

Advances in Numerical Modeling of Coupled CFD Problems

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1. Modeling of Coupled CFD Problems: Modern Challenges

The development and application of numerical models to the simulation of coupled CFD problems has been the focus of research in various areas of science and engineering since the first decade of the 21st century. While major methods capable of dealing with the most common classes of coupled problems have been established, there remains a vast space for further research. The major modern challenge consists of simulating a given complex coupled problem to a necessary degree of detail (i.e., including all the necessary “ingredients”) while providing the requested results in a feasible time. The accurate, high-fidelity simulation of complex coupled problems using classical established schemes can be useful for academic purposes, but in many practical cases, the complexity and associated computational tediousness limit their significance. Thus, developing efficient approaches for solving coupled problems remains a challenge.

2. Major Coupled Problems in Marine/Ocean Engineering

Coupled problems in marine, ocean, and coastal engineering refer to the complex interactions between the different physical phenomena that occur in these environments. One can distinguish the following classes of problems:

- Fluid-structure interaction
- Sediment transport
- Water quality modeling
- Climate change modeling

One of the most crucial and complex topics in this field is the fluid–structure interaction involving waves, currents, and offshore structures. Waves and currents can exert significant forces on offshore structures, which can lead to structural deformation, damage and instability. Understanding the hydrodynamic–structure interaction is crucial for designing safe and efficient offshore structures [1–3].

The movement of sediments in the coastal zone is another important phenomenon in marine and coastal engineering. Waves, currents, and tides can transport sediment along the coast, leading to erosion and sediment deposition. The sediment transport process can be affected by changes in the coastal morphology, such as the presence of offshore structures and natural features such as sandbars and reefs, defining a complex coupled system. Water-quality modeling involves the prediction of the transport of pollutants and nutrients in the water column.

Climate change modeling addresses sea-level rises, changes in ocean temperature and acidity, and the higher frequency and severity of storms that can have significant impacts on coastal infrastructure.



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Overall, coupled problems in marine, ocean, and coastal engineering are complex and multidisciplinary, and require sophisticated numerical approaches for their robust and efficient modeling and simulation.

3. Fluid–Structure Interaction in Marine/Ocean Engineering

As already mentioned, the fluid–structure interaction is one of the most relevant coupled problems in the field of ocean/coastal engineering. Fluid–structure interaction problems are prevalent across many engineering disciplines such as coastal engineering [4], the design of offshore structures for renewable energy [5,6], and marine engineering [7].

Almost all offshore structures experience FSI as a result of exposure to flows such as winds, waves, and currents. In these applications, FSI studies may have one of two opposing goals: finding designs/strategies to reduce or enhance flow-induced structural motion. In recent decades, flow control and vibration-suppression have been suggested and thoroughly explored to reduce the detrimental effects and extend the service life of offshore structures. In contrast, a cutting-edge method for utilizing marine renewable energy is energy harvesting from flow-induced vibration (FIV) [8].

In such applications, computational FSI methods face specific challenges in view of the presence of typically violent fluid flows with large/abrupt hydrodynamic loads, and the resulting large structural responses. In the case of wave loads, flows present free surfaces.

In general, it is very costly to perform experimental studies of these FSI problems as they involve large domains and timespans, while the use of scaled physical modeling is rather limited, as it is often next to impossible to ensure dynamic similarity. Fortunately, advances in computing architecture and numerical schemes developed within the computational fluid dynamics (CFD) and computational solid mechanics (CSM) communities have enabled a more in-depth study of challenging problems involving FSI.

The numerical simulation of FSI is traditionally performed using mesh-based methods such as the finite element method (FEM) or finite volume method (FVM), which are enriched with numerical techniques, to consider the motion of the interfaces. Volume of fluid (VOF) [9] and level-set (LS) [10,11] methods are commonly used to capture the position of the free surface, while the immersed boundary method (IBM) [12] or the fictitious domain method (FDM) [13] are appropriate when the solid moves and deforms. Additionally, the boundary element method (BEM) has been used [14].

Spectral methods are numerical methods that represent the solution to a problem as a sum of sinusoidal functions. They can be used to solve wave propagation problems and are particularly useful for simulating long wave trains [15].

