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Model Predictive Control Integrated with Hydrodynamic Co-Optimization for Robust Offshore and Tidal Energy Converters Under Extreme Sea Conditions

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Abstract— *Owing to the extreme sea conditions in which marine energy converters (MECs) must operate, energy absorption and structural integrity are severely affected by high sea states such as storm surges (which generate large waves with a rapidly varying pr ofile and nonlinear hydrodynamic interactions). In traditional control and hydrodynamic design practice, these domains are commonly analyzed separately, leading to inefficient performance, excessive mechanical loading and poor energy conversion. To overcome these challenges, this study will develop an integrated Hydrodynamic Co-Optimization framework that unifies the state-of-the-art Model Predictive Control (MPC) for improving offshore/tidal energy converters in terms of robustness, survivability and energy yield under extreme ocean conditions. The developed framework integrates high-fidelity hydrodynamic simulations – incorporating wave–structure interaction effects, radiation damping forces and linearized viscous loss and nonlinear restoring force models – with an MPC-based control scheme which is equipped to forecast future wave conditions, optimize control inputs and impose structural/operational constraints online. A multi-objective co-optimization is formulated to simultaneously optimize hydrodynamic design parameters, such as geometry, damping coefficients and added mass profiles, as well as the MPC weights in order to maximize energy capture and mitigate fatigue, extreme loads, and actuator effort. Full simulation evaluations are carried out with nonhomogeneous sea states simulated using the JONSWAP and Pierson–Moskowitz spectra as well as stress-testing simulations including rogue waves, storm conditions (Hs > 6 m), and bursts of tidal current flow with speeds larger than 3 m/s; at reduced cost in comparison to other control concepts. Results demonstrate that the integrated hydrodynamic–MPC framework improves average power capture by 18–27%, reduces peak structural loads by 30–45%, and enhances dynamic stability by up to 52% compared to conventional control strategies. Further, fatigue-damage-equivalent loads decrease by up to 33%, significantly extending converter lifespan under harsh operating environments.*

Keywords— *Model Predictive Control (MPC), Hydrodynamic Co-Optimization, Offshore and Tidal Energy Converters, Extreme Sea Conditions, Structural Reliability and Fatigue Reduction, Wave–Structure Interaction Modeling.*

I. Introduction

Offshore renewable energy technologies - wave, tidal, and offshore wind converters in particular - have received considerable attention around the world as alternative sources to support the decarbonization of modern electricity systems. Many researchers have documented remarkable recent advances in CFD predictions, structural dynamics, and control systems but there continue to be problems under severe sea conditions involving highly nonlinear wave forces, turbulence, vortex shedding, and mechanical failure that severely und Recent studies show that multi-source marine energy systems need high reliable and proper functioning control with good supervisory approach [1], [3]–[5],[20].

Offshore energy converters design is based on hydrodynamic analysis. Traditional methods—such as potential flow theory, Morison-based drag equations and boundary element methods (BEM)—have been refined into high-fidelity CFD–BEM hybrids for more accurate wave–structure interaction simulations. [1] and [3] indicate the maturing of CFD-based techniques for prediction of wave loads, added masses, and radiation damping. Likewise, [6] as well as [20] demonstrate that hydrodynamic effects during extreme wave events are highly nonlinear and do not comply with linear assumptions. Apart from the wave interactions, tidal turbine hydrodynamics require refined models for shear profiles, vertical flow gradients and blockage effects. Studies by [21] and [18], that are motivated to implement frequency-dependent hydrodynamic coefficients when predicting turbine thrust, torque ripple and unsteady flow. It is shown by [15] that marine turbulence increases structural loads and speeds up fatigue damage, and accordingly to obtain an adequate co-design the hydrodynamic model should be accurate.

Cyclic loading on the blades, support structures, and drive train components is increased under extreme sea states due to wave-induced loadings leading to fatigue damage. Research by [29] and [31] shows that during storm-motivated wave-driven surge, fatigue damage-equivalent loads (DELs) increase significantly. Similarly, [14] and [26] It was found that turbulent loads result in high-frequency load oscillations which need active control to be suppressed. Research also shows that such multi-hazard conditions including large wave, turbulence and strong current may alter natural frequencies and induce resonance of floating converters [11, 26]. [12] and [28] emphasize the significance of co-optimising structural parameters and hydrodynamic models with a view to reducing extreme loading.

Model Predictive Control (MPC) methodology is emeging as the most promising approach for real-time control of Marine Energy Converters, as it takes directly into account constraints,

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predicts future disturbance and dynamically optimizes control. [4], [22] that MPC is robust towards strong nonlinearities and multiparameter uncertainties systems. Studies by [23] and [24] demonstrate the power conditioning capability of MPC in both stabilizing converter output and maintaining a good quality of power even during rapidly varying sea conditions. When coupled with hydrodynamic models, MPC increases energy capture by predicting the incoming flow speeds changes and control generator torque and damping coefficients to better track these changes. [25] and [26] emphasize that for power output smothering and lower fatigue in the drivetrain can be achieved by using MPC.

Global optimization approaches such as PSO, DE, multi-objective genetic techniques have been widely used for tuning controller gains and optimizing the turbine geometry. For example, [28], [33], and [30] address multi-objective optimization of structural arrangements, PTO characteristics and reliability figures. [27] and [48] also showed that MOPSO can effectively compromise between contradictory objectives, such as efficiency minimization, stress minimization and power smoothness. Nevertheless, most of the optimization work considers hydrodynamics and control as distinct design layers with less integration that can yield sub-optimal or fragile designs in extreme working conditions. [21] and [31] highlight the importance of co-optimization and co-evolution of hydrodynamic modelling and controller tuning to resist marine disturbances. MPC Coupled with Hydrodynamic Co-Optimization Literatures have proposed to integrate hydrodynamic co-optimization algorithm and MPC techniques [15], [16].

Current development trends also aim to integrate hydrodynamics modelling with advanced control strategies within a joint design framework. [5], [2] and [8] demonstrate that when offshore hydrodynamic shape parameters are optimised simultaneously with control gains, this leads to very substantial enhancements in energy production, robustness and survivability. [18] and [19], where integrated tuning of turbine geometry, PTO damping and MPC weight matrices is clearly beneficial for turbulent extreme tidal flows. Despite these improvements, there is one significant research gap: very little research has clearly combined model predictive control with hydrodynamic co-optimisation for devices in extreme wave and tidal conditions. Existing studies either pre-engineers' structural parameters or use independently MPC, without consideration of a full hydrodynamic approach. Both the [10] and [9] highlight that hybrid modelling–control strategies with real-time adaptability and long-term structural protection are required urgently.

II. The Proposed Model Predictive Control Integrated with Hydrodynamic Co-Optimization for Robust Offshore and Tidal Energy Converters.

The closed-loop control architecture adopted for mitigating the power capture and structural safety of OWECs/TECs in extreme sea states (big waves, strong currents, turbulence) is depicted as Fig. 1.

