Proceedings of the 1st international Symposium on AI and Fluid Mechanics
Paper No S12 P3

Use of LLM models on the Computational Hydrodynamic evaluation of floating bodies in Waves

J S Sales Junior[1], E F De Paula Filho[2]

[1]Laboratory of Waves and Currents – LOC, Federal University of Rio de Janeiro, Brazil
[2]Program of Ocean Engineering – PENO, COPPE/Federal University of Rio de Janeiro

Keywords: Computational Fluid Dynamics, LLM AI, Floating Bodies, Wave Motions

Abstract. Computational Fluid Dynamics (CFD) and Boundary Elements Methods (BEM) play a key role in analyzing the interactions between floating bodies—such as ships, buoys, and offshore platforms—and wave environments. Traditionally, they rely on sophisticated numerical simulations to model fluid-structure dynamics, a process that demands significant computational resources and expertise. On this paper we investigate the innovative application of Large Language Models (LLMs) to enhance CFD/BEM evaluations of floating bodies in waves. LLMs are advanced AI systems designed to process and generate human-like text, and are typically utilized in natural language tasks. In CFD and BEM, however, they offer unique potential: interpreting complex simulation outputs, drafting detailed reports, and facilitating simulation setups through natural language inputs describing wave conditions or body parameters. This approach can simplify workflows and broaden accessibility for engineers lacking deep specialization. Key benefits include increased efficiency in data processing and improved interpretability of hydrodynamic results. Nevertheless, challenges remain, such as ensuring the precision of AI-driven analyses and integrating LLMs with existing tools. We ran a simplified case to access the use of LLM model and explore its capabilities. Outcomes were compared with Independent specialists reports. In conclusion, LLMs seems to be a big promise for revolutionizing the evaluation of floating bodies in waves, merging linguistic intelligence with hydrodynamic science.

1. Introduction

Designing of floating bodies subjected to wave interactions, such as semi-submersibles platforms used offshore relies strongly on both numerical calculations and experimental verification [1]. The offshore oil industry has a great know-how and large experience on designing such structures for safety and efficiency [2].

With the rise of new renewable energy systems, for offshore environment new premises and requirements for floating platforms need optimized designs to ensure stability and efficiency under complex marine conditions. A natural and logical procedure would be to take advantage of the already established field-proof solutions provided by the Oil Industry.

However, this transfer of know-how is not straight forward: Most floating platforms for Renewable Energy designs present dimensions and requirements that differ from traditional Oil Production Systems. So, even if new designs for Renewable Energy are inspired by established solutions, a great amount of verification and validation is still required.

On this paper we propose the use of the new LLM technology to help filling this Gap between both groups of premises, by training models to understand the way floating systems are designed and verified, using the large amount of bibliographic material produced through last decades by the Oil Industry, and them applying such training to leverage the analysis of new systems.

Traditionally, geometry generation and data analysis in CFD rely on manual processes or specialized software, which can be time-consuming and rigid. This paper explores the innovative application of Large Language Models (LLMs) to streamline these tasks. Specifically, we used an LLM to generate the geometry of a semi-submersible, accounting for onboard OTEC (Ocean Thermal Energy Converter [3]) equipment, and employed Capytaine for wave interaction simulations. We further leverage LLMs to process simulation output files, demonstrating their potential to enhance computational efficiency and insight generation. Our objective is to showcase how LLMs can transform CFD and BEM workflows for floating body design.

On this work it is investigated the potential of LLM models to be used to build a simulation where it is calculated the pressure field around a floating body using the BEM method. By giving the simulation and body parameters and testing the script created by the AI inside a BEM solver.
In the immediate future, the authors intend to investigate the usage of LLM models assisting with CFD simulations and creating scripts to solve more complex problems.

2. LLM Models

2.1. Definition and Foundation

Large Language Models (LLMs) are advanced artificial intelligence (AI) systems, a type of machine learning model designed for Natural Language Processing (NLP), trained with self-supervised learning on vast amounts of textual data to process and generate human-like language. These models are used in many areas and tasks, including but not limited to language processing, image generation, biology, games, or engineering.
The core of LLMs is the Transformer Architecture, introduced by [4], which allowed AI systems to perform complex language tasks, improving significantly its potential as a tool for science and engineering development. The main innovation in Transformer Architecture is the usage of Self-Attention Mechanisms instead of Recurrent Neural Networks (RNNs) or Convolutional Neural Networks (CNNs), the mechanism can compute entire sequences in parallel whereas RNNs or CNNs require sequential processing.
This approach established a new state-of-the-art in machine translation and reduced substantially processing and training time compared to RNNs or CNNs models, this efficiency comes from the parallelization the model permits.
The Transformer architecture revolutionized the field of NLP, demonstrating self-attention mechanisms can outperform RNNs and CNNs in both efficiency and accuracy. Its scalability, parallelization capabilities, and superior performance have since inspired numerous advanced AI models.

