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A parametric study of FEA monopile 1D rationalization methods. Application to mean stress independent models

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ABSTRACT: The results of the PISA joint industry project and the application of advanced Finite Element Analysis (FEA) methods in routine design have enabled significant optimization of primary steel in monopiles, the most commonly used foundation for offshore wind turbines (OWTs). This optimization has substantially reduced costs and mitigated over-conservatism in monopile design. Whilst current design guidelines recommend the use of 3D FEA in routine monopile design, they lack specificity regarding explicit FEA design checks and the 3D to 1D rationalization procedure, both of which are crucial for a robust design methodology and effective OWT substructure design.
This paper offers a comprehensive benchmarking of existing approaches for 3D to 1D rationalization and their practical implications for design. Multiple realistic cyclic Ultimate Limit State (ULS) design scenarios, using soil conditions representative of the North Sea, are examined. This research underscores the critical aspects of rationalization procedures and their impact on design efficiency and reliability, providing valuable insights into best practices and potential enhancements in monopile foundation design for OWTs.

Keywords: Offshore monopiles, soil/structure interaction; numerical modelling

1 INTRODUCTION

Structural monopile design is typically carried out using non-linear soil reaction curves (SRCs), which relate lateral displacements and rotations to the soil reactions acting on the pile. Traditionally only lateral pressures have been used, however as the L/D of monopiles decreases additional soil contributions such as the base shear, base moment and distributed moment become significant. The PISA project addressed these limitations, proposing a four-component soil reaction model (e.g. Burd et al., 2020) as a rationalisation of more complex 3D Finite Element Analyses (FEA). Whilst the application of the PISA methodology is recommended, design guidelines do not enforce it (DNVGL-ST-0126, 2021), (DNVGL-RP-C212, 2019). The only requirement is the validation of the design using advanced FEA. Therefore, workflows adopting only p-y curves are deemed acceptable provided the response of the 3D model is captured.

In this sense the challenge is to produce a 1D model that can reproduce 3D FEA results. This can be achieved through various approaches, such as exact PISA soil reaction curve extraction from performed FEA, rule-based approximations and multiplier optimisation.

This study presents a benchmark of the different methodologies using badly conditioned 3D FEA in challenging soil conditions as an exercise for comparison of the different 3D to 1D rationalization strategies in a real world scenario.

2 DESIGN SCENARIO AND DATASET

Three soil profiles from an undisclosed OWF in the North Sea and a suite of 18 load controlled 3D FEA at various embedment depths are used for this exercise. The engineering context of the benchmark is ULS cyclic 3D FEA design, which accounts for cyclic degradation of a 35h extreme storm.

The cyclic design envelope is represented as a stress-strain envelope with total accumulated strain ($\gamma_{av} + \gamma_{cyc}$) and shear stress ($\tau_{av} + \tau_{cyc}$) (Andersen, 2015). This envelope is calibrated using a total stress constitutive model, PIMS (Whyte et al., 2020) and is used at a gauss point level in 3D FEA. The steps associated with this procedure are shown in Figure 1 and are outside the scope of this paper.

2.1 Cyclic soil profiles

Figure 2 presents the selected soil profiles (SPs), comprising numerous layers of clays and sands with a wide variation in cyclic response. The reference stress value used to de-normalise each cyclic PIMS stress-strain curve is s_u for clays, and σ'_v for sands.

SP1 comprises primarily loose, followed by dense sand, overlying extremely high strength overconsolidated clay. SP2 consists of normally consolidated clay over dense sand. SP3 is clay dominated.

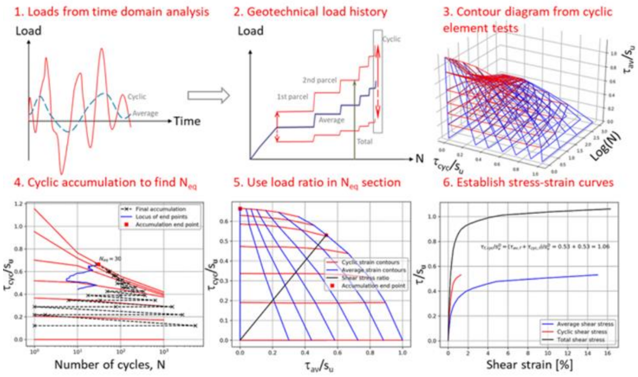

Figure 1: Workflow for cyclic design envelopes. Based on recommendations from Andersen (2015).