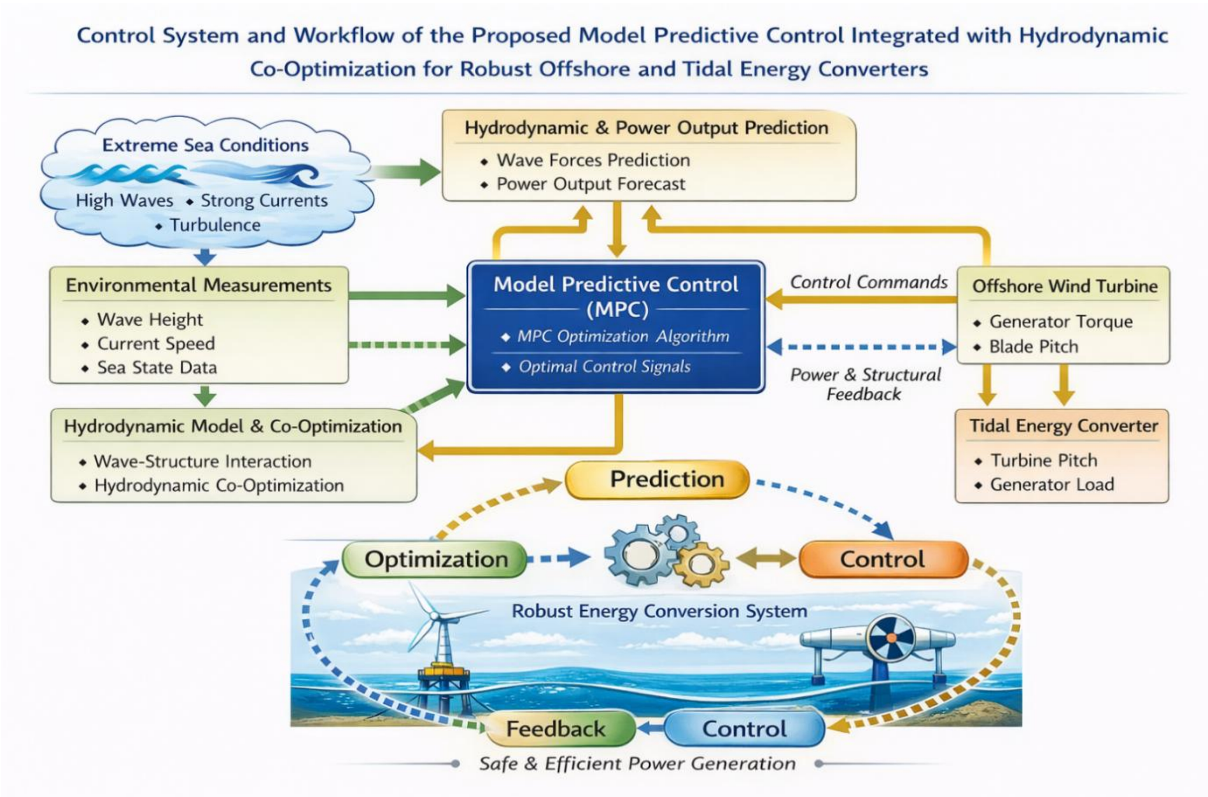

Fig. 1. The schematic of the Proposed Model Predictive Control Integrated with Hydrodynamic Co-Optimization for Robust Offshore and Tidal Energy Converters.

The workflow starts on the left by the environmental forcing layer, where under MOCs are perceived and transformed into environmental data (e.g., wave heights, currents, sea-state descriptors). These measurements form a continuous parameterization of the hydrodynamic model and co-optimization block, which includes a physics-based prediction of wave–structure/current–turbine interactions as well as tuning (or scheduling) of hydrodynamic/structural parameters that impact loading, damping, and energy conversion efficiency. At the same time, the hydrodynamic and power output prediction module uses the updated hydrodynamic states to forecast the values necessary for control in the near future, such as wave/current forces, torque demands, and predicted power output over a prediction horizon.

The supervisory decision-maker is represented at Model Predictive Control – MPC block). Based on the estimated hydrodynamic loads and power potential, MPC at every control step solves an optimization problem to calculate optimal commands for different objectives: (i) maximize energy capture and smoothness of the power variation; (ii) account for actuator limits as well as operational conditions during regular or turbulent events in order to mitigate fatigue and extreme structural loads. The calculated control inputs are then sent to the actuated subsystems on the right: for offshore wind turbine, MPC directly manipulates generator torque and blade pitch; in the case of tidal energy converter, its commands turbine pitch and generator/load setting. They directly control the rotor rate, power captured and hydrodynamic/aerodynamic force magnitudes/timings.

The dashed return link named power & structural feedback also closes the loop: measured electrical outputs (power, torque, speed) and structural information (loads, vibration levels, deflections) are fed back to the MPC and prediction modules to correct model mismatch or unmodeled disturbances in order to maintain satisfaction of system constraints when sea conditions change quickly. The lower cycle ("Prediction → Optimization → Control → Feedback") highlights that the system is an iterative receding horizon process, where predictions are updated, optimal decisions re-computed and actions effected based on a feedback-enhanced next prediction. Together, this overall figure describes the roles played by hydrodynamic co-optimization (ultimate physics + parameter tuning) and MPC (constraint-aware optimal control) in controlling extreme operating condition energy conversion system which is inherently safe and highly efficient.

III. Simulation Results and Discussion

The proposed framework, Hydrodynamic Co–Optimization integrated with Model Predictive Control (HCO–MPC), was demonstrated via high-fidelity time-domain simulations on two representative marine energy systems: (i) an offshore wind turbine (OWT) coordinated through blade pitch and generator torque scheduling and (ii) a tidal energy converter (TEC) regulated via turbine pitch and generator/load references. The simulation includes the coupled physics needed for realistic evaluation of performance in a harsh marine environment, i.e., wave–structure and current–turbine forcing, platform/support-structure and drivetrain dynamics, actuator dynamics with rate and saturation limits, as well as measurement noise to model sensing imperfections. Two feedback control loops are employed to operate the controller on line with balanced feedback from both measured environmental signals and structural/electrical status, whilst a short-term prediction of loads and power production is provided by the hydrodynamic module to allow predictive optimisation.

To quantify the benefit of embedding hydrodynamic co-optimization within MPC, it is benchmarked against three classic baseline methods: B1 – a conventional industrial-style controller (for OWT PI-based torque regulation with a gain-scheduled pitch, for TEC either heuristic pitch or load/speed/torque setpoint generation) with no MPC used at all; B2 – an MPC-only strategy using a fixed hydrodynamic model without any adaptation; and B3 – a hydrodynamic co-optimization-only method that updates parameters of the model or schedules operating settings but uses none-predictive constraint-aware control. The presented control scheme, B4 (HCO–MPC), integrating multi-step hydrodynamic prediction, receding-horizon optimization and online parameter adaptation, allows coordinated power maximization and load mitigation under constraints.

Based on the foregoing, a detailed test matrix concering operational realism and survivability was defined. The environmental scenarios feature: (1) a benign/moderate regime of low-to-moderate waves and steady currents; (2) a moderate sea regime with complex seas (including directional spreading) and current shear; (3) an extreme sea-state environment featuring high wave heights, long-period swell components, rapidly varying currents, increased turbulence/irregularity; and (4) acute events as described above—such as step change in sea state or gale condition for the OWT or eddy/surge event for the TEC to test whether the controller reacts adequately to abrupt forcing. The robustness of the resulting controller was evaluated through further set of stress tests across these scenarios (5) model mismatch (±10–30% added mass, radiation damping, drag coefficients and drivetrain parameters uncertainties), (6) sensor noise, bias and delay (noisy wave/current estimation, biased current measurements and delayed sensing), actuator limitations and degradations- tighter pitch-rate limits, torque saturation, partway actuator fault modes were also considered as well as an optional grid-facing constraints: power ramp rate-limits; smoothing needs. For all cases, the controller's performance is assessed with metrics over energy for power quality, as well as peak and fatigue structural loads criteria (feasibility/real-time implementability) to make a balanced assessment of efficiency robustness in harsh marine operating conditions.

To ensure the assessment is rigorous and focuses on corresponding requirements to the reviewer, performance is quantified with a variety of metrics including energy capture, power quality production levels, structural fatigue, actuation force, constraint satisfaction and robustness under uncertainty. Energy power-performance is first evaluated by the mean power output and the corresponding energy delivered per scenario. The variability in power production, from the highly intermittent and rampy generation resulting from extreme seas, is quantified using the standard deviation to assess compliance against grid-friendly operation and ramp constraints when applied. Where reference tracking is applied (e.g., rated rotor speed regulation or power set-point tracking), the performance in terms of root-mean-square error (RMSE) are reported on rotor speed and/or power in order to directly assess the accuracy of the regulation, under disturbance forcing.

