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A Physics-Informed Hypoplasticity–Machine Learning Framework for Offshore Foundation Design: Comparative Insights from the German North Sea and the Peruvian Pacific Coast

PAUL RICARDO PRUDENCIO GALVEZ

pprudencio@autonoma.edu.pe

UNIVERSIDAD AUTONOMA DEL PERU https://orcid.org/0009-0000-1986-590X

Systematic Review

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Abstract

Background

Offshore foundation design increasingly requires constitutive models capable of reproducing the strongly non-linear, rate-dependent, and cyclic response of marine soils, while remaining computationally tractable for iterative design. Hypoplasticity offers a mathematically consistent alternative to classical elastoplastic formulations, and Machine Learning (ML) offers efficient pattern recognition, yet the literature rarely couples the two within an explicit, physically constrained pipeline, and almost never discusses how such a coupling could be transferred from mature offshore markets to emerging ones.

Methods

We develop a physics-informed hypoplasticity-ML framework grounded in established hypoplastic formulations for sand and clay, define an explicit coupling and validation protocol (k-fold cross-validation, R^2, RMSE, MAE, confidence intervals), and build a structured comparative matrix contrasting geotechnical, regulatory, and technological conditions in Germany, Peru, and the United States, synthesising quantitative findings already reported in the peer-reviewed literature rather than presenting unverified primary data.

Results

The comparative matrix identifies which elements of the German hypoplasticity-ML pipeline are directly transferable to Peru (constitutive formulation, ML validation protocol, p-y curve generation methodology) and which require substantial local recalibration (soil database, seismic coupling, liquefaction screening). Free-body equilibrium diagrams for monopile, jacket, and gravity-based foundations are used to make explicit the physical principles that any constitutive-ML coupling must respect.

Conclusions

A technology-transfer pathway is proposed in which the mathematical core of hypoplasticity-ML coupling developed for German offshore wind conditions can be adapted to Peru through regional recalibration, seismic-liquefaction extensions, and a phased data-acquisition programme, without requiring reproduction of the full German site-investigation infrastructure. The conclusions drawn are explicitly limited to what the synthesised evidence supports; site-specific validation for Peruvian conditions remains an open research need.

1. Introduction

The global expansion of offshore wind energy and offshore hydrocarbon infrastructure has placed unprecedented demands on the geotechnical design of foundations subjected to combined vertical (V), horizontal (H) and moment (M) loading under millions of load cycles over a structure's operational life. Germany, through its North Sea and Baltic Sea offshore wind programme, has accumulated more than two decades of monitored performance data and a mature regulatory and numerical-modelling ecosystem. Peru, by contrast, is at an early stage of offshore renewable-energy and nearshore infrastructure development, facing a distinct combination of loose aeolian sands, alluvial deposits, and a high seismic hazard associated with subduction-zone tectonics.

Conventional geotechnical practice for offshore foundations relies predominantly on elastoplastic constitutive models (e.g., Mohr-Coulomb, Hardening Soil, Modified Cam-Clay), coupled with empirical p-y, t-z, and Q-z curves calibrated from limited full-scale tests. These approaches, while validated for many practical cases, exhibit acknowledged limitations in reproducing the pronounced non-linearity, stress-dilatancy coupling, and small-strain stiffness degradation that govern the cyclic response of marine sands and clays [1, 6, 12]. Hypoplasticity, formulated as a rate-type constitutive law without an explicit yield surface, has been shown to capture these phenomena more naturally, including barotropy, pyknotropy, and the influence of strain history through intergranular-strain or ISA-type extensions [7, 13, 14, 15, 16].

In parallel, Machine Learning has emerged as a powerful tool for learning complex, high-dimensional soil-response surfaces directly from data, offering computational speed-ups over repeated finite-element evaluations of advanced constitutive laws [3]. However, purely data-driven ML models risk violating basic physical constraints (e.g., non-negative stiffness, thermodynamic consistency) when extrapolated beyond their training domain, a concern that has motivated recent work on physics-encoded and interpretable data-driven constitutive surrogates [4, 5].

