the conditions (7) and using the kernel trick (Murty et al., 2016), the solution in α, b can be computed solving the linear system

$$\left[\begin{array}{c|c} \Omega + I/\gamma & 1_n^T \\ \hline 1_n & 0 \end{array} \right] \begin{bmatrix} \alpha \\ b \end{bmatrix} = \begin{bmatrix} Y \\ 0 \end{bmatrix}, \tag{8}$$

with $Y = [y_1, \ldots, y_n]^T$, $\alpha = [\alpha_1, \ldots, \alpha_n]^T$, $1_n = [1, \ldots, 1] \in \mathbb{R}^n$, $\Omega_{ij} = \phi(x_i)^T \phi(x_j) = K(x_i, x_j)$, where $K(x_i, x_j)$ is a positive definite kernel. The linear system derived earlier can be expressed as

$$\Theta_n \hat{\alpha}_n = Y_n, \tag{9}$$

where $\hat{\alpha}_n = [\alpha, b]^T$, and $Y_n = [Y, 0]^T$. Based on Mercer's theorem, the LS-SVM function approximation becomes:

$$\hat{y}(x) = \sum_{i=1}^{n} \alpha_i K(x, x_i) + b. \tag{10}$$

Because of the characteristics of the excitation force estimation problem, it is important to emphasize that the use of a dataset rich enough to catch the main interesting dynamics of sea wave would be prohibitive, and also hard to collect, to cover every possible scenario.

Subset selection and feature map approximation In order to reduce training time, prediction time, and memory usage, we combine the Nyström method for feature map approximation (Williams and Seeger, 2001) with an entropy criteria for subset selection (refer to (Cavanini et al., 2023a) for further details).

The Nyström method (Suykens et al., 2002; De Brabanter et al., 2009) considers an explicit approximation for the feature map ϕ in the primal space. The finite dimensional approximation $\hat{\phi}(x)$ can be used in the primal problem to estimate w, b.

Furthermore, using a dimensionality reduction approach, we can find a subset of support vectors with a fixed size $m \ll n$, with m fixed to balance performance with efficiency. The goal is to identify the m support vectors that yield the highest value of the approximated quadratic Rényi entropy:

$$\int \hat{p}(x)^2 dx = \frac{1}{N^2} 1_n^T \Omega 1_n \tag{11}$$

The method can be applied during the initial training of the algorithm and also during the update phase, as described in the following sections.

On-line SVM update The entropy value is evaluated for a fixed-size LS-SVM model to quantify the information gain introduced by a new sample relative to the current training dataset $\mathcal{D}_N$, which contains the predictor variables. The LS-SVM model is updated whenever the entropy associated with a new sample (x_{n+1}, y_{n+1}) exceeds a predefined threshold. This strategy enhances the model's generalization capability and overall accuracy. Given that the solution is derived from the linear system $\Theta_n \hat{\alpha}_n = Y_n$, the updated model is computed as:

$$\Theta_{n+1} \hat{\alpha}_{n+1} = Y_{n+1} \tag{12}$$

where Y_{n+1} is the vector of samples $[Y_n, y_{n+1}, 0]$. To update Θ_{n+1} efficiently upon inclusion of a new sample, without directly computing the matrix inverse, one can derive Θ_{n+1} from the previously computed inverse Θ_n using the bordering method, as shown below:

$$\Theta_{n+1} = \begin{bmatrix} \Theta_n & u \\ u^T & a \end{bmatrix} \tag{13a}$$

$$\Theta_{n+1}^{-1} = \begin{bmatrix} \Theta_n^{-1} + \frac{\Theta_n^{-1} u u^T \Theta_n^{-1}}{q} & -\frac{\Theta_n^{-1} u}{q} \\ -\frac{u^T \Theta_n^{-1}}{q} & \frac{1}{q} \end{bmatrix} \tag{13b}$$

where $q = a - u^T \Theta_n^{-1} u$, $a = \gamma^{-1} + K(x_{n+1}, x_{n+1})$, and $u = [K(x_{n+1}, x_1), \ldots, K(x_{n+1}, x_n), 1]$. When a new sample is included, the training dataset and the data vectors are incremented as follows

$$\mathcal{D}_n \to \mathcal{D}_{n+1} \tag{14a}$$

$$x_{train} = [x_{train}, x_{n+1}]^T \tag{14b}$$

$$Y_{train} = [Y_{train}, y_{n+1}]^T \tag{14c}$$

and the Lagrangian multipliers become

$$\hat{\alpha} = \Theta_{n+1}^{-1} Y_{train} \tag{15}$$

Since the incremental procedure increases memory usage and model complexity, a First-In First-Out (FIFO) decremental step is applied after each update by removing the oldest data point. To avoid matrix inversion, Θ_n is updated from Θ_{n+1} by removing its first row and column. The resulting matrix after the decremental step is given by:

$$\Theta_n(i-1, j-1) = \Theta_{n+1}(i,j) - \frac{\Theta_{n+1}(i,1)\Theta_{n+1}(1,j)}{\Theta_{n+1}(1,1)} \tag{16}$$

where $i, j = 2, \ldots, n+1$ and the training dataset and the data vectors are decremented as follows:

$$\mathcal{D}_{n+1} \to \mathcal{D}_n \tag{17a}$$

$$x_{train}(1) \to \emptyset \tag{17b}$$

$$Y_{train}(1) \to \emptyset \tag{17c}$$

4. RESULTS

This section presents the simulation performance of the proposed LS-SVM prediction algorithm. This study focuses on the study of the improvement of the proposed update approach to increase the prediction capability of the baseline SVM-based predictor. First, the prediction performance of the baseline LS-SVM predictor (i.e., without any on-line update) is evaluated. Next, the algorithm's ability to predict time-varying wave dynamics, different from those in the original training dataset, is assessed. Finally, the effectiveness of the proposed update policy is shown in terms of improved prediction capability.

The prediction metric is evaluated according to the Normalized Mean Squared Error (NMSE) performance index, computed as

$$\text{NMSE} = 100\% \times \max\left(0, 1 - \frac{\|y - \hat{y}\|_2}{\|y - \bar{y}|_2}\right) \tag{18}$$

where y collects the real values, $\bar{y}$ represents its mean, and $\hat{y}$ collects the predicted values of the excitation force.

The fixed size of the developed LS-SVM predictor algorithm is set to $m = 200$. The estimator is characterized by a Kernel matrix defined by Radial Basis Functions (RBF), and the sigma distance threshold considered to perform the update procedure with the new value provided by the KF estimator has been set to 5. This threshold value has been selected by evaluating the effect and frequency of update on the selected scenario, according to a trial-and-error approach, to ensure effective performance of the estimator. The NMSE of the trained predictor achieved on the pure sinusoidal force excitation signal is collected in Table 1 for a prediction horizon of $N_p = 5$ so that the prediction is performed for a predicted trajectory of N_p future samples, given a sampling time of 0.5 seconds.

4.1 Sinusoidal excitation

Table 1 shows how the LS-SVM predictor, trained on a repetitive dataset, is able to learn the nonlinear trajectory of ideal waves, generating a sinusoidal excitation force acting on the WEC system.

Table 1. NMSE on sinusoidal wave excitation dataset.

Algorithm	k				
	1	2	3	4	5
LS-SVM (No Update)	99.99	99.99	99.98	99.98	99.98

Table 2. NMSE on non-sinusoidal Wave excitation dataset.

Algorithm	k				
	1	2	3	4	5
LS-SVM (No Update)	4.1537	0	0	0	0
LS-SVM (Update)	92.75	78.86	56.30	28.64	2.18

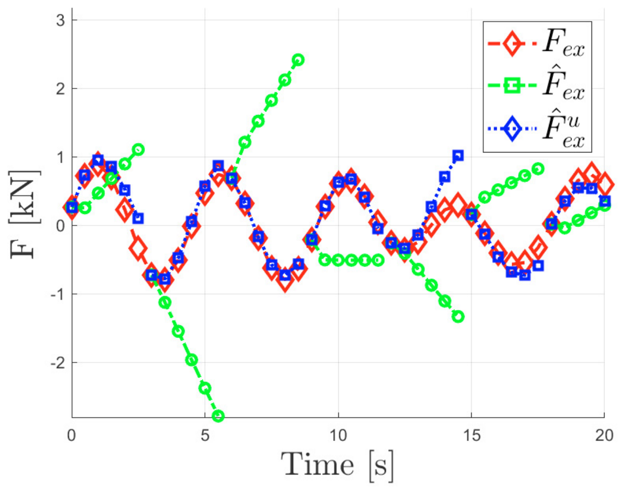

Fig. 3. Comparison of predictors: the real excitation force (red), the baseline SVM prediction (green), the prediction trajectory provided by the proposed SVM predictor with update policy (blue).

In this case, given the stationary nature of the wave excitation force, no update policy is actually needed, reaching a practically exact force prediction for a considered prediction of $k = 1, \ldots, N_p$ samples, where the maximum prediction horizon is set to $N_p = 5$. The baseline SVM prediction algorithm has been trained on this dataset featured by only stationary wave signals, that would not represent the realistic behavior of sea waves. This has been motivated to show the capability of the proposed updated policy to modify the base of knowledge of the predictor by the estimated real-world waves behavior as shown in the next section.