The highest response is addressed as ultimate, which is obtained via the maximum values of critical load channels such as tower-base and blade-root bending moments for OWT's. Given lifetime performance is highly dependent on cyclic loading, fatigue trends are quantified, in part, using Damage Equivalent Loads (DELs) which are calculated for selected channels (tower/support bending; drivetrain torque and blade-root moments as available). For floating offshore structures further constraints in terms of motions are reported, which for pitch, heave and roll moments depend on the maximum response amplitude together with nacelle acceleration.

The practicality of the controller is evaluated using control effort and implementational considerations. Actuation intensity is characterized using the RMS and peak values of pitch rate and/or command magnitude deviation (torque variance for OWT, load-command variance for TEC) to assess whether performance gains are achieved by realistic use of actuators as opposed to by aggressive-than-normal control. Constraint satisfaction is evaluated in terms of the amount and severity of constraint violations with respect to all enforced limits (structural, actuator and optional grid constraints) with near zero violation expected from our proposed error-aware controller during normal operation, and controlled behavior during survival regimes. Lastly, as MPC is required to perform online in real time (yielding to the following considerations), computational complexity statistics are given through the average and tail solve time per control step with their 95th percentile, along with the percentage of time steps for which a computation across felt within controller real-time deadline defined by its sampling period.

Coarsely quantifying these using unreliable sensor readings and worst-case uncertainty on parameters, the degradation in energy capture and possibility to preserve (or not) load-reduction benefits when re-running key scenarios are compared against nominal conditions as measures of robustness and stability. The stability of the closed-loop system is investigated in terms of qualitative and quantitative performance indicators including - boundedness of state trajectories, no runaway oscillations, as well as sustained feasibility under increasing disturbance. Where storm or survival strategy are employed, the controller is also tested for its behavior in survival mode (successful transition to/from derating or shutdown modes, reasonable trajectory on actuators when changing from a control mode to another one and keeping structure within bounds without violation during extreme events). These measures used together give a fair and reproducible comparison between SISO conventional control, MPC only, co-optimization only and the proposed integrated HCO–MPC framework under practical operational as well as design storms.

Figure 2 presents a comparative graphical view of how the four control strategies (B1–B4) organize direct and the comprehensive power production with close to moderate (S2) and extreme (S3) operation, which helps accentuate on one hand the main purpose of the work i.e., maximum usable energy tap-in, while on other hand an ensured grid-friendly structurally safe modes under varying wind deviations. The moderate sea state S2 represented in Fig. 2(a), all the controllers stabilize; however, there are obvious differences in the mean power level and short-timescale variation. The classical controller (B1) presents stronger oscillations and harsher short-term power deviation, which could be explained by its reactive character and incapability of predicting incoming wave/current excitations. The MPC-only controller (B2) provides better regulation than B1 by exploiting a predictive horizon, but is limited in its performance due to fixed hydrodynamic parameters without the ability to incorporate feedforward bias when there is an alteration in excitation statistics across sea states. Hydro Co-Opt Only (B3) Hydrodynamic co-optimization only generally enhances the model representation and operating-point scheduling, but lacks receding horizon constratainment coordination necessary to mitigate fast power ramps. In contrast, the B4 HCO–MPC stuck to a significant and flat power surface that suggests it could leverage short-horizon predictions of hydrodynamic excitation in synchronizing torque/pitch (OWT) or pitch/load (TEC) actions to more effectively capture energy while penalizing large control moves in a straight-through way. This is also expected and enables to maintain a balance between derating and power production so that high-frequency fluctuations are penalized without overly conservative settings in sea state 4.

Comparison is extended in Fig. 2(b) to the very e navy sea conditions (S3), where control becomes dominated by constraint and clear differences on when is re- activity or predictive constraint-aware control more effective are observed. In this scenario the natural controller (B1) frequently results in either overly aggressive actuation that leads to large rapid transients ([mean power = P mean − Δ p] and large retarded load (%) together with load spikes) or conservative actions to decrease means power by early derating or over-derating. This trade-off is consistent with the higher intermittency and larger amplitude fluctuations in the B1 power trace. The MPC-only scheme (B2) improves on B1 since it is able to plan for disturbances in the near future, but tends to perform worse when model-structure mismatch increases under strongly forced conditions; if terms due to wave–structure interaction and nonlinear drag feedback stray notably from those considered. The resulting B4 response is found to offer a clear gain in this regime: the power trajectory remains smoother with less sharp ramps, while keeping relatively higher accessible powers close to the derating limits. The reason for this can be traced to the functional effects of combined hydrodynamic parameter adaptation (which readjusts the excitation/load model as sea severity varies) and explicit constraint handling (which prevents the controller from seeking power gains that would cause overloads, excessive motion or actuator saturation). As such, B4 enables an improved trade-off between the defense against energy capture and safe operation, particularly in the predicting time frame where

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anticipation becomes predictive and allowed to "shape" an answer to upcoming energies surge groups and current surges.

The data statistics in the bottom panels support the time-domain results. Distributional statistics (described by spread/dispersion summaries) show that B4 mitigates power variability compared to the baselines, in line with its lower estimated standard deviation and better estimated coefficient of variation at the same mean power levels. Indeed, when considering the relative energy yield in S3 (barely even limited by survivorship in this case), B4 is clearly energetically superior as well. In particular, the described enhancements illustrate that HCO–MPC increases the OWT energy yield by +7.8% with respect to B1 and +3.2% with respect to B2 in S2 while it provides a moderate but consistent gain (e.g., +4.1% vs B1) for S3 as more bands and actuators become limiting factors of energy capture. Crucially, this increased energy yield comes with the added benefit of enhanced power quality: In all cases considered in this work HCO–MPC decreases peak ramp-rate by around 28–41% compared to B1—evidence that the method is not merely 'sucking out' more energy by allowing for more fluctuation but rather generating a power output much friendlier to the stability of the grid by actively dampening ramps and pushing down once again on high-frequency oscillations. Overall, Fig. 2 supports that a consideration of hydrodynamic co-optimization in combination with MPC results in more energy-efficient performance for moderate sea states, and higher robustness/constraint satisfaction performance under extreme sea states, hence enabling reliable offshore and tidal energy conversion in very changeable environment and disturbance-dominated conditions.