2.2. Beyond NLP

Over the years LLMs have passed through a deep extension of their capabilities, and this development granted them the ability to reach fields beyond language processing to other several scientific and engineering applications. Allowing them to interpret technical reports, generating codes in different programming languages, analyzing output from calculations or simulations. Some areas where LLM have already shown itself as a valuable tool:

- Computational Fluid Dynamics (CFD): LLMs were used to assist in generating and refining simulation scripts, grids and meshes, adjusting CFD model parameters, turbulence calculation, improving predictive accuracy and data visualization, interpreting complex hydrodynamic results. Reducing manual intervention and bringing more convenience for CFD usage [5].
- Finite Element Modeling (FEM): Reference [6] assessed the ability of ChatGPT to create finite element codes for geotechnical engineering applications from a set of prompts, testing different initial and boundary conditions, considering a hydro-mechanically coupled formulation, fluid mass diffusion in one-dimensional space, and balance and constitutive equations, problem geometry, material properties, spatiotemporal discretization and solution strategies. Although

in some cases the AI required direct human intervention, some extensive prompt augmentation and code revision, they show LLMs may greatly assist in modeling and programming of numerical models with a significant level of complexity.

2.3. Limitations

Despite their promising potential, advantages and the results LLMs have accomplished up this point, the models may need further human intervention to work properly and produce the expected outcomes, in general the AI-generated content must be validated by an experienced person before being used for major decisions. LLMs are a powerful tool to ease performing complex engineering analysis, however the interconnection between these two areas is not yet mature and requires further studies before relying entirely on AI-generated physical models and codes.

LLMs represent a transformative advancement in AI-driven engineering applications. Their potential to simplify CFD workflows, automate complex simulations, and improve data interpretation is significant. However, challenges related to reliability, integration, and computational efficiency must be addressed to fully explore their capabilities in computational hydrodynamic evaluations.

3. Methodology

The study employs a systematic methodology to analyze the wave-induced motions of a floating platform by integrating Large Language Models (LLMs) with Boundary Element Method (BEM)-based hydrodynamic simulations using Capytaine [7]. The methodology consists of six key steps, as outlined in Figure 3.1.

Step 1: Establishing Assumptions

The first step involves defining the primary assumptions and constraints based on industry standards, classification society rules, and technical reports. An LLM is used to interpret and synthesize relevant documentation to ensure compliance with regulatory frameworks and best practices.

Step 2: Definition of Key Parameters

Key design parameters, including equipment arrangement, weight distribution, hull geometry, and principal dimensions, are established using an LLM-driven evaluation. The LLM assists in assessing various design options and selecting optimal configurations based on predefined performance criteria.

Step 3: Mesh Generation for Hydrodynamic Analysis

Once the principal design parameters are defined, the platform geometry is modeled in Rhinoceros 3D [8], a widely used CAD tool for marine and offshore engineering applications. The geometric model is then converted into a computational mesh suitable for BEM analysis. The mesh generation process is automated using LLM-controlled scripting, ensuring consistency and efficiency in the discretization process.

Step 4: Hydrodynamic Simulations with Capytaine

The hydrodynamic response of the platform is computed using Capytaine, an open-source BEM solver designed for potential flow-based wave-structure interaction problems [7]. The simulations are executed using LLM-managed scripts, which automate input generation, batch processing, and result extraction to improve workflow efficiency.

Step 5: Analysis of Results and Comparison with Standards

The numerical results, including Response Amplitude Operators (RAOs), added mass, and damping coefficients, are analyzed using LLM-based evaluation. The performance is assessed against industry norms and classification rules, ensuring the validity and practical applicability of the results.

Step 6: Validation and Verification

To ensure the reliability of the numerical results, a validation process is conducted. This involves LLM-assisted cross-checking of hydrodynamic coefficients, convergence studies, and, where applicable, comparison with experimental or benchmark data. Discrepancies are identified, and refinements are made accordingly.