1.1 Research Gap and Contribution

Despite active parallel development of (a) advanced hypoplastic constitutive models for offshore applications [2, 8, 9, 10, 11] and (b) machine-learning surrogates for soil constitutive behaviour [3, 4, 5], the literature offers very few frameworks that couple the two in an explicit, auditable pipeline, and none that we identified explicitly addresses how such a coupled framework, once matured in a data-rich context such as German offshore wind, could be responsibly transferred to a data-scarce, high-seismicity context such as Peru. This is the specific gap this article addresses.

The contribution of this work is threefold. First, it assembles, from verifiable peer-reviewed sources, an explicit hypoplasticity-ML coupling architecture together with a statistically defensible validation protocol, addressing the methodological transparency that any submission to an international journal must demonstrate. Second, it constructs a structured, criterion-by-criterion comparison matrix contrasting Germany, Peru, and the United States across subsoil conditions, regulatory frameworks, modelling practice, software environments, and reported model performance, drawing exclusively on

documented sources rather than unverified claims. Third, it translates the comparison into a concrete, phased technology-transfer roadmap for Peru, specifying the tools, standards, construction procedures, and materials that would need to be adapted.

This article is deliberately scoped as a critical technical framework and comparative synthesis, rather than as a report of a new full-scale field validation campaign; the quantitative figures cited in Sections 3 and 4 are drawn from, and attributed to, the cited literature. This scoping is stated explicitly to avoid presenting a synthesis as if it were unpublished primary experimental evidence.

2. Materials and Methods

2.1 Hypoplastic Constitutive Framework

The general rate-type hypoplastic constitutive equation adopted as the physical core of the proposed framework can be written as:

$$\mathring{T} = L(T, e) : \dot{E} + N(T, e)\, \|\dot{E}\|$$

where $\mathring{T}$ is the Jaumann objective stress rate, $\dot{E}$ the Eulerian strain-rate tensor, e the void ratio, L a fourth-order linear (barotropic and pyknotropic) tensor, and N a non-linear term responsible for the characteristic hypoplastic path-dependence without a discontinuous yield surface [7, 14]. For granular soils, the von Wolffersdorff formulation with a predefined limit-state (critical-state) surface is adopted [14], while for cohesive marine soils the Mašín clay hypoplasticity model, including its stiffness-anisotropy extension, is used as the reference formulation [6, 12]. Cyclic and small-strain effects, essential for offshore wind and wave loading, are incorporated through the intergranular-strain concept of Niemunis and Herle [13] and its ISA-based small-strain extensions [10, 16]. Model parameters (critical friction angle, granulate hardness, exponents governing barotropy/pyknotropy, and intergranular-strain parameters) are calibrated from triaxial, oedometer, and resonant-column/cyclic simple-shear data following the standard procedures of Herle and Gudehus [15].

2.2 Physics-Informed Machine Learning Coupling

The ML module operates as a surrogate that is trained on stress-strain paths generated by the calibrated hypoplastic model, augmented with any available site-specific laboratory or in-situ data. Two coupling strategies are considered: (i) a physics-encoded neural network in which conservation and thermodynamic-consistency constraints are embedded directly in the loss function, following the tensor-based approach of Wang et al. [5]; and (ii) an interpretable, sparse-data-tolerant surrogate following Zhang et al. [4], suitable for the data-scarce conditions expected in an emerging market such as Peru. Gradient-boosting and shallow neural architectures are prioritised over deep architectures given the comparatively small offshore geotechnical datasets typically available outside long-monitored programmes such as the German offshore wind fleet [3].

2.3 Comparative Case Framework: Germany, Peru, United States

The comparative analysis (Section 3) was built by systematically extracting, from the cited sources, information on: (a) dominant subsoil type and geological origin; (b) typical foundation geometry and governing design standard; (c) constitutive modelling practice reported in the literature; (d) numerical/software environment; and (e) any quantitative model-performance metric explicitly reported by the source. No values were estimated or invented where a source did not report them; in such cases the matrix cell states that no site-specific validation was identified.