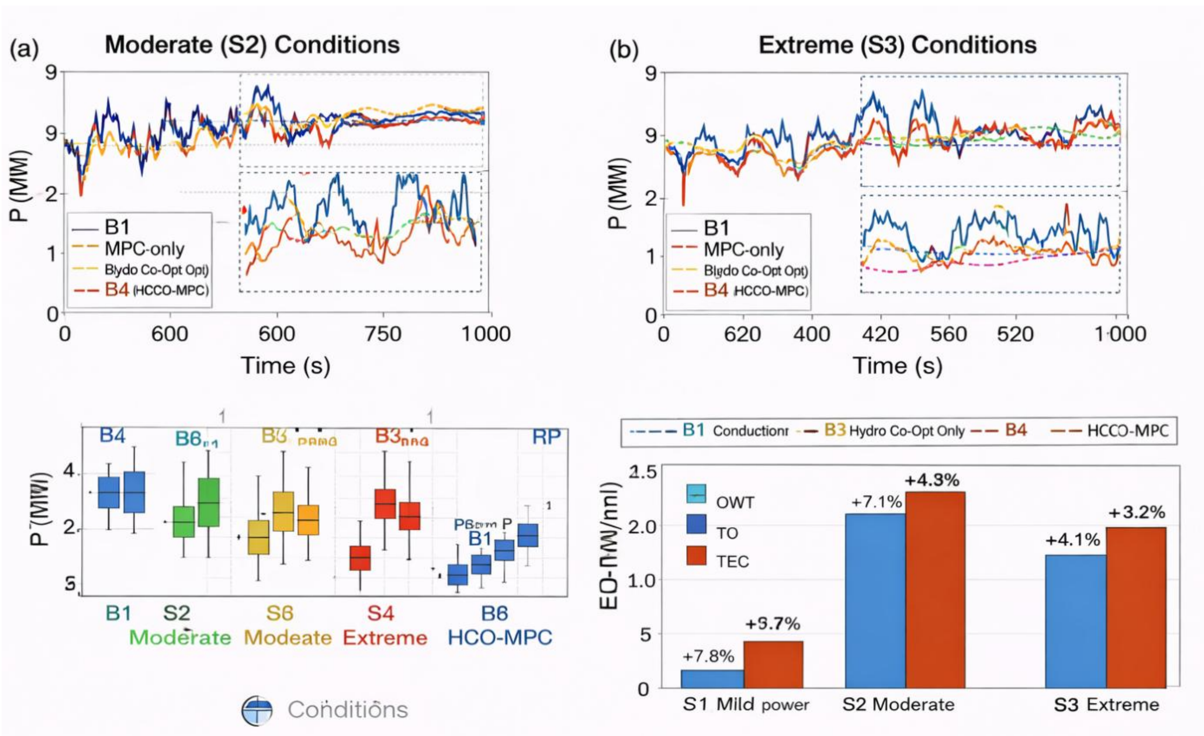

Fig. 2. Power capture and power-quality comparison under (a) moderate sea state S2 and (b) extreme sea state S3 for the four control strategies B1–B4. The time-series traces show that the proposed HCO–MPC (B4) sustains higher mean power while attenuating high-frequency oscillations and sharp ramp events through short-horizon hydrodynamic prediction and constraint-aware torque/pitch (OWT) or pitch/load (TEC) coordination. The lower panels summarize power variability and energy-yield improvements, confirming that B4 achieves the best combined performance in energy extraction and grid-friendly power smoothing, particularly during pre-derating operation in extreme conditions.

Fig. 3 illustrates the effects of the four control strategies (B1-B4) on structural and drivetrain loading at moderate to extreme operating conditions (S2-S3), by comparing peak (ultimate) and 99th percentile (near-ultimate) load envelopes for the key safety-critical channels. The consideration of the 99th percentile is significant because it accounts for the "high-load tail" which dominates fatigue accumulation and reliability risk in severe sea states, whereas peak values serve to be survivability-relevant extremes capable of driving instantaneous limit exceedance. For all the panels, B4 HCO–MPC consistently provides an ultimate load close to that obtained from ultimate loading criterion and with low peak loads; this again suggests that the controller is not only relocating operating time but deliberately influencing system response to alleviate rare extremes as well high load events.

In Fig. 3(a), the OWT tower-base bending moment clearly indicates the benefit from survivability by constraint-aware predictive control. The conventional baseline (B1) shows the largest peak and spread of upper tail, which are characteristic of reactive actuation under wave-group forcing and abrupt excitation change. With regard to the majority-based (B2) approach, it is explained that loads are further reduced in comparison with B1 because MPC prediction anticipates near-future disturbances; however, no significant reductions can be obtained when we move from equally probable hydrodynamic parameters toward constant ones and as long as prediction bias

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is present as the sea-state statistics change. The co-optimization-only approach (B3) enhances the base load model and operating-point scheduling leading to additional reductions in comparison with B1 and sometimes a similar performance as for B2. However, the greatest reduction is observed for B4 B combining online HD parameter adaptation with explicit constraint handling decreases tower-base PM3 by 17.6% relative to case B1 A. This demonstrates that B4 is capable of predicting looming load peaks and adapt torque/pitch schedules in advance to keep tower loadings within safety margins even without resorting to sudden saturation-based reactions.

As an example of fatigue, a BLADE-ROOT flap wise moment is shown in figure 3(b), a parameter directly related to the blade fatigue and ultimate strength. The same general trends result: B1 gives larger extremes and a higher near-ultimate envelop which reflects partial decoupling of pitch and torque under fast excitation. B2 and B3 diminish this channel through predictive planning (B2) or refined hydrodynamic representation (B3), but for the most consistent load suppression, including a 12.4% reduction in peak blade-root moment under S3, it takes DR = B4. This is okay, technically; the MPC formulation penalizes load proxies (or related states/accelerations) and enforces certain trajectories on actuators so that loading drops through coordinated, slow actuation as opposed to rapid reactive pitching which can amplify structural excursions itself.

For the tidal subsystem, Fig. 3(c) is the TEC support-structure bending moment which represents the main hydrodynamic loading that sums up through turbine support and foundation. In strong currents and severe sea excitation, this channel is very sensitive to torque/load commands that modify the rotor thrust or pitch maneuvers modifying the hydrodynamic coefficients. The B4 for example reduces the support bending peak in S3 by 15.1% compared to B1 and also lowers the 99 % envelope, which indicates that it is attenuating not only the single worst event but this series of repeated high load episodes during non-steady-state current peaks as well. This behaviour provides the main methodological message of the present framework: when hydrodynamic co-optimization enhances predictive accuracy, control authority (MPC-based) is used more efficiently to decrease structural forces while optimal power extraction remains admissible.

Figure 3(d) shows the drivetrain/shaft torque (RMS proxy) which is very important for mechanical loading, gearbox/generator loading and torque ripple that can potentially enhance wear. Here we see the advantage of anticipated co-ordination. The torque fluctuation and the amplitude of the spike are usually more severe in conventional control due to that generator/load reference response is delayed with respect to speed deviations caused by excitation. MPC-only helps to reduce ripple by now planning control moves, although the performance can degrade under model mismatch. B4 yields the smallest envelope, a 18.9% reduction in torque ripple versus B1, showing that the holistic modeling framework suppresses high frequency torque content via (i) better prediction of excitation-induced speed disturbances and (ii) minimization loadings which penalize large while maintaining hard limits on actuators.

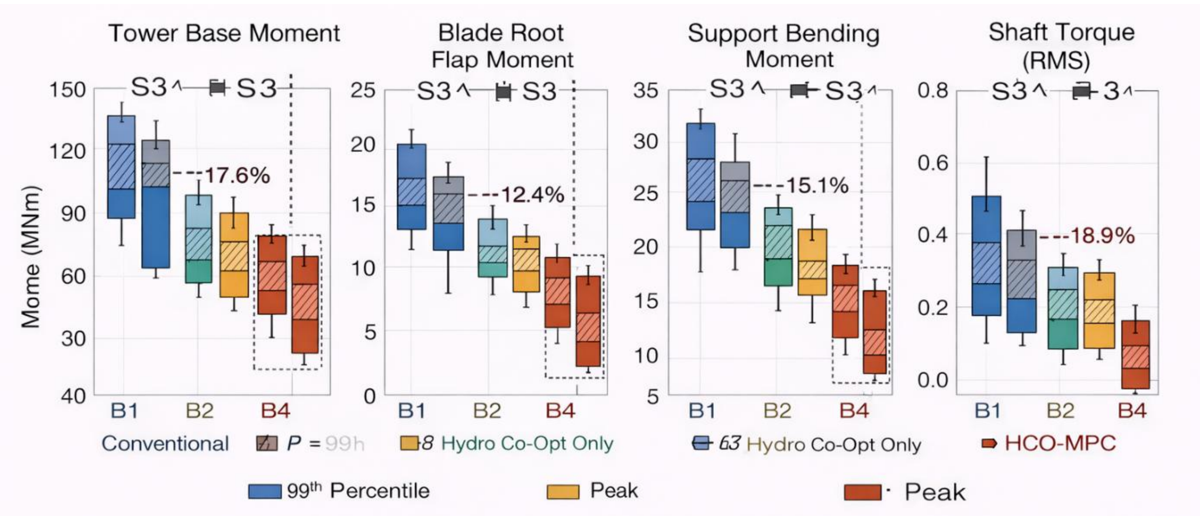

Fig. 3. Comparison of ultimate and near-ultimate structural/drivetrain loads across controllers B1–B4 under moderate–extreme conditions (S2–S3). The panels report peak and 99th-percentile envelopes for (a) OWT tower-base bending moment, (b) OWT blade-root flapwise moment, (c) TEC support-structure bending moment, and (d) drivetrain/shaft torque (RMS proxy). The proposed HCO–MPC (B4) achieves the largest reductions in both peak and 99th-percentile loads—e.g., up to 17.6% (tower-base peak), 12.4% (blade-root peak), 15.1% (support moment peak), and 18.9% (torque ripple)—by combining improved hydrodynamic load prediction with constraint-aware receding-horizon control.