This integrated methodology leverages LLM capabilities to streamline design evaluation, automation, and result interpretation, significantly improving the efficiency of hydrodynamic analysis. use of sections to divide the text of the paper is optional and left as a decision for the author. Where the author wishes to divide the paper into sections the formatting shown in table 2 should be used.

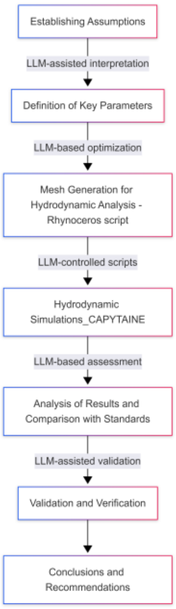

Figure 3.1 LLM based Methodology

4. Case Study

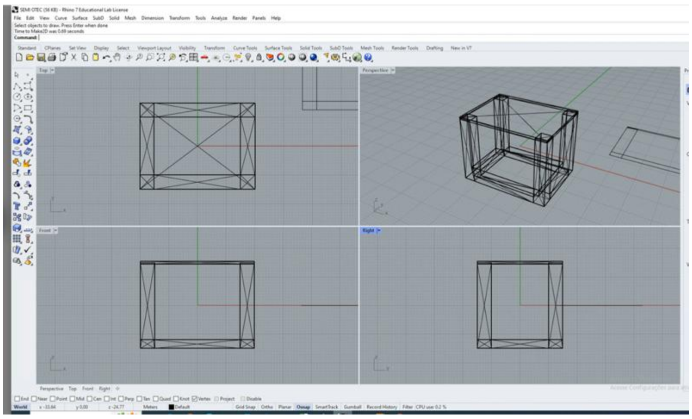

Figure 4.1 – Semi Sub Geometry generated by LLM controlled script

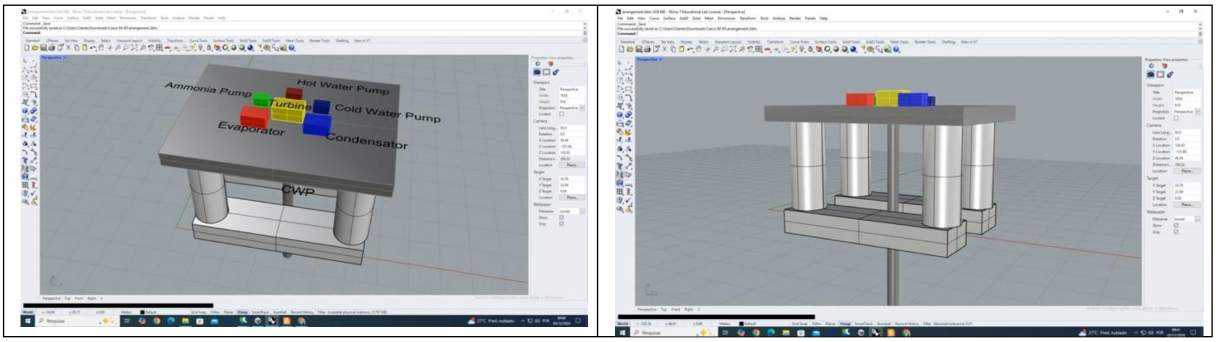

Figure 4.2 – 3D images of general arrangement for main OTEC equipment and CWP generated by LLM controlled script

5. Results and Discussion

The motion analysis of the floating platform was conducted to evaluate its hydrodynamic behavior under different environmental conditions. The study utilized Rhinoceros 3D for geometric modeling and Capytaine for hydrodynamic simulations based on the Boundary Element Method (BEM). The results were further analyzed using LLM-assisted processing to compare platform responses with relevant offshore engineering standards. A summary iss given on Table 5.1.