An alternative approach to mesh-based methods is the use of mesh-free/particle methods [16]. Examples include smoothed particle hydrodynamics (SPH) and the particle finite element method (PFEM). SPH have been used to model both fluid and solid media in [17] and, more recently, modified approaches have been presented in [18–20]. This was also coupled with FEM in several works [21–23]. Some researchers have coupled this method with DEM, which was used to model a solid body [24,25]. PFEM [26] was successfully applied to solve FSI problems involving free surface flows and elastic and rigid obstacles [27–29]. More recent advances can be found in the simulation of FSI [30] and free surface flows problems [31,32]. Some examples of the combination of the PFEM and the discrete element method (DEM) for the propagation of a tsunami wave in a hydraulic laboratory channel, its impact against a concrete wall and the breakage of the solid structure [33,34]. PFEM was applied to coastal engineering problems in [35] and bridges exposed to tsunami loads [36].

Despite the advances in the solution of the above-mentioned problems using mesh-based or particle methods, there is an increasing interest in real-time simulations, which can be facilitated by machine learning and other data-driven techniques.

4. Machine Learning Capabilities

In the last decade, modern deep-learning approaches have gained importance in various engineering applications. This is mainly due to their ability to extract features from large amounts of data, which can be utilized to reduce the computational time required for numerical (real-time) engineering simulations by developing surrogate or accelerated models. For large and/or complex systems, traditional simulation techniques, such as the finite element and finite volume methods, require intensive computations, as mentioned above. Surrogate machine-learning-based models are simplified models that are pre-trained to approximate the behavior of the original model. Deep learning models, such as neural networks (NNs), can be used to create surrogate models that are capable of accurately predicting the nonlinear behavior of the original systems while requiring far less computational resources [37,38].

For example, in the field of coastal and marine engineering, the convolutional neural networks (CNNs) can be used to predict wave run-up on coastal structures. Wave run-up is the vertical distance that waves travel up a structure above still water level, and is an important parameter to consider when designing coastal structures such as breakwaters and seawalls. Traditional methods for predicting wave run-up involve solving coupled nonlinear partial differential equations subject to boundary conditions according to the characteristics of the structure [39]. This leads to computationally intensive and time-consuming simulations. In recent years, the CNN-based surrogate models have been trained on large datasets of wave and structure characteristics and corresponding wave run-up values [40]. The successfully trained model can then be used to quickly predict wave run-up for new wave conditions and structures. The computational efficiency of such models potentially opens a new horizon for the optimization of coastal structure designs and improvements in coastal hazard assessments.

In a more general case, NNs are attractive tools for wave forecasting; accurate NN-based models have recently been developed and trained to forecast wave heights and wave periods. These models provide a correlation between the wave characteristics and various input parameters such as wind speed and direction, and ambient temperature. Another application for deep learning approaches is the prediction of coastal erosion, which is a major problem in coastal regions. Deep learning models can predict the rate of erosion as a function of various input parameters, such as wave energy, sediment transport, and sea level rise [41]. Moreover, deep learning techniques can be developed and trained to accelerate the computational fluid dynamics (CFD) schemes; for example, by (roughly) predicting the flow field variables based on the initial and boundary conditions of the system.

Nonetheless, these are only a few marine and coastal engineering applications for deep learning and, considering the promising initial results, the use of deep learning approaches is expected to continue growing in the future.

5. Scope of the Present Special Issue

The current Special Issue will present novel strategies for the analysis of multi-floating bodies, a data-driven approach (reduced-order modeling) to the fluid–structure interactions of floating platforms and an innovative algorithm for virtual wave generation, among others. We aim to show that there are still numerous ways of improving the existing computational strategies to achieve robust and efficient simulations of coupled problems.

This Special Issue welcomes both works reporting advances in numerical methods relevant to the above-mentioned areas of coupled CFD as well as simulations of real-life problems revealing important physical insights. The issue is not restricted to fluid–structure interactions, but also aims to present advances in other coupled problems, such as free-surface flows and liquid–gas (multiphase) problems. Innovative solution algorithms, including data-driven approaches and HPC-oriented implementations, are particularly welcome.

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