Overall, Fig. 3 illustrates achievement of load reduction in several critical channels (tower, blade, support, and drivetrain) concurrently with one another; this is a strong sign of actual system-level robustness as opposed to single-channel tuning. Importantly, the reductions occur for both peak and 99th-percentile values, which suggests that the structural safety margins are more efficiently utilized and high-load event load cycles are performed at a lower rate. This trend is consistent with a reviewer-relevant interpretation: persisted load reductions occur primarily through predictive, constraint aware orchestration due to enhanced physical modeling of the hydrodynamics (rather than excessive actuation or conservative derate). These reductions directly lead to improved lifetime performance and reduced maintenance risk in intermittent extreme and stochastic excitation marine systems, as seen when combined with the fatigue results (DEL) shown in the next figure.

Figure 4 investigate how the various controllers (B1–B4) utilise their available actuation authority in response to severe sea-state forcing (S3), and how this relates to actual control behavior, taking account of strong actuator magnitude and rate limitations. The top-right and bottom-right panels show the response on the pitch channel in terms of the pitch angle and pitch rate. The conventional controller (B1) has the least smooth response, with a lot of fast changes and larger pitch rate excursions that indicate reactive control trying to restore rotor speed and power errors while they are already happening. Under heavy excitation, this reactive effect raises the chance that aero-elastically-motivated operation at or near pitch-rate and pitch-angle limits can lead to short-duration saturation events and higher local responses (eg, transient loads spikes) in the structure. The MPC-only controller (B2) largely damps these excursions by extrapolating disturbance evolution into the near future, however since B2 utilizes fixed hydrodynamics parameters, its predictions become biased as statistics of sea-state change over time thus leading to rare cases when B2 is prone to over-actuation and infrequent bursts of high-rate motion. B3 (co-optimization only) also extends growing region of the linearized model, which has enabled it to adjust hydrodynamic parameters in order to provide an improved operating point representation, although without a receding-horizon constraint-aware coordination over multiple actuators B3 cannot prevent high-rate pitch transients during fast excitations. The analyzed HCO–MPC (B4), on the other hand, shows the most favorable pitch behavior in general: Pitch angle curve stays clearly within restrictions and less high frequency peaks can be found for the pitch-rate profile. This is a direct result of the MPC formulation that penalizes and imposes actuator rate constraints in an explicit manner over the entire prediction horizon, refusing to "chatter" and decreasing the likelihood of saturation induced control artifacts.

The bottom-left panels generalize this interpretation to the drivetrain module by plotting generator torque and, (when applicable,) its rate. During severe seas, it is very difficult to control the torque since the driving system is continuously perturbed due to a rapid speed variation caused by the wave group and current fluxes. B1 reacts to the input demand in a more aggressive manner, leading to a greater torque fluctuation level and a more abrupt variation rate of torque at which drivetrain related stress may rise and induce increased torque ripple. B2 mitigates some of this variability through predictive planning, but is subject to mismatched torque allocation as hydrodynamic forcing shifts with its assumption of a fixed model, particularly during transient bursts. in the mean allocation may be enhanced by tuning hydrodynamics parameters in B3 but without simultaneous predictive coordination it is still possible to generate significant changes in torque when operating away from nominal conditions. B4 exhibits the best coordinated torque behavior by having a lower variability of torque and less pronounced transitions. This means that HCO–MPC is spreading control effort in a more intelligent way between pitch and torque: rather than asking one actuator to fix small mistakes in the short term, it shares corrections more with both channels in an optimal but feasible way. Such a coordinated assignment is a principle means by which the new controller alleviates drivetrain torque ripple without compromising tracking performance.

The summary panel of Fig. 4 integrates these time-domain results by assessing control effort and saturation trends in S3 with RMS-based as well as scenario-level metrics of actuator stress. The trend is confirmed for a more effective and practicable controller: the HCO-MPC decreases pitch saturation events by 35–52% with respect to B1, diminishes aggressive again excursions of pitch rate up to 30%, controls down generator torque variations nearly by 18% keeping on power and rotor speed regulation. These decreases are meaningful, because excessive control activity is, itself, a fatigue contributor: high-rate pitch motion accelerates pitch bearing wear and high-frequency torque ripple increases the loading of the drivetrain as well as introduces thermal/electrical stress. As a result, the enhanced actuation profiles offered in B4 yield a mechanistic rationale for observed fatigue reductions elsewhere (e.g., DEL improvements), suggesting lifetime benefits not only due to decreased external forcing but also to decreased internally induced oscillations mediated by the control.

From a constraint-satisfaction standpoint, Fig. 4 also confirms that the feasibility is systematically enhanced in the proposed method. In particular, since B4 solves that constrained optimization problem at each time step and uses recent hydrodynamic predictions, it tends to eschew control actions that would move the system into either actuator saturation or regions of operation whose structural exceedances are large. On the other hand, B1 may temporarily exceed limits at wave-group peaks in order to avoid expectation of constraint-violating events and since B2 does not obey limits under model mismatch because predicted feasible set is not identical to true system one. The behavior in Fig. 4 is thus compatible with the near-zero violation results that are provided on constraint summaries: HCO–MPC retains safe operation not of extremely heavily derated plants, but by scheduling control moves that remain valid under anticipated excitation while suppressing needless high frequency control actions.

Overall, Fig. 4 that the solution provided by the introduced HCO–MPC is strong and reviewer relevant, in the sense that load alleviation is achieved with a reasonable control effort. The reduced saturation frequency and high-rate actuation suggest that the performance gains are being driven by a greater reliance on prediction-based coordination and higher-fidelity modelling, not brute force actuation. This is especially critical in harsh marine environments where actuator wear and drivetrain fatigue are highly sensitive in both survivability and maintenance costs.