Table 5.1 Summary results for operational condition Motion Analysis conducted by LLM controlled script

Result	Surge	Sway	Heave	Roll	Pitch	Yaw	Z Above Wave
Significant Amplitude	0.782 m	0.021 m	0.661 m	0.029 deg	1.020 deg	0.077 deg	1.198 m
3-Hour Max Amplitude	1.447 m	0.039 m	1.232 m	0.055 deg	1.910 deg	0.142 deg	2.297 m
Average Period	11.36 s	10.38 s	10.30 s	8.39 s	9.76 s	11.53 s	6.93 s
Velocity (Significant)	0.432 m/s	0.013 m/s	0.403 m/s	0.022 deg/s	0.657 deg/s	0.042 deg/s	1.096 m/s
Velocity (3-Hour Max)	0.805 m/s	0.024 m/s	0.755 m/s	0.042 deg/s	1.237 deg/s	0.079 deg/s	N/A
Acceleration (Significant)	0.257 m/s²	0.009 m/s²	0.263 m/s²	0.021 deg/s²	0.458 deg/s²	0.030 deg/s²	N/A
Acceleration (3-Hour Max)	0.483 m/s²	0.017 m/s²	0.496 m/s²	0.042 deg/s²	0.870 deg/s²	0.060 deg/s²	N/A

Hydrodynamic Performance

The motion response of the platform was assessed for six degrees of freedom (DOFs): surge, sway, heave, roll, pitch, and yaw. The results were obtained from Capytaine simulations and validated against empirical data from industry standards.

The platform’s Response Amplitude Operators (RAOs) were calculated across a range of wave frequencies, demonstrating a stable response in operational wave conditions. The platform exhibited low heave motion, indicating good vertical stability, which is critical for maintaining the structural integrity of cold-water intake systems.

Mooring System and Motion Response

The mooring system, designed using API RP 2SK and ISO 19901-7 guidelines, was analyzed to ensure platform stability in operational and extreme conditions. The results indicate:
Under operational conditions, maximum surge and sway amplitudes remained below 1.5 m, ensuring station-keeping stability.
During extreme storm conditions, the platform experienced increased motion, with peak heave responses of up to 2.3 m, which remained within the allowable design thresholds.

The mooring lines sustained maximum tensions of 3,900 kN, maintaining a safety factor of 1.28 according to API RP 2SK.

Comparison with Offshore Standards

The obtained results were cross-checked using LLM-assisted evaluation, comparing them to offshore engineering standards. The hydrodynamic behavior remained within acceptable limits for offshore floating platforms under similar environmental conditions.
The platform's roll response was effectively dampened, minimizing risks to onboard equipment.

Vertical motions (heave) were controlled within safe operational limits, ensuring that the platform remains functional during energy conversion processes.
The mooring system maintained compliance with international standards, with adequate safety margins for long-term operation.

6. Conclusion

LLM models can be a powerful tool for designing and verification & validation of Offshore Floating Systems. The results confirm that the floating platform is suitable for deployment in deep-water conditions, with a semi-submersible hull configuration offering superior motion stability. The integration of LLM-assisted control for automation and performance assessment further enhances the efficiency of the design.
Wave-induced motions remain within design tolerances, ensuring safe operation in offshore environments.Mooring forces are well-distributed, reducing excessive stress on anchor points.
Capytaine's hydrodynamic modeling provided reliable RAO estimations, supporting further optimization of platform configurations.

7. Acknowledgments

The authors would like to acknowledge the support from Laboratory of Waves and Currents (LOC) staff and financial support from Petrobras and Carlos Chagas Filho Foundation for Research Support of the State of Rio de Janeiro (Faperj).

8. References

[1] O. M. Faltinsen 'Sea Loads on Ships and Offshore Structures', Cambridge University Press, 1990.

[2] S. K. Chakrabarti 'Handbook of Offshore Engineering', Elsevier, 2005; ISBN: 9780080443812

[3] [Avery and Wu (1994)] Avery, W. H., & Wu, C. (1994). Renewable energy from the ocean: a guide to OTEC. Oxford University Press.

[4] Vaswani Ashish [et al.] Attention Is All You Need [Conferência] // NIPS'17: Proceedings of the 31st International Conference on Neural Information Processing Systems. - Long Beach, CA, USA : [s.n.], 2017.

[5] Liu Bohua [et al.] Application of Artificial intelligence in Computational fluid dynamics // Frontiers in Computing and Intelligent Systems. - October 2022

[6] Kim Taegu, Yun Tae Sup e Suh Hyoung Suk Can ChatGPT Implement Finite Element Models for Geotechnical Engineering Applications? International Journal for Numerical and Analytical Methods in Geomechanics. - February 2025.

[7] Capytaine Developers. Capytaine: An open-source Python-based BEM solver for wave-structure interactions. Available at: https://github.com/capytaine/capytaine

[8] McNeel & Associates. Rhinoceros 3D - NURBS Modeling for Windows. Available at: https://www.rhino3d.co