A novel disruptive data-driven approach for mooring line modeling and design in floating offshore wind

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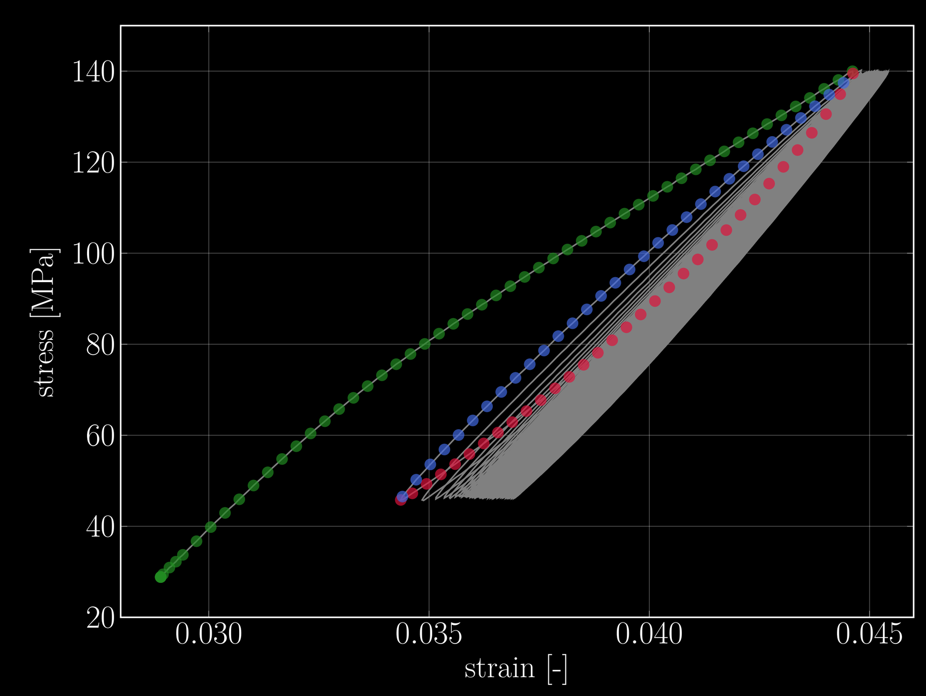
Introduction

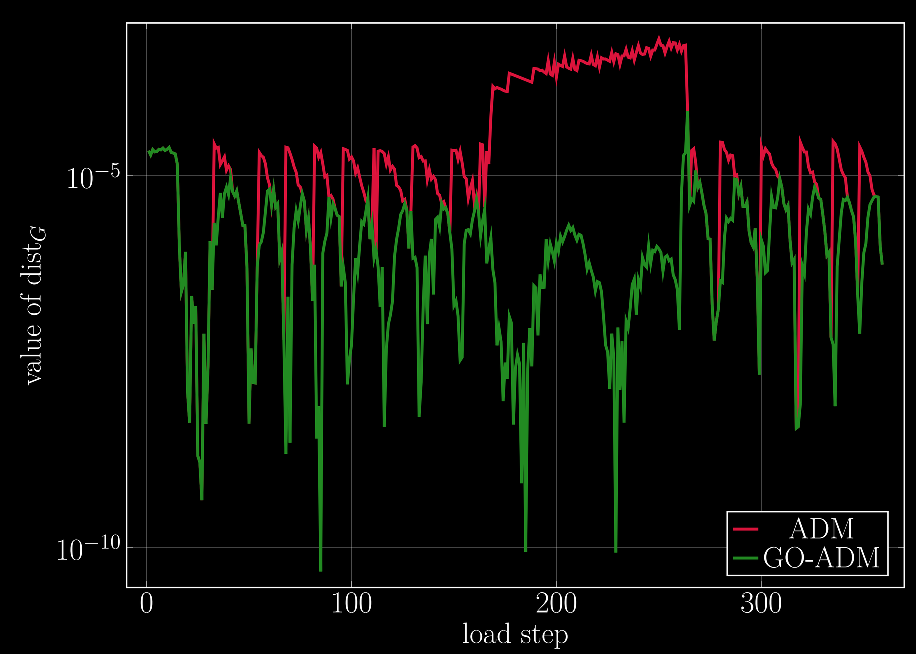
The design and analysis of mooring systems for floating offshore wind turbines traditionally rely on constitutive models that are approximations, calibrated from experimental data, and oftenly cannot capture and predict complex behaviors under highly nonlinear load conditions. In this work, we apply and investigate a novel disruptive alternative: a data-driven computational mechanics framework for modeling mooring lines, enhancing design reliability and operational safety for floating offshore wind systems. In particular, we develop a solving strategy that is a data-driven greedy optimization algorithm based on the Alternating Direction Method, called GO-ADM, enabling direct utilization of experimental data and bypassing empirical constitutive assumptions. We apply our framework to the structural analysis of a nylon mooring line using experimental data from cyclic loading tests conducted at industrial facilities. Our results underscore the potential of data-centric mechanics as a disruptive technology for next-generation offshore wind infrastructure.