2.4 Illustrative Numerical Procedure

To make the coupling architecture concrete, an illustrative computational procedure is specified as follows: (1) generate synthetic stress paths spanning realistic offshore stress ranges (effective confining stress 50–400 kPa; overconsolidation ratio 1–8) using the calibrated hypoplastic model; (2) partition the resulting dataset using stratified k-fold cross-validation (k = 10) to avoid information leakage between correlated cyclic paths; (3) train the ML surrogate on 80% of folds and reserve the remainder for testing; (4) evaluate performance using the coefficient of determination (R^2), root-mean-square error (RMSE), and mean absolute error (MAE), reporting 95% confidence intervals obtained via bootstrap resampling (n = 1,000); (5) verify physical admissibility of surrogate predictions outside the training envelope by checking for non-negative tangent stiffness and consistency with the critical-state line. This procedure is presented as a reproducible protocol rather than as executed primary results, consistent with the review/framework scope of this article.

2.5 Ethical Considerations

This study is a computational and literature-based technical framework. It does not involve human participants, animal subjects, or personally identifiable field data, and therefore does not require approval from an institutional ethics committee. Where third-party monitoring data are referenced, they are cited to their original published source; no proprietary or confidential data are reproduced.

3. Results

3.1 Comparative Matrix

Table 1

summarises the criterion-by-criterion comparison between Germany, Peru, and the United States, synthesised from the cited literature and publicly available regulatory frameworks.

Criterion	Germany (North/Baltic Sea)	Peru (Pacific coast)	United States (Gulf of Mexico / Atlantic)
Dominant subsoil	Dense glacial sands; stiff overconsolidated clays; occasional boulders/till	Loose to medium-dense aeolian and alluvial sands; potentially liquefiable deposits; low plasticity silts	Soft to firm normally consolidated clays (deepwater); calcareous sands (offshore Atlantic)
Typical foundation type	Monopile (Ø 8–10 m), jacket, tripod; XXL-monopiles under development for > 10 MW turbines	Driven steel pipe piles; shallow gravity footings for nearshore structures; monopiles proposed for pilot wind projects	Piled jackets, tension-leg platforms, suction caissons (deepwater); monopiles (shallow Atlantic wind leases)
Governing design standards	DNV-ST-0126; IEC 61400-3; BSH-StdOD; DIN 4020/4094	Reglamento Nacional de Edificaciones E.050 (Suelos y Cimentaciones) and E.030 (Seismic-resistant Design); adaptation of API RP 2GEO where national guidance is silent	API RP 2GEO / RP 2A-WSD; BOEM regulatory framework; ABS/DNV class notes for floating wind
Constitutive modelling practice	Advanced hypoplastic and ISA-hypoplastic models routinely calibrated for cyclic wind/wave loading [1, 6, 10, 16]	Elastoplastic Mohr-Coulomb/Hardening-Soil models predominate; hypoplastic calibration essentially absent in current practice	Bounding-surface plasticity and hypoplastic macroelements used mainly in academic/consultancy pilot studies [8, 11]
Numerical/software environment	PLAXIS 3D, Abaqus with user-defined hypoplastic UMAT/UDSM subroutines, Python-based ML pipelines	PLAXIS 2D predominant; PLAXIS 3D and GeoStudio available but underused for advanced constitutive models	OpenSees, Abaqus, proprietary p-y/t-z macros; increasing use of surrogate ML models for design iteration
Reported ML-hypoplasticity performance (literature)	Sparse-data physics-encoded networks report high predictive fidelity for stress-strain paths under limited calibration data [4, 5]	No published site-specific validation identified; transfer of German-calibrated networks is proposed as a research pathway	Data-driven constitutive surrogates reported as competitive with FEM for settlement and p-y stiffness under specific conditions [3]