4.2 Non-sinusoidal excitation

Here, the proposed estimator, initially trained as shown in the previous section, has been tested on a real-world case study, by considering a realistic wave excitation signal to be predicted over the considered prediction horizon of $N_p = 5$ samples. To show the capability of the proposed adaption policy, the performance of the estimator previously trained on the stationary waves dataset, has been compared with the estimation results provided by the same SVM-based estimator integrated with the proposed update policy. By using such a non-stationary wave excitation force dataset, it is possible to verify the update capability and effectiveness of the policy to adapt to the unpredictable wave excitation force dynamics considered in the following results, as shown in Table 2 and Fig. 3.

Table 2 reports the NMSEs for the different samples of the predicted trajectory over the $k = 1, \ldots, N_p$ prediction steps considered in this scenario, including both the LS-SVM without update and the proposed LS-SVM with on-line update. The LS-SVM without update proves to be inadequate in such a scenario. The NMSE drops significantly and becomes zero for $k > 2$. The LS-SVM with on-line update, instead, shows a NMSE that starts from 92.75 for $k = 1$, and the NMSE decreases for larger values of k.

Fig. 3 compares the wave excitation force prediction given by the baseline LS-SVM introduced in the previous section and the same SVM-based prediction policy featured by the proposed update policy. The graphical results show the wrong prediction provided by the baseline predictor without the update policy. Due to the limited knowledge contained in the initial training dataset, the baseline SVM is not able to provide an effective prediction of the future wave excitation force generated by waves acting on the WEC. This limit is overcome by introducing the proposed update policy in the prediction algorithm. These results demonstrate the capability to update and exploit the updated information to generate an effective prediction of the considered signal. In particular, the predicted force trajectory match the nonlinear dynamics of the wave excitation force, motivating the future usage of this policy in combination with advanced predictive control policy.

5. CONCLUSIONS

This paper presents a data-driven algorithm designed to effectively predict the excitation force acting on a Wave Energy Converter over a future time horizon of interest. The proposed approach exploits prediction capabilities of data-driven Least-Square Support Vector Machine-based algorithms. The prediction policy, trained off-line on a dataset representing only a limited set of sea wave operating conditions, is able to effectively predict the excitation force dynamics in operating conditions similar to those described in the training dataset. This performance degrades when the wave dynamic varies and does not match the features of this training dataset. By introducing the proposed update policy, the SVM-based predictor can automatically update the estimation policy by maintaining the initial computational complexity and memory footprint of the prediction algorithm. The simulation results, achieved by testing the proposed system on high-fidelity simulation software, show the superior performance of the proposed approach compared to the baseline LS-SVM. Future research will consider the integration of this prediction system within a predictive control system in a Processor-in-the-Loop test. This will allow to evaluate the performance improvement due to increased prediction capabilities, and the feasibility of the proposed approach operating in conjunction with a computationally demanding control algorithm. This study will permit to evaluate the effective possibility to exploit this approach evaluating the trade-off among computational complexity and prediction performance on a real-world control board.

REFERENCES

Babarit, A., Hals, J., Muliawan, M.J., Kurniawan, A., Moan, T., and Krokstad, J. (2012). Numerical benchmarking study of a selection of wave energy converters. *Renewable energy*, 41, 44–63.

Basit, M.A., Dilshad, S., Badar, R., and Sami ur Rehman, S.M. (2020). Limitations, challenges, and solution approaches in grid-connected renewable energy systems. *International Journal of Energy Research*, 44(6), 4132–4162.

Cavanini, L., Felicetti, R., Ferracuti, F., and Monteriù, A. (2023a). Fixed-size LS-SVM LPV system identification for large datasets. *International Journal of Control, Automation and Systems*, 21(12), 4067–4079.

Cavanini, L., Majecki, P., Grimble, M.J., and van der Molen, G.M. (2023b). Energy management control of hydrogen fuel cell powered ships. In *2023 American Control Conference (ACC)*, 4457–4462. IEEE.

Cavanini, L., Majecki, P., Grimble, M.J., and van der Molen, G.M. (2024). Battery state-of-charge estimator design based on the least-squares support vector machine. In *2024 IEEE International Conference on Automation Science and Engineering (CASE 2024), IEEE Robotics and Automation Society*, 1–6. IEEE.

Corrini, F., Mazzoleni, M., Ferracuti, F., Cavanini, L., and Previdi, F. (2024). An information theory approach for recursive LPV-ARX model identification via LS-SVM. *IFAC-PapersOnLine*, 58(15), 486–491.