Cyclic test of a nylon rope

- A nylon rope of initial length of 17.010 m.
- A cross-sectional diameter of 0.208 m.
- Cyclic tensional loading over 55 minutes with measured strains.



Provided dataset, consisting of more than 16, 500 discrete points.



Values of the global objective function.

Conclusions and outlook

A solving strategy, combining a greedy optimization algorithm and the alternating direction method, GO-ADM [3,4], is introduced. Our approach reduces the global objective function, better approximating the global optima. This, however, comes at the expense of higher computational cost in terms of the number of iterations and computing time. We applied and demonstrated this via a cyclic test of a nylon rope, using real experimental dataset.

Future work includes accelerating approaches for the GO-ADM solving strategy, data initialization approaches for nonlinear systems, and extending GO-ADM for more complex structural models, such as geometrically exact beams, shells, and solid elements.

References

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Nonlinear data-driven one-dimensional elasticity

Consider a bounded domain $\Omega \subset \mathbb{R}$ and a physical body that occupies the closure $\bar{\Omega}$, which is represented as a one-parameter curve $\boldsymbol{\varphi} = \boldsymbol{\varphi}(\xi) \in \mathbb{R}^2$, where $\xi \in [0, L_0]$ is the arc-length coordinate. Let $\boldsymbol{u} \in H_0^1(\Omega)$, $e \in L^2(\Omega)$, $s \in L^2(\Omega)$ denote the displacement, axial strain, and stress fields, respectively, $\boldsymbol{\lambda} \in H_0^1(\Omega)$, $\mu \in L^2(\Omega)$ the dual fields of Lagrange multipliers. Let Θ define the enforcement of the equilibrium and the compatibility conditions using Lagrange multipliers:

$$\begin{aligned} 0 = \Theta(z, x; \boldsymbol{f}) &:= \langle \boldsymbol{\lambda}, \mathcal{B}^T s - \boldsymbol{f} \rangle_{L^2(\Omega)} + \langle \mu, \epsilon(\boldsymbol{u}) - e \rangle_{L^2(\Omega)} \quad \forall z \in Z, \\ \text{with } x &:= (\boldsymbol{u}, e, s) \in X := H_0^1(\Omega) \times L^2(\Omega) \times L^2(\Omega), \\ y &:= (e, s) \in Y := L^2(\Omega) \times L^2(\Omega), \\ z &:= (\boldsymbol{\lambda}, \mu) \in Z := H_0^1(\Omega) \times L^2(\Omega). \end{aligned} \tag{1}$$

In this work, we consider the following displacement-based strain and corresponding strain-displacement operator:

$$\epsilon(\boldsymbol{u}) = \boldsymbol{\Phi}' \cdot \boldsymbol{u}' + \frac{1}{2} \alpha \boldsymbol{u}' \cdot \boldsymbol{u}', \qquad \mathcal{B}(\cdot) = \boldsymbol{\Phi}' \cdot (\cdot)' + \alpha \boldsymbol{u}' \cdot (\cdot)', \quad \alpha \in \{0, 1\}, \tag{2}$$

respectively, where $\boldsymbol{\Phi} = \boldsymbol{\Phi}(\xi)$ denotes the reference configuration of the physical body, which relates to the current configuration as $\boldsymbol{\varphi} = \boldsymbol{\Phi} + \boldsymbol{u}$. Here, α is a factor that has either a value of 0 or 1 to neglect or consider the nonlinear term in the definition of $\epsilon(\boldsymbol{u})$, respectively. Consider a given closed data set of stress-strain pairs $\mathfrak{D}$. One can construct the corresponding strain and stress fields from $\mathfrak{D}$ as follows:

$$\mathcal{D} := \{ \tilde{y} := (\tilde{e}, \tilde{s}) \in L^2 \times L^2 : (\tilde{e}(\xi), \tilde{s}(\xi)) \in \mathfrak{D} \ \forall \xi \in \Omega \}. \tag{3}$$