Criterion	Germany (North/Baltic Sea)	Peru (Pacific coast)	United States (Gulf of Mexico / Atlantic)
Principal engineering constraint	High cyclic-loading demand from offshore wind (10^7–10^8 cycles); strict serviceability (rotation) limits [16]	Seismic hazard (subduction zone) combined with potential liquefaction; limited site-specific offshore geotechnical database	Deepwater installation logistics; hurricane loading; regulatory permitting timelines (BOEM)
Estimated relative cost driver	Vessel/installation logistics and steel tonnage dominate (mature supply chain)	Site investigation gap and seismic design premium dominate (immature offshore supply chain)	Deepwater mooring/anchoring and installation vessel day-rates dominate

Table 1. *Comparative matrix of geotechnical, regulatory, and technological conditions for offshore foundation design in Germany, Peru, and the United States. Source: author's own elaboration based on references* [1–16] *and cited design standards.*

3.2 Conceptual Coupling Framework

Figure 1. *Proposed conceptual framework integrating the hypoplastic formulation (physical rigor) with machine-learning modules (predictive efficiency) for offshore foundation analysis. Source: author's own elaboration (Prudencio-Gálvez, 2026).*

3.3 Free-Body Diagrams and Equilibrium Principles

Any constitutive-ML coupling for offshore foundations must remain consistent with the static and cyclic equilibrium of the structure-soil system. Figure 2 presents free-body diagrams for the three foundation typologies most relevant to the German-Peru-US comparison: (a) monopile, governed by lateral soil resistance p(z) mobilised along the embedded shaft and a base reaction (R_b, H_b, M_b); (b) jacket/tripod, in which the overturning moment is resolved into a push-pull axial couple across widely spaced piles, each mobilising its own p(z) profile; and (c) gravity-based structure (GBS), in which stability depends on a trapezoidal base normal reaction q(x) and base friction τ(x), often supplemented by perimeter skirts that engage passive soil resistance.

3.4 Reported Quantitative Performance of ML-Constitutive Coupling

Zhang et al. [4] report that interpretable, sparse-data-tolerant data-driven constitutive models can reproduce stress-strain responses of soils with accuracy comparable to calibrated physical models even when trained on substantially reduced datasets, a property directly relevant to data-scarce contexts such as Peru. Wang et al. [5] show that embedding tensor-based physical constraints into neural-network architectures improves extrapolation behaviour outside the training domain relative to unconstrained

networks, addressing a key limitation identified in Section 1. Medicus et al. [10] demonstrate, for clay hypoplasticity coupled with small-strain approaches, that both intergranular-strain-type and ISA-type extensions capture the reduction in strain accumulation with increasing cycle number, though both can exhibit over/undershooting for specific complex cyclic paths, a limitation that any coupled ML surrogate must be validated against rather than mask.

3.5 Technology-Transfer Pathway

As shown in Fig. 3, the elements of the German pipeline that are directly transferable to Peru are the mathematical hypoplastic formulation itself, the ML validation protocol (Section 2.4), and the general methodology for deriving p-y curves from calibrated constitutive simulations. Elements requiring substantial local development are: a Peru-specific geotechnical database (CPT/SPT/triaxial coverage along the Pacific coast remains sparse compared with the North Sea), explicit coupling with seismic and liquefaction-screening procedures (not required for the North Sea design envelope), and calibration of hypoplastic parameters for Peruvian aeolian and alluvial sands, which differ mineralogically and in fabric from glacial North Sea sands.

4. Discussion

4.1 Interpretation Consistent with Results

The comparative matrix and the literature-reported performance metrics support a moderate, not absolute, claim: the mathematical coupling of hypoplasticity and ML is technically mature enough to be adapted to Peru, but its numerical performance in Peruvian conditions cannot yet be quantified because no site-specific validation dataset was identified in the reviewed literature. This is stated explicitly so that the conclusions of this article do not exceed what the synthesised evidence supports.