Davis, A.F. and Fabien, B.C. (2020). Wave excitation force estimation of wave energy floats using extended kalman filters. *Ocean Engineering*, 198, 106970.

De Brabanter, K., Dreesen, P., Karsmakers, P., Pelckmans, K., De Brabanter, J., Suykens, J., and De Moor, B. (2009). Fixed-Size LS-SVM Applied to the Wiener-Hammerstein Benchmark. *IFAC Proceedings Volumes*, 42(10), 826–831. 15th IFAC Symposium on System Identification.

Falnes, J. (2007). A review of wave-energy extraction. *Marine structures*, 20(4), 185–201.

Gallutia, D., Fard, M.T., Soto, M.G., and He, J. (2022). Recent advances in wave energy conversion systems: From wave theory to devices and control strategies. *Ocean Engineering*, 252, 111105.

Garcia-Rosa, P.B., Fosso, O.B., and Molinas, M. (2020). Switching sequences for non-predictive declutching control of wave energy converters. *IFAC-PapersOnLine*, 53(2), 12295–12300.

Hals, J., Falnes, J., and Moan, T. (2011). Constrained optimal control of a heaving buoy wave-energy converter.

Infield, D. and Freris, L. (2020). *Renewable energy in power systems*. John Wiley & Sons.

Jama, M., Wahyudie, A., and Mekhilef, S. (2020). Wave excitation force estimation using an electrical-based extended kalman filter for point absorber wave energy converters. *IEEE Access*, 8, 49823–49836.

Lawson, M., Yu, Y.H., Ruehl, K., and Michelen, C. (2014). Development and demonstration of the wec-sim wave energy converter simulation tool.

Murty, M., Raghava, R., Murty, M., and Raghava, R. (2016). Kernel-based svm. *Support vector machines and perceptrons: Learning, optimization, classification, and application to social networks*, 57–67.

Ogden, D., Ruehl, K., Yu, Y.H., Keester, A., Forbush, D., Leon, J., and Tom, N. (2022). Review of wec-sim development and applications. *International Marine Energy Journal*, 5(NREL/JA-5700-83366).

Richter, M., Magana, M.E., Sawodny, O., and Brekken, T.K. (2012). Nonlinear model predictive control of a point absorber wave energy converter. *IEEE Transactions on Sustainable Energy*, 4(1), 118–126.

Ruehl, K., Keester, A., Forbush, D., Grasberger, J., Husain, S., Leon, J., Ogden, D., and Shabara, M. (2024a). Wec-sim v6.1. doi:10.5281/zenodo.10023797. URL `https://doi.org/10.5281/zenodo.13770349`.

Ruehl, K., Keester, A., Forbush, D., Grasberger, J., Husain, S., Leon, J., Ogden, D., and Shabara, M. (2024b). Wec-sim v6.1.2. doi:10.5281/zenodo.14549050. URL `https://doi.org/10.5281/zenodo.14549050`.

Shi, S., Patton, R.J., and Liu, Y. (2020). Robust data-driven estimation of wave excitation force for wave energy converters. *IFAC-PapersOnLine*, 53(2), 12346–12351.

So, R., Starrett, M., Ruehl, K., and Brekken, T.K. (2017). Development of control-sim: Control strategies for power take-off integrated wave energy converter. In *2017 IEEE Power & Energy Society General Meeting*, 1–5. IEEE.

Suykens, J., Van Gestel, T., De Brabanter, J., De Moor, B., and Vandewalle, J. (2002). *Least Squares Support Vector Machines*. World Scientific.

Wang, H. and Zhu, S. (2024). Latching control: A wave energy converter inspired vibration control strategy. *Mechanical Systems and Signal Processing*, 208, 110912.

Williams, C. and Seeger, M. (2001). Using the nyström method to speed up kernel machines. In *Advances in Neural Information Processing Systems 13*, 682–688. MIT Press.

Windt, C., Faedo, N., Penalba, M., Dias, F., and Ringwood, J.V. (2021). Reactive control of wave energy devices–the modelling paradox. *Applied Ocean Research*, 109, 102574.

Zhang, Y., Zhao, Y., Sun, W., and Li, J. (2021). Ocean wave energy converters: Technical principle, device realization, and performance evaluation. *Renewable and Sustainable Energy Reviews*, 141, 110764.

Zidek, R.A., Kolmanovsky, I.V., and Bemporad, A. (2021). Model predictive control for drift counteraction of stochastic constrained linear systems. *Automatica*, 123, 109304.