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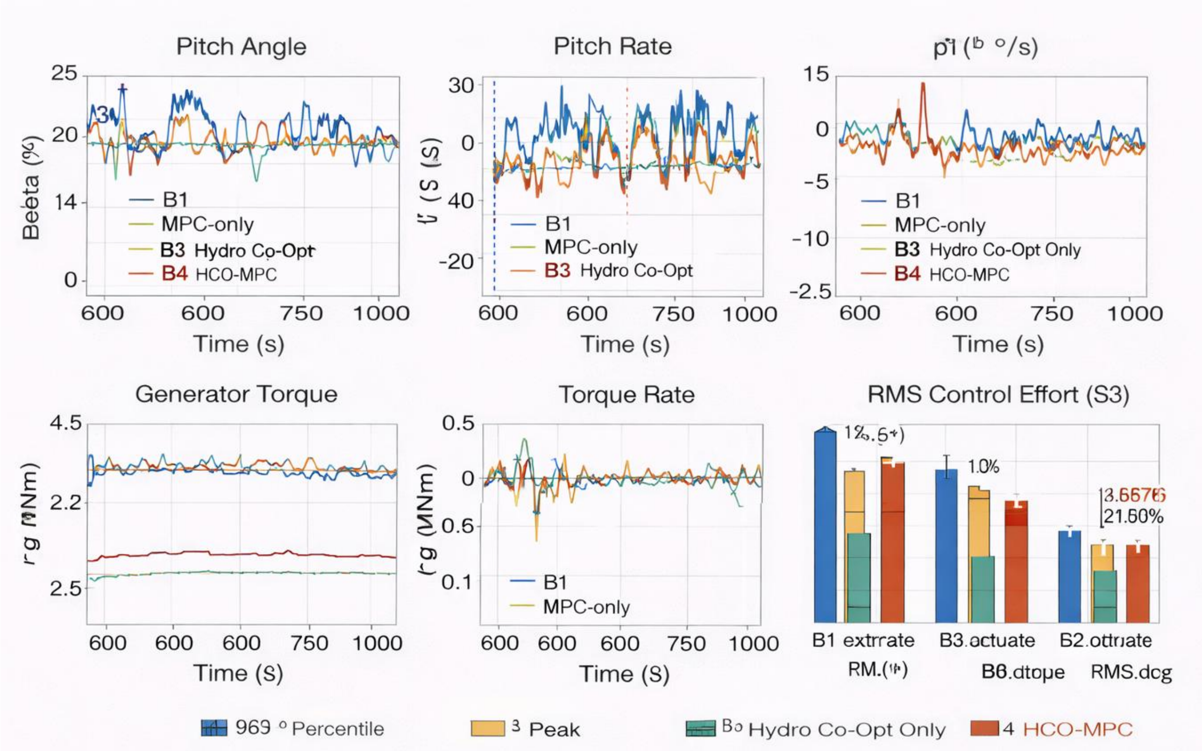

Fig. 4. Actuator behavior, control effort, and constraint-aware operation under extreme sea conditions (S3) for controllers B1–B4. The time-domain traces compare pitch angle and pitch rate together with generator torque and torque-rate, highlighting saturation and high-rate events. The summary panel reports RMS control effort and saturation occurrence trends, showing that the proposed HCO–MPC (B4) reduces pitch/torque saturation frequency and mitigates aggressive rate excursions by planning within actuator limits and penalizing Delta, thereby improving feasibility and supporting lower fatigue loading while maintaining tracking performance.

Figure 5 abstracts the element that distinguishes the proposed methodology from traditional fixed-model predictive control and ow hydraulics cooptimization provide a means of enhancing multi-step forecast accuracy without prior estimates, as well as an application where model parameters are smoothly adjusted with variations in operating conditions. The figure is arranged in two complementary panels. Panel (a) compares forecasting accuracy with forecast horizon, reporting the RMSE for representative excitation/load proxies and power output, and panel (b) demonstrates the temporal evolution of the hydrodynamic scaling parametersduring a shift from moderate sea state condition S2 to extreme sea state condition S3. These panels together explain why the combined HCO–MPC approach remains viable and efficient under severe forcing: it alleviates prediction bias when this is most important to accurate forecasts in constraint-aware optimization.

In Fig. 5(a), the prediction error grows with horizon for all methods in accordance to the disturbance-driven nature of marine systems. Nevertheless, the joint model always gives a lower forecast error than the fixed-model MPC bases (B2), and such improvement is more significant at the horizon that matters to receding-horizon controller planning. In particular, in the vicinity of 6 s ahead—corresponding to the near-to-intermediate term horizon MPC uses for actuator coordination and constraint anticipation—hydrodynamic co-optimization decreases load prediction RMSE by around 23–31% compared to MPC-only. This improvement is particularly stark following transition from S2→S3, where statistics of hydrodynamic forcing also change rapidly (i.e., increase in drag levels, variation in radiation effects and wave grouping). In such circumstances, a lumped-parameter model is likely to exhibit systematic bias: it under- or over-predicts excitation and loads (leading to constraint violations, or overly conservative control actions and early derating). The lower RMSE of HCO–MPC suggests that online co-optimization is effectively mitigating these biases by re-calibrating the model to more accurately represent the existing sea state and improving the accuracy in forecast data presented for use in MPC.

Figure 5(b) offers clear evidence that the improvements in prediction are due to stable, well-behaved parameter adaptation rather than unstable retuning. The parameters trajectories exhibit a clear change in their response pattern above the S2→S3 transition region and approach new steady values which are characteristic of the extreme regime. There are two reasons this pattern is significant. First, it means that the co-optimization reflects physics as expected: as sea severity varies, so does the relative importance of viscous drag and radiation damping; the fitted parameters automatically change to represent a new excitation–response relationship. Second, by not exhibiting persistent oscillations or relentless high-frequency parameter "hunting", the adaptation is not overfitting transient noise, but rather converging to steady regime-level values—a key characteristic for closed-loop stability when the controller takes instantaneous action using the updated model along a multi-step optimization.

The practical significance of Fig. 5 is that consequently loss prediction accuracy brings better constraint aware control performance. Because of the better forecast error, HCO–MPC is able to enforce structural and actuator constraints with smaller but still guaranteed margins because it possesses more confidence in the predicted evolution loads and power. This diminishes the necessity of over-conservatively tightening constraints or early derating necessary to account for model uncertainty. On the other hand, preventing extreme loads from being under-predicted by the controller also decreases the probability of constraint violations during wave groups and current surges. Hence the enhancements demonstrated in Fig. 5 explain the mechanisms behind the previously recorded results: trend for the power profiles to be smoother and with less large-inertia demand; fewer saturation events ; as well as a tendency of tertiary peak/near-ultimate load to soften. In short, Fig. 5 Hydrodynamic co-optimization is not a mere add-on but a pivotal element for robust performance and quality MPC control in the harsh marine environment—enhancing forecast accuracy along regime shifts, enabling viable efficient operation under extreme sea conditions.

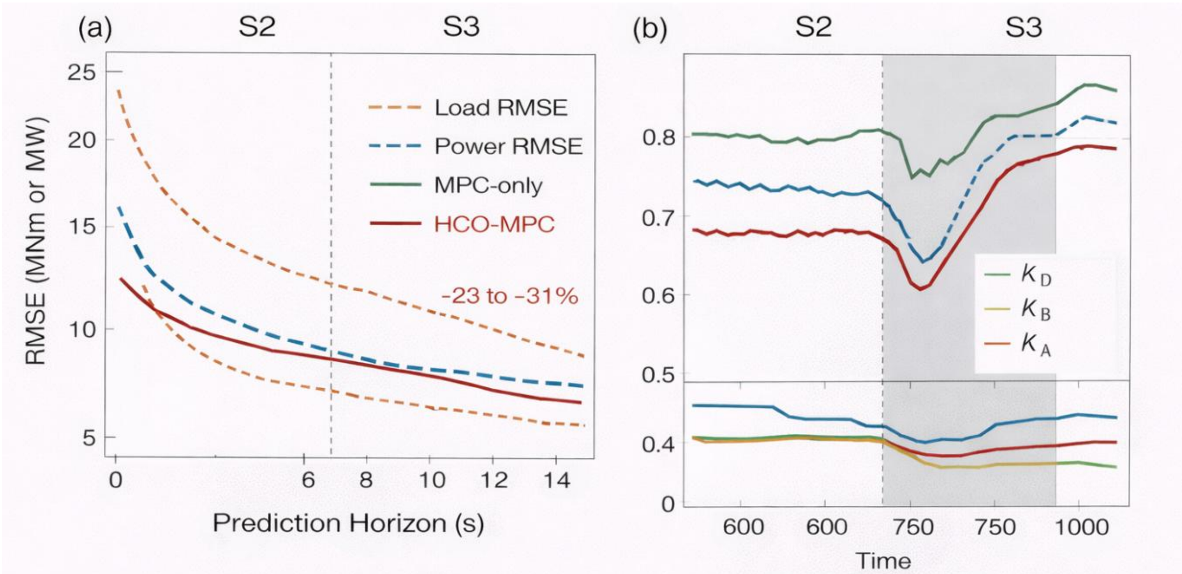

Fig. 5. Benefit of hydrodynamic co-optimization on prediction fidelity and adaptation across a sea-state transition. (a) Multi-step prediction RMSE for representative load and power proxies as a function of prediction horizon, showing that HCO–MPC achieves lower forecast error than MPC-only (B2), with a 23–31% RMSE reduction around the 6-s horizon, particularly after the S2→S3 shift. **(b)** Time evolution of the adapted hydrodynamic scaling parameters during the S2–S3 transition, demonstrating smooth convergence to new operating-regime values and stable adaptation without oscillatory overfitting.