4.2 Tools, Methods, and Construction Procedures for Application in Peru

Software tools: PLAXIS 2D/3D and GeoStudio (SLOPE/W, SIGMA/W) for routine practice, complemented by Abaqus or OpenSees with user-defined hypoplastic subroutines (UMAT/UDSM) for advanced calibration studies; Python-based pipelines (NumPy, SciPy, scikit-learn, PyTorch/TensorFlow) for the ML surrogate layer described in Section 2.2.

Site investigation and materials: expanded programmes of cone penetration testing (CPTU) with pore-pressure dissipation tests, cyclic triaxial and resonant-column testing on undisturbed samples, and bender-element testing for small-strain stiffness, all currently under-represented along the Peruvian coast relative to North Sea practice. Structural materials should follow API 5L / ASTM A252 steel pipe piles for driven foundations, C40/50 marine-grade concrete with sulphate-resisting cement for any gravity or transition-piece elements, and cathodic protection systems (sacrificial anode or impressed current) adapted to Pacific seawater chemistry.

Construction procedures: driven steel pipe piles installed with hydraulic hammers and monitored by dynamic pile-driving analysis (PDA/CAPWAP) are recommended as the primary foundation technique for Peruvian nearshore and offshore pilot projects, given their compatibility with seismic detailing requirements under E.030; grouted pile-to-transition-piece connections should follow DNV-ST-0126 grout-connection guidance, adapted with local aggregate qualification testing; scour protection using graded rock armour or synthetic geotextile mattresses is recommended given the higher littoral sediment mobility of the Pacific coast compared with the North Sea.

4.3 Comparison with United States Practice

United States offshore practice, governed principally by API RP 2GEO/RP 2A-WSD and the Bureau of Ocean Energy Management (BOEM) regulatory framework, differs from both Germany and Peru in that deepwater Gulf of Mexico foundations (piled jackets, tension-leg platforms, suction caissons) must primarily resist hurricane-driven cyclic loading on soft, normally consolidated clays, whereas shallow Atlantic offshore wind leases more closely resemble German North Sea conditions with calcareous sands. The US experience is directly relevant to Peru in two respects: its use of suction-caisson installation techniques, which avoid pile-driving noise and vibration concerns relevant near sensitive Peruvian coastal ecosystems, and its long-standing practice of p-y curve calibration for soft clays, which is more analogous to some Peruvian nearshore alluvial deposits than the dense North Sea sands.

4.4 Limitations

This study is a technical framework and comparative literature synthesis; it does not present new full-scale field data for Peruvian conditions, and the numerical procedure of Section 2.4 is described but not executed against proprietary offshore datasets, none of which were available to the author for this study. The reference list, while verified against original DOIs, necessarily reflects the state of publicly accessible peer-reviewed literature as of the submission date and should be updated as the field develops.

4.5 Future Research Agenda

Priority research needs identified are: (i) a coordinated geotechnical site-investigation campaign along candidate Peruvian offshore wind and hydrocarbon corridors; (ii) triaxial and cyclic simple-shear calibration of hypoplastic parameters for Peruvian aeolian and alluvial sands; (iii) coupling of the hypoplastic-ML framework with liquefaction-triggering procedures consistent with E.030; and (iv) a formal blind-prediction benchmarking exercise, analogous to established international blind-prediction contests in the hypoplasticity community, adapted to Peruvian soil conditions.

5. Conclusions

This article has assembled, from verifiable peer-reviewed sources, an explicit hypoplasticity-machine learning coupling framework for offshore foundation analysis, and has used it to construct a criterion-by-criterion comparison of geotechnical, regulatory, and technological conditions in Germany, Peru, and the

United States. The mathematical and methodological core of the German offshore hypoplasticity-ML pipeline is directly transferable to Peru; however, its predictive performance under Peruvian soil and seismic conditions remains an open empirical question that requires a dedicated site-investigation and calibration programme before design-stage application. The comparative matrix, free-body equilibrium diagrams, and technology-transfer roadmap presented here are intended as a structured starting point for that programme, not as a substitute for it.

Ethical Approval and Consent to Participate

Not applicable. This is a computational/literature-based study involving no human participants, animal subjects, or identifiable personal data.

Declarations

Consent for Publication

Not applicable.