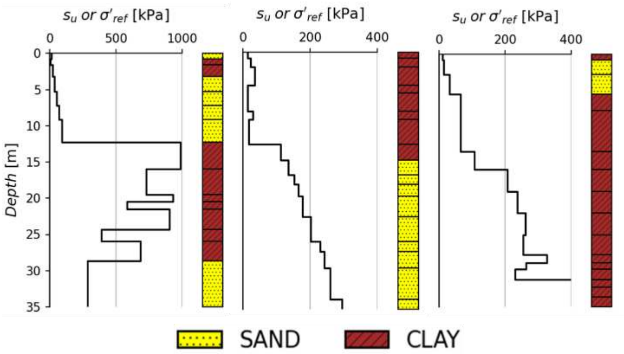

Figure 2. Cyclic SPs used in this study, showing undrained shear strength / reference stress profile with depth and soil-type stick Left: SP1, Middle: SP2, Right: SP3.

2.2 Monopile dimensions and loading conditions

For all analyses, the monopile diameter was 11.5 m with L/D between 2.0 and 2.8. Each analysis was carried out in load controlled conditions with a prescribed lateral load of 25 MN, at an eccentricity of 60 m above mudline.

Table 1 presents the range of Pile Penetration Depths (PPDs) and L/D ratios. The large diameters and L/D ratios of between 2-3 are representative of current and future trends of the industry.

2.3 FEA Analysis

3D FEA was conducted using the commercial software Plaxis 3D 2024. The PIMS constitutive model was implemented as a user defined soil model. Lateral soil pressures, distributed moment, base shear and base moment were extracted directly from the interface gauss points of each step of the 3D FEA solution, allowing for direct comparison to monopile reactions and internal forces obtained using a 1D approach.

Table 1. Summary of monopile geometries and loading conditions.

Soil profile	Diameter [m]	PPD range [m]	L/D range [-]
SP1	11.5	23.50-25.50	2.0-2.2
SP2	11.5	25.75-31.25	2.3-2.7
SP3	11.5	29.50-32.00	2.6-2.8

The analyses, summarised as mudline load-displacement curves in Figure 3, show distinctly different responses and utilizations for each of the soil profiles. Note that the numerical analyses are badly conditioned for optimization adopting load controlled conditions, with a number of simulations not reaching the target lateral load of 25 MN.

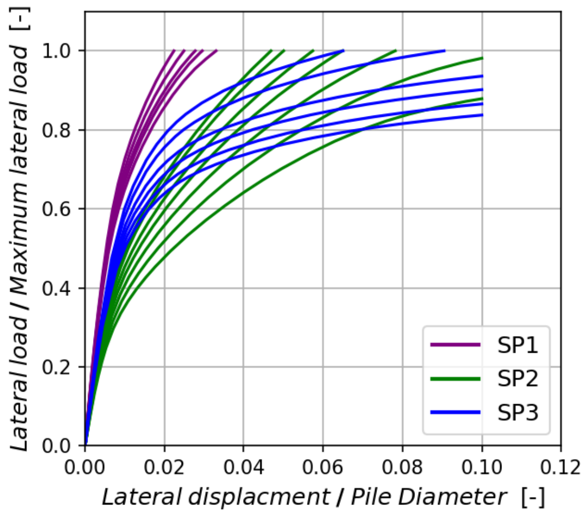

Figure 3. Normalised load-displacement curves for 3D FEA analyses.

3 METHODOLOGY

The scope of this paper is to assess the capability of different industry standard approaches to represent the above scenario. The objective is to derive 1D FEA models that mimic the 3D FEA response. State of the art p-y only models versus the PISA rule-based models and exact FEA extracted PISA reactions (e.g. Burd et al., 2020) are compared, prior to optimization of each method.