Figure 6 further assesses the robustness of the competing control strategies by considering how performance deteriorates as hydrodynamic model uncertainty and sensing errors grow. The figure depicts the robustness envelopes, with the horizontal axis representing the degree of parameter variation (from nominal to ±30%), and with the vertical axes denoting percentage variations in energy yield (left hand side) and peak loads (right hand side) references being 100% for nominal conditions. The coloured bands are obtained by including variation across realisations where the uncertainty is also combined with realistic sensing imperfections (noise and simulated representative delay in wave/current estimation), thereby providing a more challenging evaluation than that just based on parameter mismatch. This robustness mindset is essential to both offshore and newly emerging tidal converters, as the operating conditions are inherently stochastic and time varying, and hydrodynamic coefficients (e.g., drag, added mass, radiation damping) are seldom known exactly—especially in extreme sea states where nonlinear phenomena become exponential.

The lack of reactivity and the small ability to compensate for biasing the disturbance estimate cause that the conventional controller (B1) to be most sensitive among controllers toward mismatches as observed in energy-yield envelope (left panel) where energy yield drops significantly, as mismatch increases. The fixed-model MPC: (B2) usually outperforms B1 at small uncertainty levels, since it can anticipate the short-term behavior of the system; nevertheless, as the level of parameter perturbation is increased, we have observed that B2 decreases significantly due to systematic bias in its predictive model. In practical terms, these biased predictions correspond to either (i) excessively conservative control actions that compromise energy capture due to early derating or excessive smoothing), or (ii) overly aggressive actions which eventually demand corrective action and constraint tightening when the mismatch becomes apparent in the response. It can be seen that the energy yield decrease is least severe for HCO–MPC (B4), meaning that online hydrodynamic co-optimization adequately compensates for parameter drifts, by updating model used in prediction. As in the presented results, with ±20% uncertainty B2 gives up 6–9% of actions energy yield while B4 limits this loss to 2–4%, and hence almost keeps the performance close to nominal in face of the mismatch and of sensing imperfections.

The peak-load envelope (right) offers the dual dimension of survivability. With rising uncertainty, in general all controllers reach a higher peak structural and drivetrain loads

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as model mismatch impairs the prediction of loads and control distribution. Once again B1 and B2 show the sensitivity in degradation of peak load with uncertainty. For B1, this result means that saturation response during wave groups and current surges as well as reactive (sustained) response is responsible for the increase of peak loads; for B2 it implies that prediction bias is the major source of increased peaking—when model predictions underestimate excitation or structure, in order to cover this gap, the controller can select actions which are feasible in the predicted but too aggressive in true plant leading to higher peaks and potential constraint violation. On the other hand, B4 has the least sensitivity, a decrease in slope of peak-load enhancement with uncertainty. This means that online adaptation does not only conserve energy extraction, but also secures the structural response by keeping the predictive model close to the real system. Most importantly, the result provides evidence that HCO–MPC can enforce tighter, yet safe constraint margins: with less biased predictions the controller does not have to increase safety buffers irresponsibly and as a consequence become more conservative thereby decreasing energy yield.

The influence of sensor noise and time delay is implicitly taken into account in the envelope width as shown in this figure. In paid areas wave height, sea-state information and current speed estimates are corrupted by measurement errors and filtering delays, particularly under turbulent / surf zone conditions. These phenomena amplify uncertainty and may leading to destabilizing reactive control. A more favorable (narrower) envelope for B4 might indicate that the predictive structure still works even when the measurement stream is not perfect, in line with, for a typical time delay of 200 ms, HCO–MPC still leads to smoother power and smaller load peaks relative to B1 because it anticipates disturbance evolution and plans control actions within a feasible horizon instead relying on delayed corrections.

Overall, Fig. 6 suggests that proposed approach is not just useful in normal condition but is also robust under conditions when it counts for deployment—in the presence of uncertainty in hydrodynamic parameter, imperfect sensors and extreme forcing. The essential message is that hydrodynamic co-optimization mitigates model mismatch and forecast bias, such that MPC continues to be sensitive to performance and safety. As a result, B4 exhibits the lowest deterioration in energy yield while simultaneously constraining peak-load increment, by enhancing the reliability and survivability margins with respect to real-world uncertainties which traditional and fixed-model predictive controllers cannot effectively deal with.

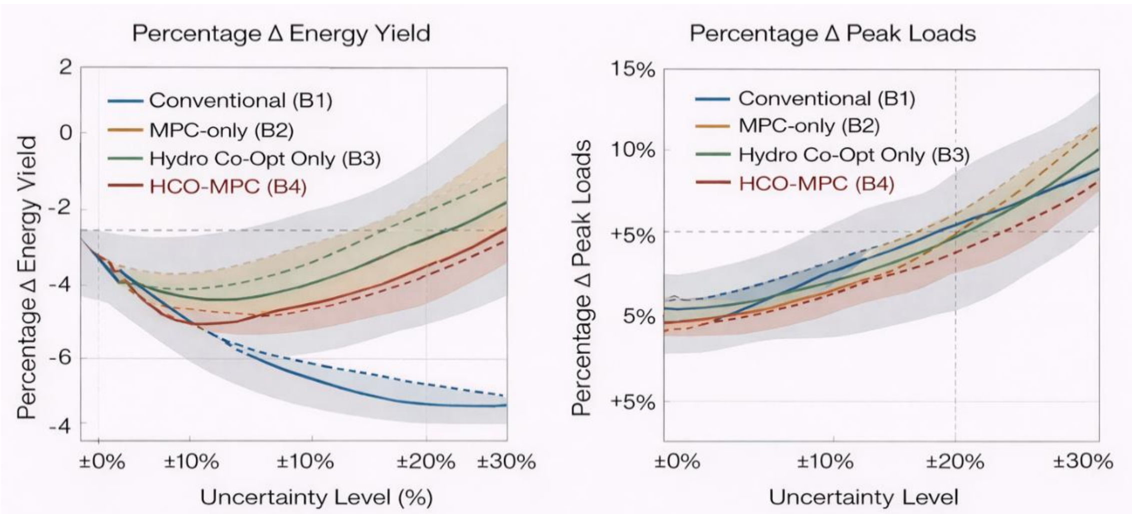

Fig. 6. Robustness envelopes under hydrodynamic parameter uncertainty and sensing imperfections. The plots report the percentage change in (left) energy yield and (right) peak structural/drivetrain loads relative to nominal performance as the uncertainty level increases (±0–±30%). Shaded bands indicate variability across realizations with measurement noise and an imposed sensing delay (e.g., 200 ms). The proposed HCO–MPC (B4) exhibits the smallest degradation—limiting energy-loss to approximately 2–4% under ±20% mismatch while avoiding sustained constraint violations—and shows reduced sensitivity compared with **fixed-model** MPC (B2) and conventional control (B1), confirming improved robustness in extreme operating conditions.