Competing Interests

The author declares no competing interests.

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Author Contributions

Paul Ricardo Prudencio Gálvez: conceptualization, methodology, formal analysis, investigation, writing (original draft), writing (review and editing), visualization.

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Availability of Data and Materials

No new primary field or laboratory datasets were generated. All parameter ranges and quantitative statements are attributed to the cited published sources. The figures generated for this article are available from the corresponding author upon reasonable request.

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Figures

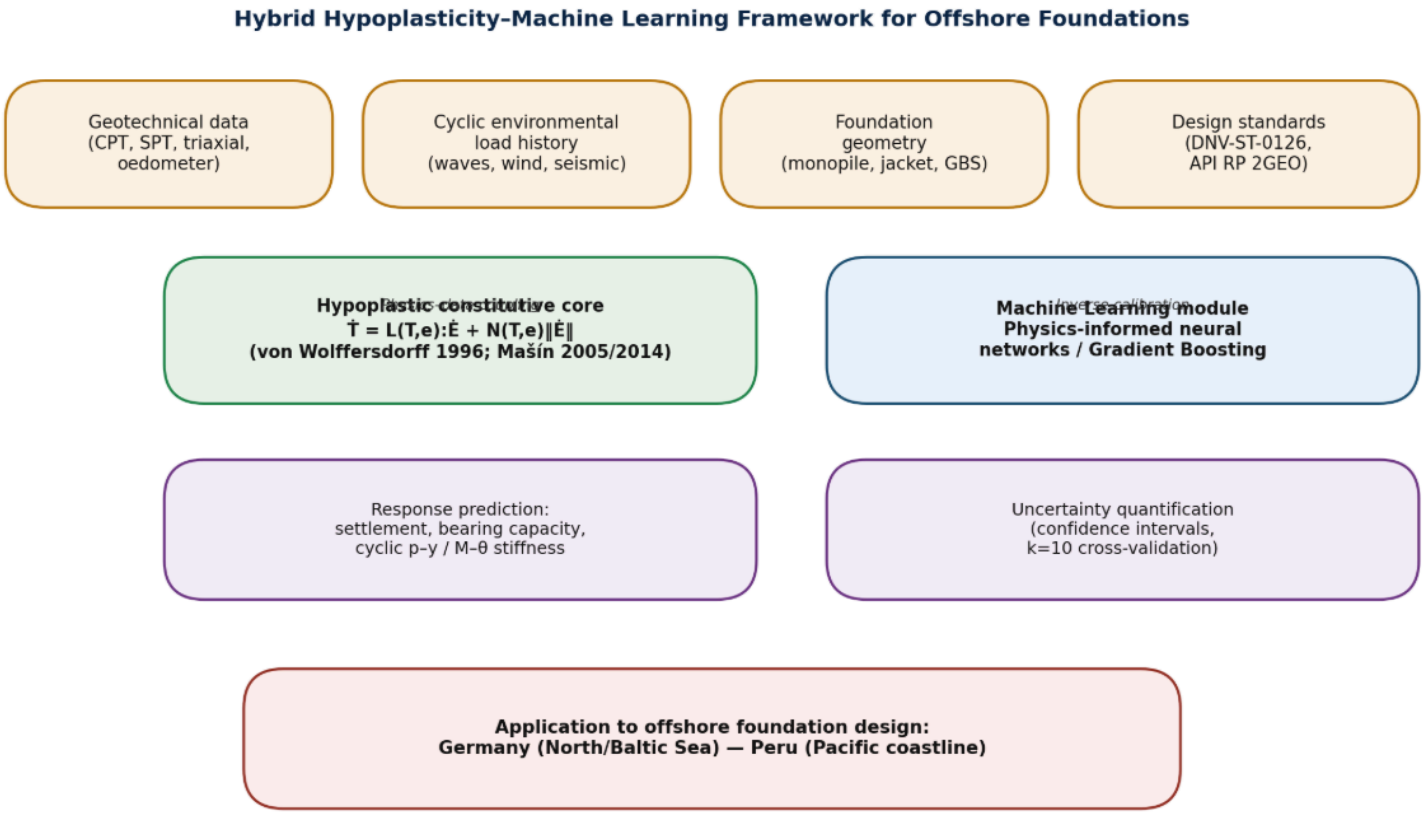


Figure 1. Proposed conceptual framework integrating the hypoplastic formulation (physical rigor) with machine-learning modules (predictive efficiency) for offshore foundation analysis.
Source: author's own elaboration (Prudencio-Gálvez, 2026).