3.1 Baseline soil reaction curves

In the context of undrained soils, Jeanjean et al. (2017) proposes a method to derive p-y curves based on direct scaling of DSS stress-strain curves. Given the context of the ULS FEA design (Andersen, 2015) and the formulation of PIMS the applicability of DSS scaling is straightforward. First, an in-house DSS scaling approach is defined followed by the approach proposed by Jeanjean.

For notation purposes, the in-house linearly scaled DSS curve is defined as the PIMS p-y curve. The scaling rules are the following: the shear strain is related to the displacement normalised by the diameter, while the strength ratios between shear and ultimate lateral capacity are proportional (τ/S_u) ~ (p/p_u). Figure 4 shows the procedure of scaling from a DSS curve to a normalized p-y curve.

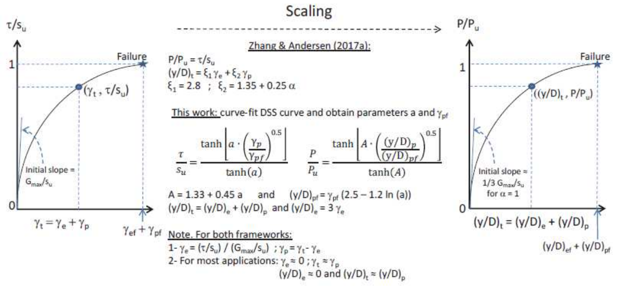

Figure 4: Illustration of scaling (from Jeanjean et al., 2017)

In addition to linearly scaled p-y curves, the rule-based expressions of Jeanjean included in ISO (2025) are also benchmarked. In this sense it is possible to test the conclusions in Jeanjean et al. (2022) and compare against PISA optimization under the same umbrella. For the PISA SRCs the normalization of Cowden (Byrne et al., 2020) is used as the soil is modelled with a mean stress independent model.

3.2 Optimization procedure

There are several different ways to rationalize a 1D FEA model against a 3D FEA model. The bespoke PISA methodology demands significant computational effort for postprocessing, fitting, and rationalizing all FEA reactions, especially when compared to other approaches, such as applying multipliers to rule-based p-y curves.

To overcome computational limitations and tight timelines industry has developed hybrid schemes using rough, rule-based initial guesses (blind predictions) followed by a general optimization procedure. The advantage of such schemes is that the step of soil reaction extraction can be omitted and the number of degrees of freedom (DOFs) is reduced, at the expense of a less accurate representation of the soil reactions compared to those in the 3D FEA.

Nevertheless, the use of optimization procedures is not only limited to p-y approaches, but also recommended in PISA as a refinement step after exact soil reaction extraction (Burd et al., 2020). For the current benchmark a general purpose optimization procedure based on the MINPACK and LAPACK libraries are used. The optimization scenarios investigated include:

1. PIMS and Jeanjean rule-based p-y only predictions followed by optimization (p-y and incorporated base shear only)
2. PISA Cowden rule-based predictions followed by optimization (p-y, m-theta, base shear, base moment)
3. FEA derived reactions averaged for each soil layer followed by optimization (p-y, m-theta, base shear, base moment)

The number of DOFs of the optimization problem depend on the number of baseline SRCs and number of layers. In the context of p-y only, as the 1D model does not include distributed moment, the multipliers have been set with more generous bounds than for the PISA baseline expressions. On the other hand, the bounds for PISA optimization are set narrow, as the initial approximation resulting from soil reaction extraction is generally good. The DOFs and bounds are:

1. PIMS: 50% to 200% on displacement (y) multipliers
2. Jeanjean: 50% to 200% on displacement (y) multipliers and 75% to 150% in the "A" factor
3. PISA clay: 90% to 110% multipliers in k, n, x_u and p_u for p-y and m-theta reactions

3.3 Per Layer Minimization problem

For consistency across all problems each layer is assumed to have constant parameters, note that the design cases of this benchmark include greater than 10 layers, with thin layers only 2 metres thick. The optimization problem assembles all DOFs from each baseline soil reaction model in each layer and builds a 1D FEA model mimicking the 3D FEA in load controlled conditions.