The static structural analysis of the physical body can be formulated as a discrete-continuous quadratic optimization problem [1,2] as follows: Find $x \in X$ such that:

$$\begin{aligned} &\inf_{x, \tilde{y}} \sup_{z \in Z} \operatorname{dist}_G(y, \tilde{y}) + \Theta(z, x; \boldsymbol{f}) \ \text{ s.t. } \tilde{y} \in \mathcal{D}, \\ &\text{with} \quad \operatorname{dist}_G(y, \tilde{y}) := \frac{c}{2} \| e - \tilde{e} \|^2_{L^2(\Omega)} + \frac{1}{2c} \| s - \tilde{s} \|^2_{L^2(\Omega)}, \end{aligned} \tag{4}$$

where c is a constant weighting scalar to ensure unit consistency. Here, $\operatorname{dist}_G(\cdot, \cdot)$ denotes the global objective function. The first-order necessary optimality conditions (Karush-Kuhn-Tucker (KKT) conditions) state the resulting stationary problem as follows: Given a fixed $\tilde{y} = (\tilde{e}, \tilde{s}) \in \mathcal{D}$:

$$0 = \delta (\operatorname{dist}_G(y, \tilde{y}) + \Theta(z, x; \boldsymbol{f})) = \boldsymbol{g}(\boldsymbol{q}), \tag{5}$$

where $\boldsymbol{q}^T = \left[\boldsymbol{u}^T \, e \, s \, \mu \, \boldsymbol{\lambda}^T \right]^T$. To tackle Eq. (5), we employ the Newton-Raphson and finite element method. For the explicit expression of (5), the resulting spatially discrete problem, and the final matrix equations, we refer to [3], which also includes further discussions.

GO-ADM-solver

Input: solution guess q_0, initial selected data $\tilde{y}_0$, dataset $\mathfrak{D}$, external force vector $\boldsymbol{f}$
Output: q, $\tilde{y}^*$

1: q, $\tilde{y}$ = ADM-solver $(q_0, \tilde{y}_0, \boldsymbol{f}, \mathfrak{D})$ ▷ First results, using standard solver [1]
2: dist$^{(0)}$ = dist$_G(\hat{y}, \tilde{y})$ ▷ Evaluate global objective function
3: $k = 0$ ▷ Number of "greedy" searches
4: **while** $k \le k_{\max}$ **do** ▷ "Greedy" search algorithm
5: d_i = dist$_E(\hat{y}_i, \tilde{y}_i)$, $i = 1, \ldots, M$ ▷ Evaluate element objective function
6: Ξ = sort$(d_1, \ldots, d_M)$ in descending order
7: **for** i in Ξ **do**
8: k+ = 1; $\tilde{y}^n$ = copy$(\tilde{y})$ ▷ Copy $\tilde{y}$ in new $\tilde{y}^n$
9: d_j = dist$_E(\hat{y}_i, \tilde{y}_j)$, $j = 1, \ldots, n_D$
10: q, p = argmin $(d_1, \ldots, d_{n_D})$ ▷ Indices of 2 best alternatives to $\tilde{y}_i$
11: **if** $\tilde{y}_i^n \ne \tilde{y}_q$ **then**
12: $\tilde{y}_i^n = \tilde{y}_q$ ▷ Try the best alternative.
13: **else**
14: $\tilde{y}_i^n = \tilde{y}_p$ ▷ Try the 2nd-best alternative.
15: **end if**
16: q, $\tilde{y}^n$ = ADM-solver $(q_0, \tilde{y}^n, \boldsymbol{f}, \mathfrak{D})$ ▷ Recompute with new $\tilde{y}_i^n$ in $\tilde{y}^n$
17: Collect $\hat{y}$ from q
18: dist$^{(k)}$ = dist$_G(\hat{y}, \tilde{y}^n)$ ▷ Reevaluate global objective function
19: **if** dist$^{(k)}$ < dist$^{(k-1)}$ **then**
20: $\tilde{y}_i = \tilde{y}_i^n$; break ▷ Overwrite the current element data pair. Switch to line 4.
21: **end if**
22: **end for**
23: **end while**

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Presenter's homepage

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