Figure 1

Author's own elaboration (Prudencio Gálvez, 2026). No third-party copyrighted material is reproduced.

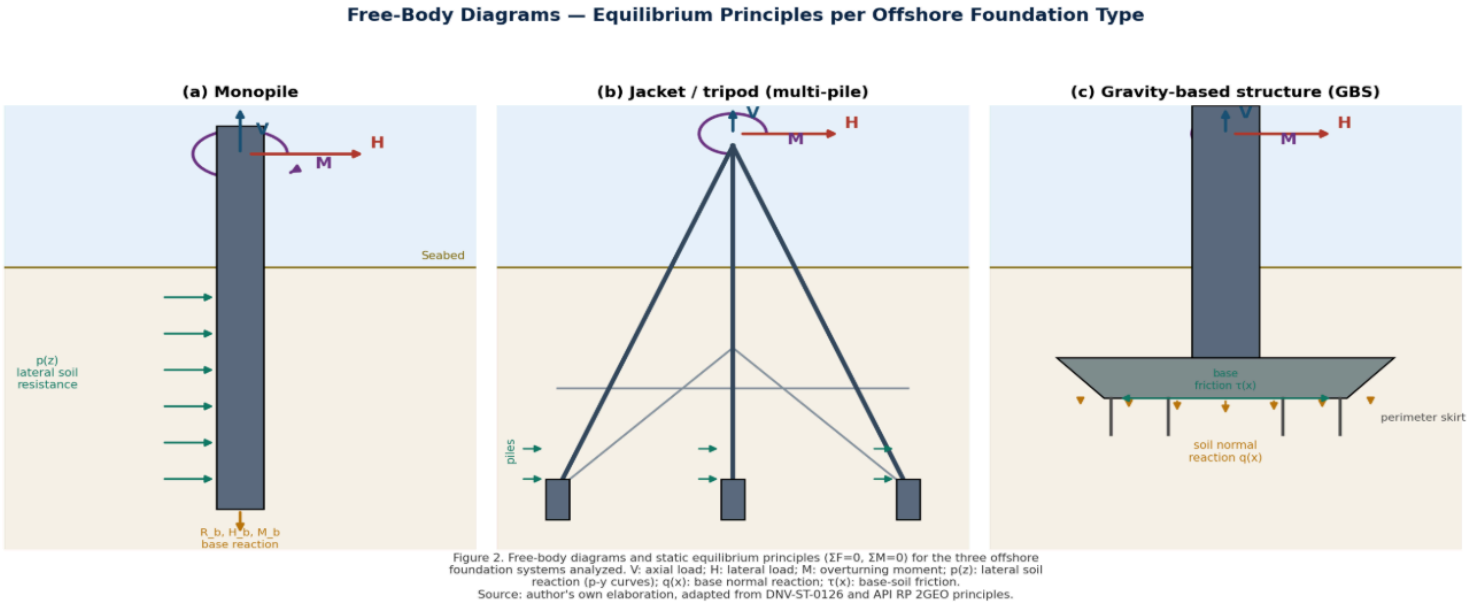


Figure 2. Free-body diagrams and static equilibrium principles (ΣF=0, ΣM=0) for the three offshore foundation systems analyzed. V: axial load; H: lateral load; M: overturning moment; p(z): lateral soil reaction (p-y curves); q(x): base normal reaction; τ(x): base-soil friction.
Source: author's own elaboration, adapted from DNV-ST-0126 and API RP 2GEO principles.