Depending on the problem the number of DOFs can range from 10 to 100 depending on the selection of the model and benchmark, where typically p-y only models require less DOFs and hence lower computational cost. Each 1D model consists of 100 Timoshenko beam elements modelled with non-linear springs in line with PISA 1D soil reactions.

3.4 Error metrics

The error metric and reward function is defined as a combination of the absolute and relative displacements difference between the 1D and 3D deflected shapes over several steps of the FEA solutions.

The combined weight between absolute and relative error spreads the reward function across the problem aiming to fit deflected shapes for low and high utilisations. A total of 10 linearly spaced load steps are used in the optimization assembly.

4 RESULTS OVERVIEW

A total of 8 optimization procedures have been run for each of the 18 3D FEA analyses, based on 8 first-order predictions.

The results of the error metric are detailed in Table 2 and

Table 3. The error metric is defined as the absolute percentage displacement error at the associated ULS load. Given some of the piles in the FEA solution batch were very close to failure and the optimization parametric space did not allow scaling of the ultimate capacity, a few of the rule-based models could not reach the maximum load of the FEA solution (see Table 2 and Table 3.), metrics for these models have been excluded.

This occurred mainly for analysis in SP3, with a few occurrences in SP2 (Figure 3), which at 100% ULS load show failure and very high deflection and rotations. For robust comparison of the different strategies, it was decided to run the optimization to 50% and 100% ULS load to assess the robustness of load controlled optimization. Table 2 and Table 3 show the overall error before and after the optimization procedure for p-y and PISA approaches respectively.

4.1 Result Summary

Optimising exact parametrised PISA reactions extracted directly from 3D FEA analysis proved the most effective and robust of all methods at representing the 3D FEA response but was by far the most computationally demanding. A graphical summary of the results, before and after optimization, is shown in Figure 5. PISA SRC extraction plus optimization generally results in errors of less than 1 % across all cases.

Conversely, the application of linearly scaled PIMS p-y curves to a 1D model (Jeanjean et al., 2017) predicted reasonably well for a fraction of the computational cost. This validates the conclusions in (Jeanjean et al, 2022), nevertheless the fit is not perfect and the resulting soil reactions do not generally match the 3D FEA reactions.

An interesting observation is that when assessing the fits using Jeanjean rule based expressions the resulting fit parameters were well outside the bounds that ISO recommends, this was expected as the benchmark had piles with low L/D ratios with significant distributed moment contributions. The p-y approach of Jeanjean was reasonably effective but consistently overestimated soil resistance for SP2, whilst the PIMS approach seemed to be more effective using half the DOFs as Jeanjean.

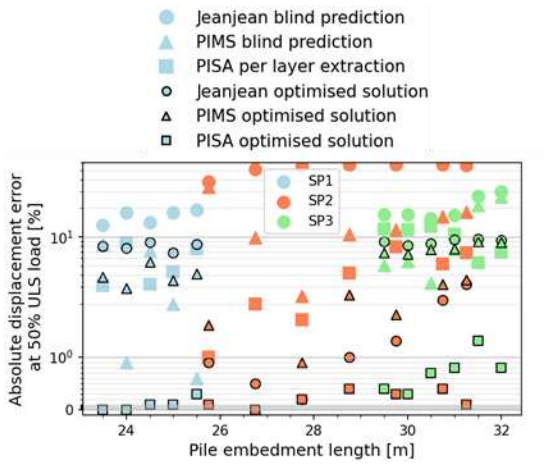

Figure 5: Visual summary of error metrics before and after optimization

Another interesting result showed the importance of the first approximation (blind predictors). This is observed in the PISA benchmarks when applying the depth variation factors of Cowden, against exact 3D FEA SRC extraction. For these cases the blind prediction error was the poorest, highlighting the fact that the rule-based Cowden expressions should be used cautiously as average error was in the 30% region, too far for the optimization to reach the optimal solution within the defined optimisation bounds.