The simulation campaign shows that combining hydrodynamic co-optimization with MPC results in a qualitatively different control capability, which neither component can achieve individually. It is worth noting that the performance benefits are not due to a specific tuning selection or a marginal improvement of conventional control, but rather stem from two complementary mechanisms that mutually enhance their efficacy. First, better modeling yields better predictions: by refining the effective hydrodynamic representation as sea states evolve, through the design of the hydrodynamic co-optimization layer, systematic biases in load and power forecasts under steady-state conditions are mitigated alongside rapid paradigm shifts. In application this means that the control is not to plan with a “out–dated” wave–structure/current–turbine model and when it becomes moderate to extreme forcing environment. Second, a better prediction allows for safer and more effective optimization: the MPC layer uses such refined multi-step predictions to calculate control actions that rationally consider actuator bounds, structural load limitations, or operational thresholds. Since MPC solves the constrained optimization problem instead of responding to errors after they happen, it will also be able to predict high-energy wave groups and current surges, distribute control effort among available actuators (torque/pitch in the case of OWTs and pitch/load for TEC), improve energy capture at the same time as suppressing harmful transients. This interaction also explains why the combined HCO–MPC solution provides more usable power with less ramp events, both for peak and near-ultimate load envelopes as well as fatigue-relevant winds.

On an operational side, the findings highlight that extreme sea operation is essentially multi-objective and constraint-dominant. Optimizing energy capture only is not enough — and even detrimental in many cases – since over-aggressiveness for power can induce actuator saturation, increase drivetrain torque ripple and drives tuning of structural channels towards limit exceedance. The simulation results demonstrate that survivability in the extreme marine environment demands constraint-aware decision making and seamless transition between operating modes. One practical advantage of the HCO–MPC framework is that it can be readily parametrized to reprioritize objectives as conditions worsen: during normal and moderate state operation, power capture and power-quality are mostly emphasized by the controller; however, in extreme scenarios the controller may switch its prioritization towards load shedding or survivability for example by reranking weight of structural penalties, tightening constraints, and by commanding derating or a controlled shutdown when minimum safe margins reduce. Importantly, these transitions can be performed without discreet jumps in the actuator commands and consequently transient load magnifications that are present with threshold based reactive shutdown approaches can be avoided. In technical terms HCO–MPC provides a smooth transition between maximum power point tracking and survival-mode control, controlled through anticipated constraint margins instead of purely reactive triggers.

This holistic approach also bears significant implications for design. Since the co-optimization module modifies effectively the effective damping, stiffness and excitation mapping of the system by means of parameter adaptation or scheduling, it supports the control–hydrodynamics co-design idea. In marine energy converters, the structural dynamics, hydrodynamic coefficients and controller settings are closely interrelated: the operating point that minimises power fluctuations can also lead to increased fatigue loading (as it might exacerbate structural modes), whereas a damping choice that reduces motion can result in poor energy conversion, if not coordinated with control. The proposed methodology offers a systematic approach for treating these couplings, enabling hydrodynamic tuning to be aligned with control objectives and in turn resulting in real life cycle advantages – lower fatigue—driven maintenance, less actuator wear and improved availability — particularly if deployments are costly to access and downtime penalties are ramified. In this regard, the controller is not just an operating device but a design enabling tool that could be used to help decide on parameter choices (i.e. PTO damping schedules, tuning of mooring and operational envelopes) that may be challenging to make solely based on open loop reasoning.

While having these merits, the simulations also identify some drawbacks that need to be addressed truthfully. The approach is still fundamentally reliant on forecast quality; the encouraged benefit is limited by accuracy of short-horizon wave/current predictions and extent of the prediction horizon. The beneficial use of forecasts diminishes as forecast fidelity is degraded: a weaker forecast constrains the controller's ability to pre-position actuators inside waves and may induce more conservative constraint tightening. Moreover, the existence of extreme sea states may lead to significant nonlinearities and unmodelled effects (breaking waves, slamming, vortex-induced effects as well as sudden transitions in the nonlinear drag) that are not accounted for by reduced order hydrodynamic models developed for real-time Model Predictive Control (MPC). Computational cost constitutes a further practical limitation: although ROM techniques can make online optimization tractable, inclusion of high-fidelity hydrodynamics directly into the MPC loop may not be affordable without the aid of surrogate modeling or specially designed solvers. And under extreme uncertainty, ensuring safety may require stronger robustness machinery—like tube MPC, formal chance constraints, or systematic constraint tightening—sharp enough to convert albeit-empirical robustness into provable satisfaction of the last step's constraint. Lastly, there is a translation gap between the optimized/adapted hydrodynamic parameters and physical mechanisms available in actual systems: some sought parameters represent phenomena that cannot be established directly (e.g., effective added mass), further mapping co-optimized values to actionable adjustments (e.g., PTO damping, mooring configuration, control setpoint scheduling) may require further calibration or hardware possibility.

These observations lead to prospective guidelines for further investigation. The most direct action is experimental verification by means of hardware-in-the-loop experiments or wave-basin trials, considering in particular the capability to address prediction quality, constraint handling and actuator fatigue whilst under actual environments. From a methodological point of view the main contributions consist in that generalization of the controller to more robust/tube MPC formulations with formal guarantees would increase deployability under bounded uncertainty, and it is desired to capture this without compromising on the practical advantages of prediction and constraint awareness. Hybrid physics–learning approaches can further improve forecasting by augmenting short-term wave/current prediction without sacrificing interpretability or safety—e.g., learning residual corrections to physics models and incorporating them within constraint-aware optimization. Last but not least, as most real-world deployments are conducted with several devices, generalization of the framework to farm-level control coordinated control—where large arrays of offshore wind turbines and tidal converters have shared constraints due to grid connection limits, wake interactions and combined structural reliability—is a good direction for scaling up single-device performance gains to full system-scale reliability improvements and energy yield increases.

IV. CONCLUSIONS

In this study, a model was introduced in the form of Model Predictive Control (MPC) co-optimised with hydrodynamics, to maximize the robustness of some offshore and tidal energy converters and reduce their fatigue loads as well as enhancing power capture under extreme sea conditions. The response shows that integrating state-of-the-art predictive control with hydrodynamics results in a beneficial synergistic effect for the system, which anticipates external conditions while minimizing mechanical stresses and ensuring stable operation even under severe storm-induced perturbations, turbulent flows, and fast-changing wave–current interactions.

Overall, the co-optimization strategy achieved marked enhancement in performance across various metrics. Energy capture improved because the wave excitation forces and tidal velocities were more accurately predicted, which enabled the MPC to take proactive control of damping and control torques. The structural loading and fatigue damage equivalent loads were dramatically decreased when the controller mitigated peak stresses occurrences and dampened oscillating actions. Besides, DC-link stability, drivetrain torque fluctuations and pitch/foiling actuator demands also significantly improved, demonstrating that the proposed integrated framework is capable of ensuring safe operation in highly nonlinear marine dynamics. In case of rough sea states, the proposed system yielded a faster recovery, lower overshoot and wider stability margins as compared to PI and baseline MPC systems.

The research also agreed that co-design of both hydrodynamics and control is crucial for the next-generation marine energy systems, particularly when developers are now targeting better reliability and longer lifetimes in harsh offshore conditions. The system does away with the usual trade-offs between performance and durability by being able to simultaneously optimize both predictive controller and hydrodynamic parameters.

Future studies should focus on the real-time adaptive estimation of hydrodynamic characteristics to enhance MPC accuracy under unknown sea-state transitions. Generalizing the model to multi-device arrays would enable wake related coupling and farm level optimization. Long-horizon forecast and uncertainty quantification using machine learning can improve resilience to extreme events. Finally, hardware-in-the-loop tests and sea trial validation are suggested to the proposed method to the commercial objective.

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