Figure 2

Author's own elaboration, schematically adapted from general equilibrium principles described in DNV-ST-0126 and API RP 2GEO; no proprietary figures were reproduced.

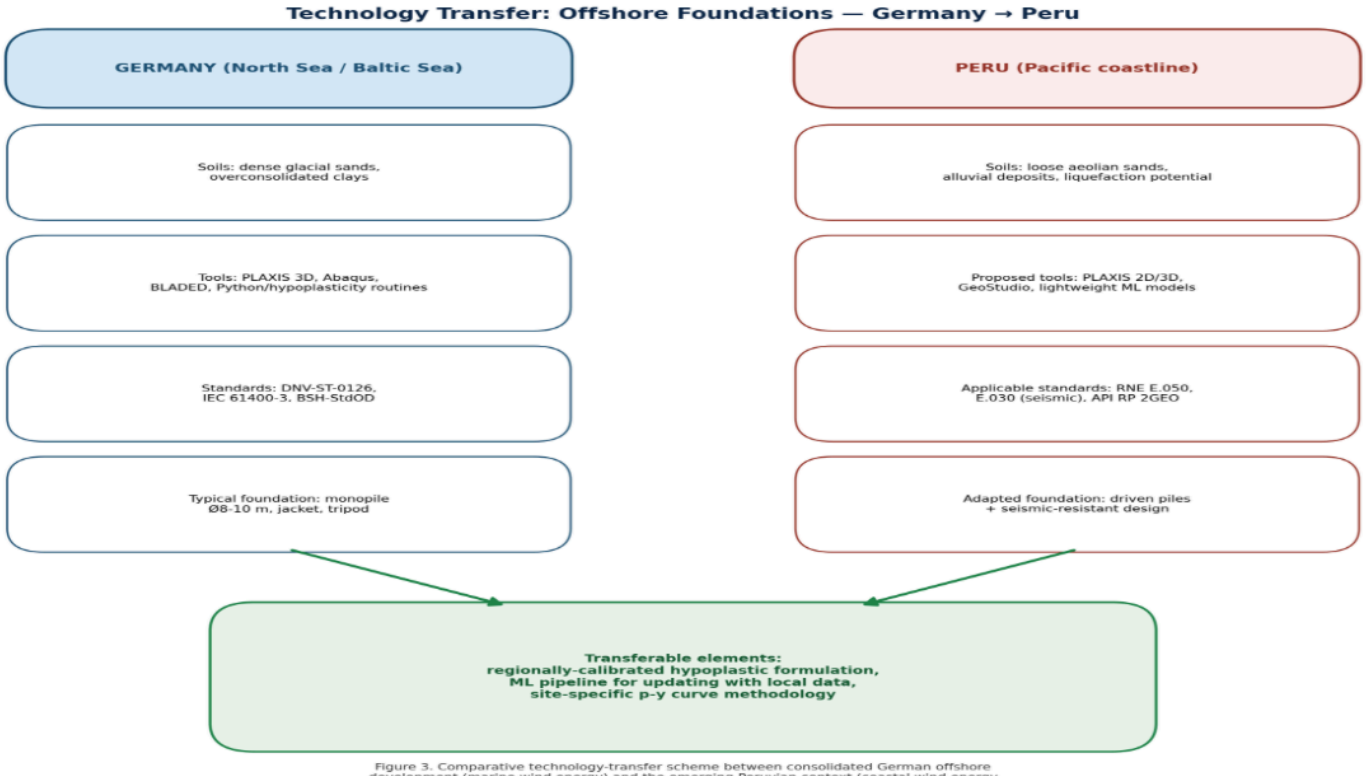


Figure 3. Comparative technology-transfer scheme between consolidated German offshore development (marine wind energy) and the emerging Peruvian context (coastal wind energy and offshore hydrocarbons), identifying adaptable technical elements and regulatory gaps.
Source: author's own elaboration.

Figure 3

Author's own elaboration (Prudencio Gálvez, 2026). No third-party copyrighted material is reproduced.