However, in the context of the Cowden blind predictions the fact that the optimisation bounds were set narrowly produced poor performance as the bounds did not allow the scaling parameters to exceed 10% of their initial values. This does not invalidate the approach, as the approach should be able to reach an exact solution with larger bounds.

Table 2:Summary of p-y only approximations

Analysis	Error 50% ULS load [%]				Error at 100% load [%]			
	Blind prediction		Optimised		Blind prediction		Optimised	
	PIMS	Jeanjean	PIMS	Jeanjean	PIMS	Jeanjean	PIMS	Jeanjean
SP1, L=25.50	0.6	19.1	4.1	8.4	28.9	21.7	0.1	6.4
SP1, L=25.00	2.0	17.9	3.5	6.9	24.3	27.7	0.3	7.0
SP1, L=24.50	7.2	14.3	5.5	8.9	25.5	47.8	0.1	8.7
SP1, L=24.00	0.9	17.9	2.9	7.7	10.0	28.0	0.6	28.0
SP1, L=23.50	8.3	13.4	3.8	8.0	18.3	72.4	0.8	11.0
SP2, L=31.25	18.3	56.7	3.6	3.2	29.2	62.7	1.6	2.7
SP2, L=30.75	16.4	57.1	3.2	2.2	30.3	61.9	2.5	3.5
SP2, L=29.75	11.9	57.0	1.8	1.3	28.4	55.6	0.8	5.7
SP2, L=28.75	10.7	57.1	2.5	1.0	28.8	48.6	0.2	8.4
SP2, L=27.75	2.4	55.7	0.9	0.2	22.7	21.3	0.4	14.5
SP2, L=26.75	9.8	51.3	0.0	0.5				
SP2, L=25.75	33.5	37.9	1.6	0.9				
SP3, L=32.00	26.3	29.9	8.8	9.2	18.3	11.2	0.2	0.4
SP3, L=31.50	21.4	26.6	9.0	9.6				
SP3, L=31.00	7.4	16.9	7.5	9.4				
SP3, L=30.50	3.3	15.7	7.4	8.5				
SP3, L=30.00	5.6	17.2	6.6	8.1				
SP3, L=29.50	5.1	17.3	6.8	9.0				
Mean	10.6	32.2	4.4	5.7	24.1	41.7	0.7	8.6

Note: Blank values mean that that the p-y approach was unable to reach 100% of the ULS load without scaling of the ultimate capacity.

Table 3:Summary of PISA 1D models

Analysis	50% ULS load [%]				100% ULS load [%]			
	Initial		Optimised		Initial		Optimised	
	Cowden	Exact	Cowden	Exact	Cowden	Exact	Cowden	Exact
SP1, L=25.50	32.2	7.5	13.7	0.3	12.8			
SP1, L=25.00	31.9	6.9	8.3	0.1	12.7	90.2**	2.4	0.4
SP1, L=24.50	30.1	7.7	8.6	0.1		62**		0.5
SP1, L=24.00	42.2	8.7	5.6	0.0	26.7		2.3	
SP1, L=23.50	40.8	7.2	7.9	0.0	22.4	37.0	0.3	0.1
SP2, L=31.25	47.0	6.9	0.1	0.1	35.1	20.7	4.0	0.9
SP2, L=30.75	47.2	5.2	0.5	0.4	33.3	13.8	2.1	0.0
SP2, L=29.75	46.6	7.9	1.2	0.3	21.7	24.8	3.4	1.1
SP2, L=28.75	52.7	4.2	4.3	0.4	32.7	20.3	6.1	0.7
SP2, L=27.75	52.2	1.7	4.4	0.2	19.6	12.8	7.6	0.3
SP2, L=26.75	48.9	2.0	1.6	0.0				
SP2, L=25.75	36.3	1.0	0.6	0.1				
SP3, L=32.00	20.8	7.0	13.8	0.8				
SP3, L=31.50	16.8	5.4	12.7	1.3				
SP3, L=31.00	13.9	10.7	6.7	0.8				
SP3, L=30.50	17.4	12.9	4.5	0.7				
SP3, L=30.00	11.8	12.0	37.4	0.3				
SP3, L=29.50	6.6	12.1	6.4	0.4				
Mean	33.1***	7.1	7.7***	0.4	23.5	35.2	10.0	0.5

Note: Blank values mean that that the PISA approach was unable to reach 100% of the ULS load without scaling of the ultimate capacity.
**The PISA soil reaction extraction and averaging diverged
*** All optimization DOF parameters in bounds

4.2 Discussion

When converting 3D FEA to 1D models there is always a loss of information. It is the responsibility of the designer to decide the engineering limits of their assumptions, hence the selection of which approach is better is relative. This is very clear in the example given in Figure 6, where badly conditioned soil profiles are used with low L/D ratios.

This example highlights the practical impacts of different optimized rationalization methods. The figure shows the resulting soil pressure, distributed moments, shear and bending moments of the different assumptions. The black line shows the 3D FEA exact soil reaction directly extracted from the interfaces of the 3D FEA model, while the blue and green line show the resulting reactions from the optimization procedure (1D model).

When using a p-y only approximation the distributed moment *(m)* resistive mechanism is transferred numerically to the soil pressure *(p)*. Hence, when using p-y only the lateral soil pressure will be generally overestimated. However, this does not have a significant impact on the structural bending moment, which is the main structural design driver, instead impacting only the structural shear force.

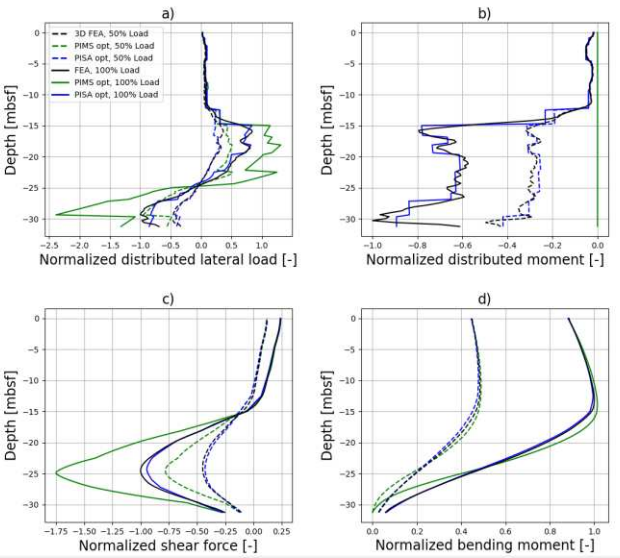

Figure 6: Reactions and internal forces for analysis SP2, L=31.25 at 50 % ULS load and 100 % ULS load. Each plotted result is normalized by the maximum of the 3D FEA result over the depth range for each load level.

In contrast, by extracting 3D FEA reactions and optimising on a per layer basis, a more detailed pile response can be constructed, leading to an excellent match on internal forces (Figure 6, bottom-left, bottom-right). This highlights the benefits of the PISA approach and its potential for optimising structural design in detailed design scopes using exact FEA reactions and an optimization procedure with strict bounds.

5 CONCLUSIONS

The results of the current benchmark delve into various 3D to 1D rationalization strategies and their implications. It is found that for detailed design scopes an exact 3D FEA soil layer extraction and PISA optimization is the most robust and precise, at the expense of computational cost. On the other hand, direct DSS to p-y scaling (e.g. Jeanjean et al, 2017) appears to be the most efficient regarding computational cost with acceptable accuracy.

In this sense, the most effective strategy depends on the stage of the project, where DSS scaling is a good approach for concept and FEED design with limited FEA analyses, whilst exact PISA SRC extraction from 3D FEA is more accurate and robust for detailed design scopes.

AUTHOR CONTRIBUTION STATEMENT

J. Alexander: Formal Analysis, Writing - Original draft. **D. Abadias**: Supervision, Writing, Conceptualization, Software. **S. Elliot** Data Curation, Validation.

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